Developing Hybrid Intelligent Methods to Manage Systemic Risks in the Integration of Smart Wearables in Manufacturing

by

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Développement de méthodes hybrides intelligentes pour la gestion des risques systémiques liés à l'intégration des dispositifs portables intelligents dans la fabrication

Ali KAREVAN

RÉSUMÉ

L'intégration croissante des dispositifs portables intelligents, tels que les lunettes et les gants connectés, dans les systèmes de production modernes promet des avancées en matière de guidage des opérateurs, d'ergonomie et de suivi en temps réel. Toutefois, ces technologies introduisent également de nouveaux risques systémiques que les méthodes traditionnelles de gestion des risques peinent à anticiper et à évaluer. Des approches systémiques avancées, telles que STAMP–STPA et FRAM, rendent mieux compte de la complexité des systèmes sociotechniques, mais demeurent encore largement qualitatives.

Cette thèse développe et valide trois méthodes hybrides combinant des modèles de risque systémique avec l'optimisation par essaims particulaires (PSO), afin de renforcer l'évaluation quantitative et les stratégies de mitigation. Premièrement, le cadre STPA–PSO étend l'Analyse des Processus Systémiques (STPA) en quantifiant les actions de contrôle et en appuyant des stratégies semi-automatisées de réduction des risques. Deuxièmement, le cadre FRAM–PSO intègre la Méthode de Résonance Fonctionnelle (FRAM) à PSO pour modéliser la variabilité des performances et, pour la première fois, inclure les dimensions de durabilité — économique, environnementale et sociale — dans la mitigation des risques systémiques. Troisièmement, le cadre BN–PSO utilise les réseaux bayésiens, optimisés par PSO, afin de représenter les dépendances probabilistes entre actions de contrôle, aléas et pertes, permettant ainsi une quantification systémique des risques fondée sur les parcours de risques ainsi qu'une analyse de sensibilité.

Ces cadres méthodologiques ont été mis en oeuvre dans trois études de cas portant sur une ligne d'assemblage, un atelier , et un processus de désassemblage, avec un focus particulier sur l'introduction et l'intégration de dispositifs portables intelligents multiples. Les résultats mettent en évidence trois constats majeurs : (1) l'usage combiné des lunettes et des gants intelligents génère de nouveaux couplages et interdépendances qui reconfigurent le portrait des risques ; (2) les trois cadres hybrides présentent des forces complémentaires — STPA–PSO se prête aux phases de conception , FRAM–PSO à l'évaluation de la variabilité et de la durabilité aux phases d'opérations, et STPA-BN–PSO permet un suivi opérationnel des risques ; et (3) l'intégration des principes de durabilité permet non seulement une réduction mesurable des risques systémiques, mais aussi une mise en cohérence avec les objectifs industriels et sociétaux plus larges.

En résumé, cette recherche fait progresser l'évaluation des risques en hybridant les modèles systémiques avec une optimisation méta-heuristique. Elle démontre que les approches qualitatives et quantitatives peuvent être judicieusement combinées. Ce travail enrichit les méthodes systémiques existantes par de nouveaux cadres hybrides, il illustre l'applicabilité au moyen d'études de cas impliquant plusieurs dispositifs portables, et offre aux décideurs des méthodes pratiques pour parvenir à une production plus sûre, plus durable et centrée sur l'humain. À travers cette contribution, la thèse s'inscrit pleinement dans les principes de l'Industrie 5.0, en soulignant la complémentarité entre l'humain et les technologies intelligentes dans la construction de systèmes sociotechniques résilients pour l'avenir.

Mots-clés: Industrie 5.0; Gestion des risques; Dispositifs portables intelligents; Durabilité; FRAM; STPA; Réseaux bayésiens; PSO; Fabrication hybride

Developing hybrid intelligent methods to manage systemic risks in the integration of smart wearables in manufacturing

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ABSTRACT

The increasing integration of smart wearables, such as smart glasses and smart gloves, into modern manufacturing systems promises benefits in worker guidance, ergonomics, and real-time monitoring. However, these technologies also introduce new systemic risks that traditional risk management methods struggle to capture. Advanced systemic approaches such as STAMP–STPA, and FRAM more accurately capture the complexity of socio-technical systems; however, they remain predominantly qualitative.

This dissertation develops and validates three hybrid methods that combine systemic risk models with Particle Swarm Optimization (PSO) to enhance quantitative assessment and mitigation. First, the STPA–PSO framework extends System-Theoretic Process Analysis by quantifying control actions and supporting semi-automated mitigation strategies. Second, the FRAM–PSO framework integrates the Functional Resonance Analysis Method with PSO to model performance variability and, for the first time, embeds sustainability dimensions—economic, environmental, and social—into systemic risk mitigation. Third, the STPA-BN–PSO framework applies Bayesian Networks optimized with PSO to capture probabilistic dependencies among control actions, hazards, and losses, enabling path-based systemic risk quantification and sensitivity analysis.

These frameworks were applied to three case studies in sequential assembly, job-shop assembly, and disassembly, with a focus on the introduction and integration of multiple smart wearables. The results highlight three main findings: (1) the combined use of smart glasses and smart gloves creates new couplings and dependencies that reshape the risk landscape; (2) the three hybrid frameworks provide complementary strengths—with STPA–PSO suited to early design, FRAM–PSO to variability and sustainability evaluation, and STPA-BN–PSO to operational risk monitoring; and (3) embedding sustainability principles enables not only measurable reductions in systemic risk but also alignment with broader industrial and societal objectives.

In summary, this research advances the state of risk assessment by hybridizing systemic models with metaheuristic optimization. This shows that qualitative and quantitative approaches can be meaningfully combined. The work extends existing systemic methods with new hybrid frameworks and demonstrates their applicability through case studies involving multiple wearables, and provides decision-makers with practical methods to achieve safer, more sustainable, and human-centered manufacturing. Through this contribution, the thesis advances the principles of Industry 5.0, emphasizing the complementary roles of humans and intelligent technologies in shaping resilient socio-technical systems of the future.

Keywords: Industry 5.0; Risk management; Smart wearables; Sustainability; FRAM; STPA; BN; PSO; Hybrid manufacturing

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LIST OF ABREVIATIONS AND ACRONYMS

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
AR	Augmented Reality
ATHEANA	A Technique for Human Error Analysis
BN	Bayesian Network
BWM	Best Worst Method
CA	Control Action
CAST	Causal Analysis based on STAMP
CPT	Conditional Probability Table
CREAM	Cognitive Reliability Error Analysis Method
DAG	Directed Acyclic Graph
DBN	Dynamic Bayesian Network
DoF	Degrees of Freedom
DR	Diminished Reality
ELECTRE	ELimination Et Choix Traduisant la REalité
ETA	Event Tree Analysis
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
FMV	FRAM Model Visualizer
FRAM	Functional Resonance Analysis Method
FTA	Fault Tree Analysis
GA	Genetic Algorithm
HEART	Human Error Assessment and Reduction Technique
HEP	Human Error Probability
HMI	Human-Machine Interface
HRA	Human Reliability Analysis

HRC	Human-Robot Collaboration
HUTEC	Human error probability estimation through TH simulation with exhaustive conditions
IoT	Internet of Things
MCS	Monte Carlo Simulation
OHS	Occupational Health and Safety
PDLC	Polymer Dispersed Liquid Crystal
PRA	Probabilistic Risk Assessment
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
RAG	Resilience Assessment Grid
RCA	Root-Cause Analysis
SHERPA	Systematic Human Error Reduction and Prediction Approach
SI	Swarm Intelligence
SLIM	Successive Likelihood Index Method
SPAR-H	Standardized Plant Analysis Risk-Human Reliability Analysis
SPC	Scenario Performance Condition
STAMP	Systems Theoretic Accident Model and Processes
STPA	System Theoretic Process Analysis
THERP	Technique for Human Error Rate Prediction
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UCA	Unsafe Control Action
VPN	Variability Propagation Number
VR	Virtual Reality
WOS	Web of Science

INTRODUCTION

Manufacturing has always been central to economic development, but it is also one of the most risk-sensitive domains. Despite advances in automation and digitalization, human reliability remains a decisive factor in determining safety, productivity, and quality. Research shows that between 50% and 90% of industrial incidents are caused by human error (Castiglia & Giardina, 2013), which often stems from weaknesses in task and tool design that are intended to support human work. These errors, ranging from misinterpretation of instructions to inappropriate decision-making, not only increase operational costs but also compromise worker well-being and system resilience (Mannan, 2013; S. Singh & Kumar, 2015).

The last decade has been marked by the adoption of Industry 4.0 technologies, including IoT, cyber-physical systems, and big data analytics, all intended to reduce human intervention and improve system efficiency (de Paula Ferreira, Armellini, & De Santa-Eulalia, 2020; Jasiulewicz-Kaczmarek & Gola, 2019). However, while Industry 4.0 delivered productivity gains, it often overlooked the human dimension, leading to ergonomic and cognitive burdens when humans interacted with highly automated systems (Angelopoulou, Mykoniatis, & Boyapati, 2020). This limitation has motivated the shift toward Industry 5.0, which emphasizes human–machine collaboration, sustainability, and worker well-being (Adel, 2022; Nahavandi, 2019; Reiman, Kaivo-oja, Parviainen, Takala, & Lauraeus, 2021).

One of the most visible manifestations of this new paradigm is the introduction of smart wearables into industrial contexts. Devices such as smart glasses and smart gloves allow operators to receive real-time instructions, capture and share data, and interact seamlessly with digital systems while keeping their hands free (Krzywdzinski, Pfeiffer, Evers, & Gerber, 2022; Nadeau, Bruder, & Hof, 2021). When multiple wearables are integrated within the same process—for example, using smart glasses for visual guidance while using smart gloves for hand-motion tracking in assembly or disassembly—new opportunities arise for error reduction, training support, and productivity improvements. At the same time, however, this integration also introduces new risks: increased cognitive load, data security vulnerabilities, ergonomic strain, and complex dependencies between human, technological, and organizational factors (Coccia et al., 2024; Digiesi, Facchini, Mossa, & Vitti, 2023).

Traditional risk analysis techniques, such as FMEA, FTA, and PRA, remain widely used but assume linear cause and effect relations and are poorly suited for modeling variability and interdependencies (Stamatelatos et al., 2011). Also, these techniques work by decomposing the system, which is not possible in the case of complex systems (Melanson & Nadeau, 2019). Systemic approaches such as STAMP–STPA (Leveson, 2004) and FRAM (Hollnagel & Goteman, 2004) better capture emergent properties and dynamic interactions, but they are qualitative (Patriarca, Di Gravio, & Costantino, 2017). From another perspective, Bayesian Networks (BN) provide a probabilistic framework for uncertainty (Pearl, 1985), yet their effectiveness depends on accurate parameterization, which is difficult in real industrial settings.

This highlights a gap: the lack of hybrid methods that combine qualitative systemic insight with quantitative rigor to evaluate the risks of integrating multiple wearables in complex socio-technical manufacturing systems. To address this gap, this thesis develops three hybrid frameworks that combine systemic safety approaches with PSO, a metaheuristic optimization algorithm (Jain, Saihjpal, Singh, & Singh, 2022; Talbi, 2009):

- STPA–PSO: extends System-Theoretic Process Analysis by quantifying unsafe control actions associated with smart wearables.
- FRAM–PSO: integrates the Functional Resonance Analysis Method with PSO to model performance variability and design sustainability-oriented mitigation strategies for wearable-enabled systems.
- BN–PSO: applies Bayesian Networks optimized via PSO to capture probabilistic dependencies between control actions, hazards, and losses in systems where multiple wearables interact during assembly and disassembly.

This thesis makes four main contributions. First, it introduces a set of hybrid risk-assessment frameworks that integrate qualitative and quantitative methods. Second, it demonstrates how the simultaneous use of multiple wearables changes the risk landscape, requiring new modeling approaches. Third, it incorporates sustainability considerations—economic, social, and environmental—into risk mitigation. Finally, it validates the proposed methods through case studies in sequential assembly, job-shop assembly, and disassembly, showing that hybrid approaches can assess and analyze systemic risks while providing actionable mitigation strategies for decision-makers.

The remainder of this thesis is organized as follows. Chapter 1 provides an introduction on industrial revolutions, complexity, risk, metaheuristic algorithms, and the review of the literature. Chapter 2 defines the research problem, objectives, case studies, and methodology. Chapter 3 develops the STPA–PSO framework for smart glasses in assembly. Chapter 4 extends the framework to hybrid assembly/disassembly systems involving both smart glasses and smart gloves. Chapter 5 presents the FRAM–PSO framework, emphasizing variability propagation and sustainability-driven mitigation. Chapter 6 develops the BN–PSO framework to capture systemic risk propagation when multiple wearables are integrated. Finally, the thesis concludes with a synthesis of findings, overall contributions, and recommendations for research and practice.

CHAPTER 1

CRITICAL REVIEW OF LITERATURE

This chapter provides a structured review of the literature that frames the central themes of this research. It is organized into five sections:

- **Industrial revolutions**: an overview of advancements from Industry 4.0 to Industry 5.0, with particular attention to the role of wearables in manufacturing.
- **Complexity**: definitions and distinctions between simple systems, complex systems, and sociotechnical systems.
- **Risk**: a discussion of industrial and occupational health and safety risks, with emphasis on human error in manufacturing and methods for quantifying such risks.
- **Meta-heuristic algorithms**: an introduction to optimization approaches relevant to complex problem-solving.
- **Review of the literature**: an explanation of the process used to identify relevant references, along with a summary of the key findings.

1.1 Industrial revolutions

Manufacturing is the basis of the economy of most countries (Friedmann, 1978). The first industrial revolution of 1784 highlighted the importance of industry worldwide. Following that, the number of workshops and production factories continued to grow, as did the number of employees in different categories. During the second industrial revolution, which took place about a century after the first one, mass production flourished with assembly lines helping to speed up production (Popkova, Ragulina, & Bogoviz, 2019; Pozdnyakova, Golikov, Peters, & Morozova, 2019). It then took another century for computers and peripheral devices to be developed, which not only accelerated production lines but also improved accuracy (M. C. Jensen, 1993).

1.1.1 Industry 4.0

As part of Germany's long-term strategy to improve its competitiveness in manufacturing, Industry 4.0 was introduced at the Hannover Fair in 2011 (de Paula Ferreira et al., 2020). The concept of Industry 4.0 aims to make manufacturing systems more adaptable to design changes and better able to support employee training (B. He & Bai, 2021). In many cases, Industry 4.0 is described as a design framework supported by enabling technologies that help companies execute their manufacturing and operational strategies (de Paula Ferreira et al., 2020). By reducing development and innovation cycles, individualizing demand, and maximizing resource efficiency, Industry 4.0 was born and is driven by technological innovations, including the IoT, big data, artificial intelligence, collaborative robots, and simulation, which have allowed us to advance and access information, communication, and automation (de Paula Ferreira, Armellini, de Santa-Eulalia, & Thomasset-Laperrière, 2022). Artificial Intelligence (AI) has become popular during the last decade because using it improves the reliability, resilience, and quality of the product (Kutz, Neuhüttler, Spilski, & Lachmann, 2022). The main enabling technologies of Industry 4.0 are shown in Figure 1.1.

The Internet of Things (IoT) can be regarded as a fundamental cornerstone of Industry 4.0, as it has the capability to gather data from the environment and facilitate communication with other objects. This versatility allows IoT to find applications across various industries, tailored to their specific requirements (Mofidi Naeini & Nadeau, 2022b). In manufacturing, IoT refers to the network of sensors linked to outputs, inputs, components, materials, or tools, enabling seamless connectivity and data exchange (Riso, 2021). When IoT is integrated into factory processes, manufacturers can reduce reliance on human decision-making and transform their facilities into smart factories characterized by high levels of connectivity and digitalization (Riso, 2021).

Designing a workplace that considers both the physical and cognitive requirements of workers is important. Achieving an appropriate balance between human and machine elements in the work environment is necessary for performance and well-being(Alogla & Alruqi, 2021). Effective organizations treat OHS as a core component of success, alongside quality, productivity, and cost reduction (Badri, Boudreau-Trudel, & Souissi, 2018). Sustained profitability and growth can be supported through the development of ergonomics and health and safety initiatives (Nadeau, 2005).

Despite advancements in Industry 4.0, accidents caused by unsafe acts or human error may still occur, leading to delivery delays and product failures (Angelopoulou et al., 2020). This highlights the importance of appropriate technology selection and deployment, particularly with respect to utility, usability, risk, and practicality (Nadeau & Landeau, 2018; Torres, Nadeau, & Landau, 2021b).

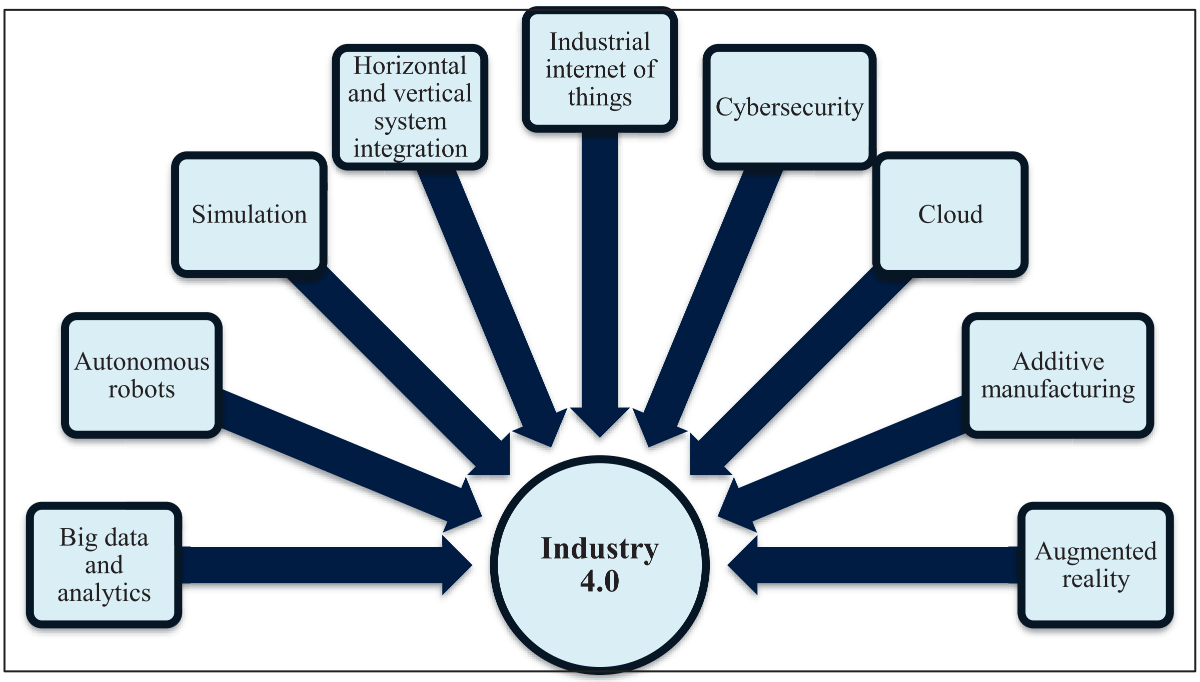

Figure 1.1 Industry 4.0 main enabling technologies

Machine learning and artificial intelligence can outperform humans in specific, well-defined tasks and enable a certain level of product personalization. However, they still lack the flexibility and adaptability of human intelligence, which makes human intervention essential for achieving true personalization in Industry 4.0 (Selvaraj, 2019). A large number of research efforts seek to enhance performance through smarter technologies, but the human element does not seem to be adequately considered in Industry 4.0 processes. In much of the Industry 4.0 literature, humans are often positioned primarily as end-users or consumers rather than active participants in production processes. The human factor is largely neglected during the design phase of systems, according to various studies (Angelopoulou et al., 2020). The human operator must be provided with adequate skills so that he or she can master and sustain the transition towards Industry 4.0 (Angelopoulou et al., 2020).

1.1.2 Industry 5.0

The fifth industrial revolution strives to reintegrate humans into production by combining human intelligence and creativity with precise, efficient machines (I. Sharma, Garg, & Kiran, 2020). The European Commission formally established Industry 5.0 in 2021 (Adel, 2022), emphasizing human-machine collaboration (Raya, 2022).

A fundamental concept of this new paradigm is the notion that humans can harness their innovation and knowledge alongside the productivity and speed of execution offered by machines and equipment, including collaborative robots, to achieve the most efficient results. By using robots, humans can enhance the efficiency of their most valuable tasks and responsibilities, ultimately improving safety, productivity, and overall performance (Gaiardelli, Spellini, Lora, & Fummi, 2021).

According to ISO 10218, human–robot collaboration refers to robot operation in which humans and robots share a workspace under defined safety conditions, enabling various forms of concurrent or sequential interactions without full physical separation (ISO, 2025). Below are four ways humans and robots can collaborate (Raya, 2022):

- Humans and robots perform their tasks concurrently on the same part.
- Both robots and humans work sequentially on the same part.
- Despite sharing the same workspace, the robot performs different functions from a human.
- Occasionally, the robot and the human approach each other but work independently.

Through the delegation of repetitive tasks to robots, Industry 5.0 can enhance production quality by enabling humans to focus on critical and creative tasks (Maddikunta et al., 2022). This paradigm supports industrial sustainability by addressing not only economic objectives but also the central role of human workers in production processes. In addition, Industry 5.0

promotes environmental sustainability through the use of renewable energy sources and waste reduction practices (Javaid & Haleem, 2020; Xu, Lu, Vogel-Heuser, & Wang, 2021). The key challenges associated with Industry 5.0 are summarized in Figure 1.3.

Figure 1.2 Core values in Industry 5.0
Taken from Xu et al. (2021, p. 4)

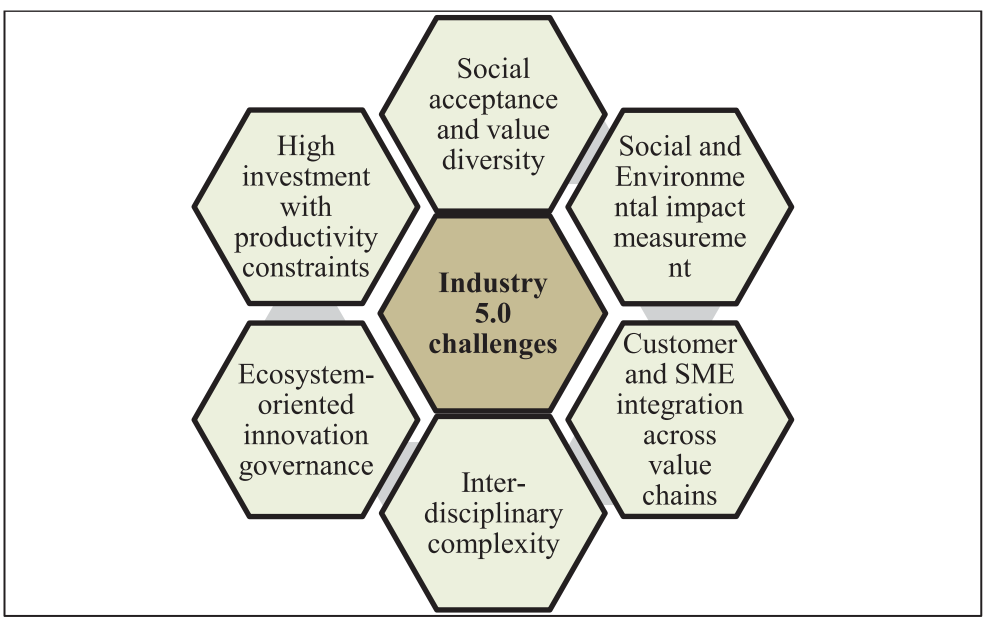

Figure 1.3 Industry 5.0 challenges

The main characteristics of Industry 4.0 and Industry 5.0 are summarized in Table 1.1.

Table 1.1 Main characteristics of I4.0 and I5.0

Dimension	**Industry 4.0**	**Industry 5.0**
Introduction	2011	2021
Main objective	Maximize productivity and efficiency through digital technologies	Combine human creativity with intelligent, precise machines for human-centric and sustainable production
Production approach	Mass customization	Mass personalization
Role of humans	Focus on automation and reduced human intervention	Revive human role through collaboration with machines
Orientation	Technology-driven	Value-driven
Environmental Focus	Environmental considerations not a primary focus	Promote sustainable and eco-friendly solutions
Key technologies	Automation, data exchange, and smart systems	Integration of humans and machines in production
Worker well-being	Limited emphasis on worker well-being	Prioritize well-being and safety
Economic impact	Enhance productivity through intelligent devices	Foster skilled job creation via human-machine collaboration
Human–technology relationship	Humans adapt to increasingly automated systems	Technology serves human needs

1.1.3 Wearables

Electronic monitoring systems and wearable devices are integral components within the IoT. These devices serve multiple functions, including the monitoring of work processes and employee performance, which, in turn, informs management decisions (Riso, 2021). The IoT finds application across various fields and products, with wearables being a notable example (Mofidi Naeini, 2022; Mofidi Naeini & Nadeau, 2022a). Additionally, applications developed for mobile operating systems (OS) can extend their functionality to wearable devices, offering features beyond health and fashion (D. Kim & Choi, 2021).

Wearable devices transmit, process, and detect signals (electrical or optical) and are designed to be attached to users and must be easy to use and comfortable (Tao, 2005). Researchers have found that the weight and positioning of wearable computers affect the comfort of users. Comfort also includes psychological responses such as embarrassment or anxiety caused by wearing the device. Also, wearable systems may cause awkwardness, leading users to consciously adjust their movements (Knight & Baber, 2007).

With sensors controlling various parameters, the IoT can decrease the risk of injury and hazards in the workplace, contributing to a healthier work environment (Riso, 2021). Wearables can range from small wrist-mounted devices to larger backpack computers (Billinghurst & Starner, 1999). It is possible to use wearable electronics as sensors or as computers with input, output, and a motherboard that includes transistors (Tao, 2005). They provide managers with real-time operational data (Krzywdzinski et al., 2022). Wearables have applications in the following sectors (Tao, 2005):

- Information and communications
- Healthcare and medical applications
- Fashion, leisure, and home applications
- Military and industrial applications

Wearable computers should be mobile, and provide context-sensitive information (Billinghurst & Starner, 1999). Using wearables equipped with IoT sensors in manufacturing or healthcare can trigger automated alerts in the event of hazardous conditions (Riso, 2021). Despite the potential of wearable technology in the manufacturing industry, the challenge remains how to properly incorporate these devices into manufacturing systems to improve productivity (Hao & Helo, 2017). Economic, social, and cultural effects are associated with wearable technology (Tao, 2005). In a report by (Krzywdzinski et al., 2022), several wearing scenarios are listed below:

- Picking: Wearable systems can support order picking by displaying task-relevant information and enabling item or order confirmation.
- Worker guidance in production: Wearable devices can assist workers by guiding and verifying assembly or production sequences..
- Remote maintenance: Wearables enable remote support by allowing experts to observe equipment and provide guidance through real-time communication.
- Maintenance and servicing: Wearable technologies can support maintenance activities by guiding inspection steps, sequencing tasks, and verifying task completion.
- Training: Wearable systems can assist training by monitoring task execution and providing feedback to support skill development and error detection.
- Occupational safety, ergonomics: Wearables can support safety and ergonomics by monitoring worker actions and providing warnings related to hazards or ergonomic risks.

Connecting manufacturing resources to IoT allows for comprehensive monitoring and streamlining of the entire production process. Wearable devices play a pivotal role in augmenting and extending the capabilities of IoT within industrial settings (Hao & Helo, 2017). The primary aim of incorporating wearable technology in the workplace is to equip employees with context-specific information, empowering them to optimize their performance while also gathering and transmitting data to the company's IT systems. Wearable devices serve as interfaces that provide employees with relevant information, thereby supporting task execution (Krzywdzinski et al., 2022). The IoT is characterized by the presence of wearable technologies, associated with an estimated 8.5% increase in employee productivity and a 3.5% improvement in quality of life and job satisfaction (Hao & Helo, 2017; Nadeau et al., 2021).

However, introducing wearables into complex socio-technical systems also creates novel failure modes and dependencies, motivating a formal analysis of risk (Section 1.3)

1.1.3.1 Smart glasses

Smart glasses are wearable devices that allow users to connect to computing facilities and clients to handle complex tasks with ease (N. M. Kumar, Singh, & Peddiny, 2018). As well as displaying visual information (such as text messages, videos, and pictures), smart glasses also provide audio content and positional information in real-time and run mobile applications (Nadeau et al., 2021). Different frameworks exist for altering how a wearer perceives visual information (Schweizer, 2014):

- Virtual reality (VR): In this scenario, the user sees only the virtual world; external light sources do not affect the user's vision.
- Augmented reality (AR): Using a computing device and an additional light source, the user can see the world as it is, while also perceiving virtual content generated by the device.
- Diminished reality (DR): This technique is used to remove objects from scenes by filtering the light reflected or emitted by those objects. Augmented reality is often used in combination with this technique to replace diminished objects with virtual ones.

Smart glasses interact with their users through a touch button or a natural language command processing system reliant on voice recognition. These glasses capture real-time images and videos of the surroundings through a camera situated on the front of the device (D. Kim & Choi, 2021). Smart glasses are utilized in several areas of business, including managing field services, assembly, and remote technical support, as well as navigation and mapping (Hao & Helo, 2017). A few features of smart glasses are as follows (N. M. Kumar et al., 2018):

- Location identification
- Image capturing
- Information storage
- Video and voice recording
- AR, VR & MR
- Voice command to text
- Report generation

In remote collaborative work contexts where workers must be highly mobile, while both hands are busy, or when they must work simultaneously or asynchronously, smart glasses can be useful (Nadeau et al., 2021). Smart glasses enable the monitoring station or controlling station to receive data from the work site (N. M. Kumar et al., 2018).

The use of smart glasses in industrial settings requires timely and accurate feedback to the worker, ensuring error reduction, operational flexibility, durability, and usability (Nadeau et al., 2021). Smart glasses come in three forms: electrochromic, suspended particle, and PDLC. Each type has its own principle, advantages, and disadvantages (Wong & Chan, 2014). When designing and fabricating smart glasses, the following design factors need to be taken into consideration: aesthetic appearance, battery life, compatibility, compactness, data security, design frame, durability, dust resistance, ergonomics, field view, hands-free, powering, privacy, reliability, voice control, weight, and water resistance (N. M. Kumar et al., 2018).

There are three components of smart glasses: 1) a head-mounted display for presenting data from a background information system, 2) a wearable computer for processing and computing power, and 3) multiple sensors for capturing data (Nadeau et al., 2021). It is also possible to use smart glasses in conjunction with traditional tools or equipment, as well as with other smart devices, and automate some processes with smart glasses (Nadeau et al., 2021).

Various parameters need to be considered when a company or an individual wants to buy data glasses, such as: price, weight, field of view, battery life, optics, camera, open API, audio, sensors, controls, processors, storage, memory, connectivity, operating system, durable against dust and water (Syberfeldt, Danielsson, & Gustavsson, 2017; Valdesse Eko'olaa & Nadeau, 2025).

Application of smart glasses

In recent years, smart glasses have gained popularity in a wide range of sectors, finding their application and scope to solve real-time problems. Below are a few applications that have been explored:

1. **Aerospace and Avionics:** With smart glasses, one can give virtual instructions. This allows sophisticated, nano, and micro level operation and maintenance (N. M. Kumar et al., 2018). The technology has already been applied to some commercial jets flying

at various altitudes and with varying degrees of sunlight exposure (Wong & Chan, 2014).

2. **Health Care and Medical:** Medical institutions are developing technologies to assist workers using smart glasses, disability support technologies to assist disabled people, and therapy that supports treatment (D. Kim & Choi, 2021).
3. **Automotive industry:** Smart glasses and head-up display technologies are increasingly applied in automotive contexts, including mirrors and windshields. The large glass surface area of vehicles facilitates their integration, with potential benefits for driver safety and awareness (Wong & Chan, 2014).
4. **Manufacturing:** Work support, maintenance, and safety are included in the industry field (D. Kim & Choi, 2021).
5. **Productivity:** It might be possible to track employees' eye movements using smart glasses and analyze that data to figure out if they are overworked and need a break or if they have run out of work (Schweizer, 2014).
6. **Education:** Several studies have examined the use of smart glasses in educational settings. Smart glasses can support learning by enabling remote monitoring of procedures and facilitating immersive learning experiences through virtual or augmented reality (Wrzesińska, 2015).
7. **Entertainment:** Smart glasses can be used in cinema environments to enhance 3D viewing experiences and provide personalized subtitles in the viewer's chosen language (Schweizer, 2014).
8. **Remote Control Operations:** It is possible to enable remote control operations (e.g. maintenance) with smart glasses in many sectors. These special features can include voice-activated commands, report generation, visual imagination, and location detection, among others (N. M. Kumar et al., 2018).

1.1.3.2 Smart glove

Throughout our everyday lives, we interact with our environment and manipulate it in countless ways. Consequently, it is not surprising that much research effort has been dedicated to developing technologies that study interaction and manipulation as well as augment our ability to perform these activities. One of the commonly used wearables is the smart glove. Smart gloves are equipped with sensors (magnetic, optic, ultrasonic, and inertial). Over the past 40 years, smart gloves have been developed to enhance human-computer interaction (Caeiro-Rodríguez, Otero-González, Mikic-Fonte, & Llamas-Nistal, 2021). They are sensor-equipped gloves designed to track finger movements as well as provide proprioception and haptic feedback (Mofidi Naeini & Nadeau, 2022a). A growing number of researchers are interested in the development of glove-based systems for capturing hand movements in recent years (Dipietro, Sabatini, & Dario, 2008).

As a commonly used wearable textile item in everyday life, most of the time, gloves are comfortable to wear and match the brain's operation logic, making them perfect carriers for realizing posture recognition (Xia, Li, Duan, Lei, & Wu, 2022). These devices have been referred to by many different names: “cyber gloves”, “data gloves”, “force-feedback gloves”, “glove-based systems”, “haptic gloves”, “sensory gloves”, “smart gloves”, “virtual gloves”, and “VR gloves” (Caeiro-Rodríguez et al., 2021). These gloves can be used in conjunction with hand tracking devices and provide haptic feedback (Mofidi Naeini & Nadeau, 2022a). Smart gloves enhance immersion, embodiment, and presence in virtual/mixed realities (Caeiro-Rodríguez et al., 2021).

Touching and manipulating virtual objects with smart gloves is intended to be more intuitive and direct. Aside from providing sensitive stimuli that the human hands can perceive, they also provide kinesthetic and tactile feedback that replicates touching and manipulating objects (Caeiro-Rodríguez et al., 2021). It is very useful to receive feedback in the manufacturing process (Mofidi Naeini, 2022). To operate smart gloves, it is necessary to understand the anatomy and physiology of the human hand (Djefour, Nadeau, & Landau, 2024). Degrees of freedom (DoF) describe the basic movements that the hand and fingers can perform (Caeiro-Rodríguez et al., 2021). A number of factors should be considered when choosing smart gloves, and Figure 1.4 shows these factors.

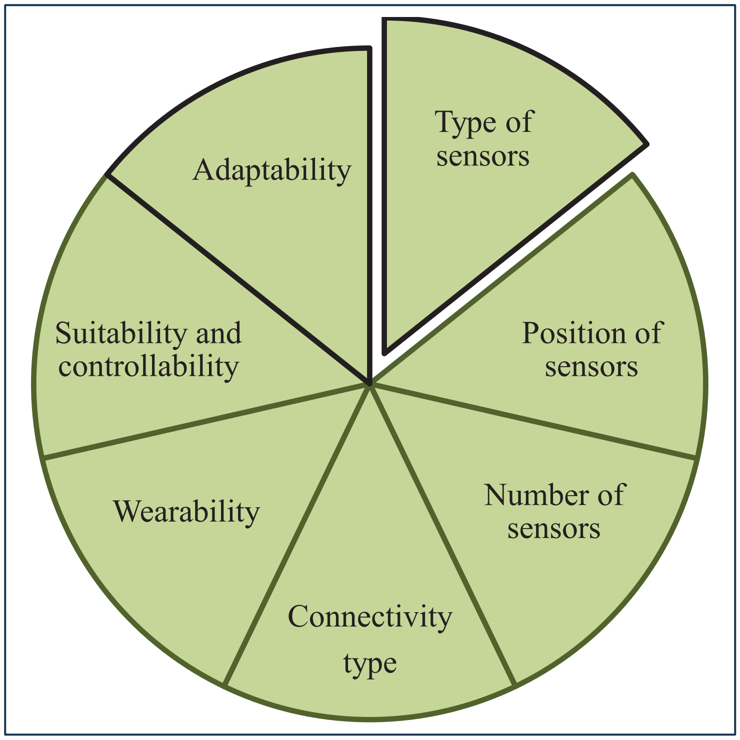

Figure 1.4 Important factors in choosing data gloves

Smart gloves for commercial use can be classified as follows (Caeiro-Rodríguez et al., 2021):

- Exoskeleton: The string or rigid links attached to the fingers provide kinesthetic feedback to the hands through this structure located at the back of the hand.
- Fabric: There are sensors and actuators integrated into the fabric to execute the desired function for the hand and fingers.
- Strips of fabric, plastic, or other materials: Fingers and hands are not completely covered by smart gloves. In this type of glove, the sensors and actuators are located in the fabric, plastic, or other materials, making them easier to fit to different finger shapes and forms.
- Open fingertips: Open fingertips are a feature of some smart gloves that facilitate the use of touch screens and other activities that require finger sensitivity. They can in addition, facilitate a better glove fitting.

A growing demand for smart gloves in manufacturing makes it necessary to consider the associated risks of the use of a data glove while introducing it into a system, as well as the interaction it may have with other system components (Mofidi Naeini & Nadeau, 2022a).

A smart glove's usability is influenced by ergonomics and wearability concepts. Key usability features include (Caeiro-Rodríguez et al., 2021):

- Easy to wear
- Easily adjustable
- Allow users to perform their activities without restriction or limitation
- Reduce user fatigue
- Lightweight
- Despite the failure of the system, the user should not be injured.
- Wireless

Application of smart gloves

Smart gloves are used in various industries with different approaches. The following summarizes key application areas.

1. **Medicine & remote healthcare:** Smart gloves have been used in medical and remote healthcare applications, where they may be worn by patients or clinicians to assess fatigue and monitor hand tremors associated with Parkinson's disease (Mofidi Naeini & Nadeau, 2022a).
2. **Ergonomics:** Aside from motion analysis, gloves can also be used to optimize products, tasks, or environments through hand movement recordings (Dipietro et al., 2008).
3. **Motion capture:** As one of the main applications of motion capture, the gloves are designed to capture movements for the purpose of entertainment. In recent years, this type of capture has been extensively used in film and television and music concerts (Caeiro-Rodríguez et al., 2021).
4. **Video game:** The glove recognizes hand gestures by monitoring the bend states of five fingers, and controls a custom VR shooting game as a demonstration (Xia et al., 2022).
5. **Robotics:** Programming robots can be made more natural and easier with glove-based systems, especially through methods based on teleoperation or automatic programming (Dipietro et al., 2008).

6. **Simulation & training:** The tasks involved in these activities are related to the training and learning of the use of various types of devices or their simulation (Caeiro-Rodríguez et al., 2021).
7. **Manipulation of 3D objects:** When manipulating objects, the hand must make contact with the object. This contact can involve the fingertip or the entire finger (Caeiro-Rodríguez et al., 2021).
8. **Design and manufacturing:** Smart gloves enable intuitive interactions and manipulation of virtual 3D models, while visualization of designed environments or artifacts is provided through computer screens or head-mounted displays, either on-site or remotely via the Internet. This approach allows design validation before construction or manufacturing, reducing the need for physical mock-ups (Dipietro et al., 2008).

1.2 Complexity

The term "complexity" has been increasingly used over the past decade in academic publications addressing industrial systems, human–machine interaction, and system safety. The term is often used as an adjective in different contexts. In one sense, complexity refers to the structure of a system. Examples include complex structures, complex networks, complex processes, complex information processing, and complex management (Érdi, 2008). In addition to dynamic complexity, there is also periodic and irreversible complexity, which can be observed in neuronal oscillations or weather prediction (Slim, 2020).

System components are generally defined as elements that cooperate to perform a common function. A system can also be a component of a larger or more complex system (Slim, 2020). The static structural complexity of software can be described by knowing the number of cycles in a program. Programs containing more cycles should be considered more complex (Érdi, 2008).

There are two main types of systems: simple and complex (Slim, 2020). An understanding of the studied system is essential to achieving the research's objectives (Mofidi Naeini, 2022).

1.2.1 Simple systems

A simple system has the following characteristics (Érdi, 2008):

- Single cause–single effect
- Small changes in cause produce small changes in effect
- Predictability

The concept of "single cause and single effect" can often be found in common sense thinking and problem-solving (Érdi, 2008). A simple system can usually be understood by describing the properties of one element or the interactions of a few elements (J. B. Smith, 2003). A simple system consists of a few components that are organized in an understandable way (Slim, 2020). This does not imply linearity, but rather that the system’s behavior remains predictable. In technical terms, if small changes are made to the parameters (or to the structure of the system), then the system's behavior will not be qualitatively altered (Érdi, 2008). As simple systems can be decomposed into parts, they can be analyzed during the design stage. This makes them well-suited to traditional assessment methods (Slim, 2020).

1.2.2 Complex systems

A complex system has the following characteristics (Érdi, 2008):

- Circular causality
- Feedback loops
- Logical paradoxes
- Strange loops
- A small change in cause produces dramatic effects
- Unpredictability

A system is considered complex when several of these characteristics occur together, rather than from any single feature alone (Mofidi Naeini, 2022). Complex systems are non-deterministic (Slim, 2020). A complex system consists of numerous interconnected components whose behavior cannot be simply inferred from the behavior of the individual components (J. B. Smith, 2003). It is impossible to predict the behavior of a system as a whole, despite knowing the functions of its individual components (Slim, 2020). Although these systems are studied in different scientific domains, researchers generally agree they share key components and properties (J. B. Smith, 2003).

There is no easy way to explain a complex system mathematically, and it contains so many elements that it cannot be described formally (J. B. Smith, 2003). Furthermore, there is no substitute for individual elements of a complex system, and the failure of one component can adversely affect others (Slim, 2020).

1.2.3 Sociotechnical systems

Five key characteristics distinguish sociotechnical systems (Slim, 2020):

- Interdependence among system components
- Adaptability of objectives to external conditions
- Separation yet interdependence of technical and social subsystems
- Multiple pathways to achieve systemic objectives depending on design choices
- Joint optimization of human, organizational, and technological factors

In sociotechnical systems, social and technical elements are integrated into a defined objective (Hettinger, Kirlik, Goh, & Buckle, 2015). Individuals and organizations represent the social aspects of sociotechnical systems. Any technology used to perform a function—such as a machine, a tool, or a resource—can be considered a technical element (Slim, 2020). Based on these characteristics, sociotechnical systems encompass a wide range of complex systems worldwide. It is possible to consider sociotechnical systems like the economy, manufacturing, healthcare, and education (Mofidi Naeini, 2022).

Simulation and modeling can help reduce unintended consequences and negative interactions in sociotechnical systems (Hettinger et al., 2015). It is imperative to consider both technical and human factors when designing or assessing an application. From a sociotechnical resilience perspective, humans should be seen as system components interacting with technical elements, rather than as isolated individuals (Mofidi Naeini, 2022).

1.3 Risk

To design a new system or improve an existing one, engineers try to anticipate future patterns of system operation under a variety of circumstances or uncertainty (Zio, 2013). The notion of risk is based on the uncertainty of outcomes rather than the certainty of them (Gorrod, 2003). There are many definitions of risk. For example, in OHS, risk is defined as "the chance or probability that a person will be harmed or experience an adverse health effect if exposed to a hazard. It may also apply to situations with property or equipment loss, or harmful effects on the environment." (Canadian Centre for Occupational Health and Safety, 2017).

From the economic perspective, risk is the probability of any event that causes the loss of profit or capital of a company or person (Karevan & Vasili, 2018). Baranoff, Brockett, and Kahane (2009) provide a concise definition of risk: "a consequence of uncertainty" . In this study, we adopt the definition that risk is the possibility of a negative deviation from the expected or desired outcome (Vaughan & Vaughan, 2007). There are different types of risks, and they vary across industries (Baranoff et al., 2009). In this study, we focus on OHS, financial, industrial, social, and environmental risks:

- OHS risks include events that affect human health, such as short-term pain, dizziness, burns, broken bones, excessive bleeding, and death. OHS risks can also include long-term health consequences, such as chronic illnesses, respiratory diseases, and cancer. It is important to identify and assess potential risks and to develop safety protocols to protect workers from harm.
- Financial risks include activities that cause economic losses, such as breakage of parts or materials, reworking, or stoppage. These financial risks can result in increased costs and reduced profits. It is essential to minimize these losses by reducing operational inefficiencies, improving quality control, and maintaining equipment effectively.
- Industrial risks often arise from the speed and technical nature of activities, which can lead to production stoppages. To prevent this, measures need to be taken, such as increasing the level of expertise of personnel and introducing more efficient technologies. Additionally, proper equipment maintenance should be carried out to reduce the likelihood of breakdowns.

- Social risks relate to factors that influence workers' well-being. This may include stress, job insecurity, limited communication, or conflicts among employees and management. Persistent social risks can reduce engagement, increase turnover, and impair performance. Mitigation efforts should focus on fostering a supportive and inclusive work environment, promoting work–life balance, and providing opportunities for skill development and participation in decision-making.
- Environmental risks involve adverse impacts of industrial operations on ecosystems and natural resources. Examples include air, water, and soil pollution; excessive energy or material consumption; and improper waste management. These risks can also stem from noncompliance with environmental regulations. To address them, organizations should adopt cleaner production technologies, improve energy efficiency, reduce emissions and waste, and integrate sustainability principles into their operational strategies.

1.3.1 Human error risks in manufacturing

A widely cited definition of human error is provided by Swain & Guttmann (1983): "Any member of a set of human actions that exceed some limit of acceptability, i.e., an out-of-tolerance action, where the limits of tolerable performance are defined by the system" (Torres et al., 2021b).

A variety of occupational accidents can be attributed to human error due to factors such as variability in attention, perception, decision-making, and physical performance. To reduce the occurrence of accidents, a deeper understanding of human error and accident causes is necessary (Wiegmann & Shappell, 2001). Human variability makes errors inevitable and prevents their complete elimination (Torres et al., 2021b). Human errors can arise from various factors, such as insufficient operator qualifications, inaccuracies during task execution, inattentiveness, and misinterpretation of instructions (Stojiljkovic, Bijelic, & Cvetkovic, 2018). When the cause of failure is traced to human error, responsibility is often attributed to the individual, rather than to deeper system interactions (Norman, 2013). Beyond understanding how individual components and human fallibilities affect the system independently, it is also necessary to examine their interactions (Irshad, Hulse, Demirel, Tumer, & Jensen, 2021).

Human reliability is a critical factor influencing both workplace accidents and productivity (Hasibuan, Daeng, & Hasibuan, 2020). Human reliability integrates two key areas: reliability engineering and human factors. The goal of reliability engineering is to predict and improve the reliability of the entire system. By contrast, the performance of a person is examined when it comes to human factors. As a result, human error is compared to the failure of a device (Torres et al., 2021b). Human reliability analysis focuses on identifying errors, identifying reasons for faults, and reducing the likelihood of human error (A. M. Kumar, Rajakarunakaran, & Prabhu, 2017). In manufacturing, human behavior is shaped by interactions with machines, systems, and organizational structures (Bubb, 2005). HRA aims to optimize safety, reliability, and productivity by predicting and mitigating errors (Torres et al., 2021b).

1.3.2 Risk quanitification

Risk probability can be quantified using inputs from multiple stakeholders, including operators and risk analysis experts, to support early identification and mitigation of hazardous scenarios (Castillo et al., 2016). Addressing risks at early design stages is essential to avoid costly redesign and rework, which can be achieved by prioritizing hazardous scenarios, integrating mitigation strategies into system design, and quantifying interactions between component failures and human error (Irshad et al., 2021).

Traditional Probabilistic Risk Assessment (PRA) methods are widely used to quantify failure likelihoods and consequences (Stamatelatos et al., 2011). Common approaches include Failure Modes and Effects Analysis (FMEA) (Baig & Prasanthi, 2013), Fault Tree Analysis (FTA) (Vesely, Goldberg, Roberts, & Haasl, 1981), and Event Tree Analysis (ETA) (Ericson, 2015). Human error risks are typically quantified using methods such as the Systematic Human Error Reduction and Prediction Approach (SHERPA) (Torres, Nadeau, & Landau, 2021a) and the Technique for Human Error Rate Prediction (THERP) (Boring, 2012).

Table 1.2 Examples of the risk analysis methods

Method	Author, Date	School of thought	Qualitative/ Quantitative
Functional Resonance Analysis Method (FRAM)	(Hollnagel & Goteman, 2004)	Resilience engineering	Qualitative
Systems Theoretic Accident Model and Processes (STAMP)	(Leveson, 2004)	Systems theory	
Failure Modes and Effects Analysis (FMEA)	(Military, 1949)	Safety engineering	
Fault Tree Analysis (FTA)	(Watson, 1961)		
Successive Likelihood Index Method (SLIM)	(Embrey, Humphreys, Rosa, Kirwan, & Rea, 1984)		Quantitative
Technique for Human Error Rate Prediction (THERP)	(Kirwan, 1983; Swain, 1964)	Reliability engineering	
Human Error Assessment and Reduction Technique (HEART)	(Williams, 1986)	Human reliability	
Systematic Human Error Reduction and Prediction Approach (SHERPA)	(Embrey, 1986)		
Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H)	(Gertman, Blackman, Marble, Byers, & Smith, 2005)		
A Technique for Human Error Analysis (ATHEANA)	(Cooper, Ramey-Smith, Wreathall, & Parry, 1996)		
Cognitive Reliability and Error Analysis Method (CREAM)	(Hollnagel, 1998)	Cognitive systems engineering	
Bayesian Network (BN)	(Pearl, 1985)	Artificial intelligence	

While effective for identifying hazardous scenarios, these methods rely on detailed system and component models, thereby limiting their applicability during early design phases (Irshad et al., 2021). Quantitative human reliability techniques such as the Cognitive Reliability and Error Analysis Method (CREAM) have also been proposed to estimate human error probabilities (Guo et al., 2022). Table 1.2 shows some of the widely used risk analysis methods.

To address system complexity, several studies have employed a combination of qualitative and quantitative methods. For example, STAMP has been integrated with Genetic Algorithms to model dynamic risk evolution, while FRAM has been coupled with Bayesian Network variants to assess resilience and risk in maritime and chemical systems (De Linhares et al., 2021; Guo et al., 2022; Hu et al., 2022; Qiao et al., 2022; Zinetullina et al., 2021).

These hybrid approaches aim to capture systemic interactions and uncertainty better. However, despite these advances, quantitative integration of wearable-induced risks within complex manufacturing systems remains limited, representing a gap directly addressed by this thesis.

1.4 Meta-heuristic algorithms

Optimization involves finding the best result among the available alternatives, and it can include maximizing or minimizing objectives, with or without constraints, depending on the problem (Jain et al., 2022). Several methods for designing and implementing exact optimization algorithms are commonly used, including dynamic programming, backtracking, and branch-and-bound (Neapolitan & Naimipour, 2004). Even though these algorithms perform well in various problems, they do not work well in large-scale combinatorial or highly nonlinear optimization problems (Beheshti & Shamsuddin, 2013). Optimization aims to obtain the best possible result under defined circumstances (Rao, 2019). Since exact methods have limitations, it is preferable to use an approximate approach. Heuristics and meta-heuristics play a vital role in approximate methods (Jain et al., 2022).

Metaheuristics are considered a prominent subfield of stochastic optimization (Luke, 2013). The term “heuristic” derives from the Greek word “heuriskein”, which refers to figuring out new strategies and rules to solve problems, while the prefix “meta” refers to the higher level of the methodology used (Talbi, 2009). In limited-resource situations, metaheuristic algorithms help determine what should be done when faced with a problem (Luke, 2013). A problem can be solved using two resources: time and space. In algorithmic terms, time complexity refers to the number of steps required to solve an *n-dimensional* problem (Talbi, 2009).

It may be challenging to find an optimal solution in a principled manner when knowledge of the solution is insufficient and heuristic information is limited. A potential solution can be tested and evaluated for effectiveness (Luke, 2013). Optimization decisions are generally driven by minimizing effort or maximizing expected benefit. It is possible to find a maximum or minimum value of a function through optimization by identifying the conditions under which it can be achieved (Rao, 2019). In science and engineering, metaheuristics are used to solve tricky, complex problems in a reasonable amount of time (Talbi, 2009). In complex optimization problems, meta-heuristic algorithms can improve calculation accuracy, reduce computational burden, and generate high-quality optimal solutions (Nesmachnow, 2014). Meta-heuristics are high-level strategies that guide underlying heuristics to solve problems (Glover & Laguna, 1997). To produce high-quality solutions efficiently, meta-heuristics guide and modify the operation of subordinate heuristics (Voß, 2000).

There are multiple optimization methods available for handling different types of optimization problems since a single method cannot handle all optimization problems efficiently (Rao, 2019). Decision-making must become more rational and efficient as the world becomes more complex and competitive. It has been shown that metaheuristics are efficient and effective at solving large and complex problems. There is no doubt that metaheuristics have proven to be invaluable in optimization, and they can be applied to various domains, as shown in Figure 1.5 (Talbi, 2009). A metaheuristic algorithm can be classified as belonging to one of three main categories (Table 1.3) evolutionary algorithms, which rely on natural selection and genetics; physics- and chemistry-based algorithms, whose names indicate that they are inspired by chemistry and physics; and swarm intelligence algorithms (Jain et al., 2022).

Table 1.3 Meta-heuristic algorithms

Evolutionary algorithms	**Physics and chemistry-based algorithms**	**Swarm intelligence algorithms**
Genetic	Galaxy-based search	Particle swarm optimization
Cultural	Big bang–big crunch	Ant colony optimization
Biogeography-based	Spiral optimization	Firefly
Differential search	Electro-magnetism optimization	Artificial bee colony
Differential evolution	Black hole	Lion algorithm

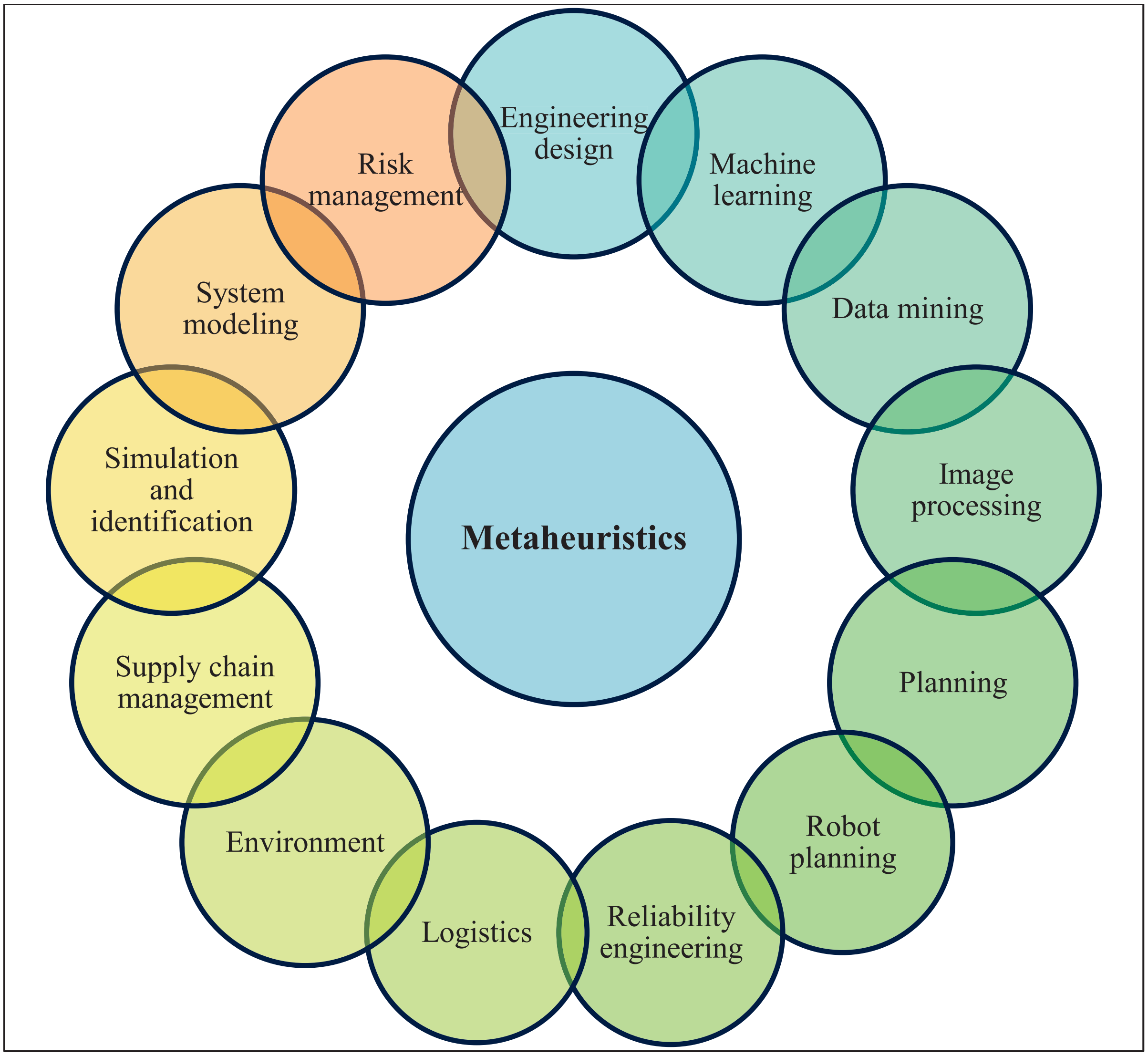

Figure 1.5 Use of metaheuristics

1.5 Review of the literature

1.5.1 Database selection

In this study, Web of Science (WoS) and Scopus were selected as the primary research databases. These databases index extensive collections of journals, books, and conference proceedings across disciplines and provide citation metrics that support the evaluation of research impact (Zorzenon, Lizarelli, & Daniel, 2022).

1.5.2 Keywords strategy

The literature review was conducted in several stages. First, relevant keywords were identified and grouped to maximize coverage. As illustrated in Figure 1.6, keyword groups were combined systematically. Each keyword was used in both its full form and common abbreviations. For example, the searches included both “OHS” and “Occupational Health and Safety” as well as “HRA” and “Human Reliability Analysis.”

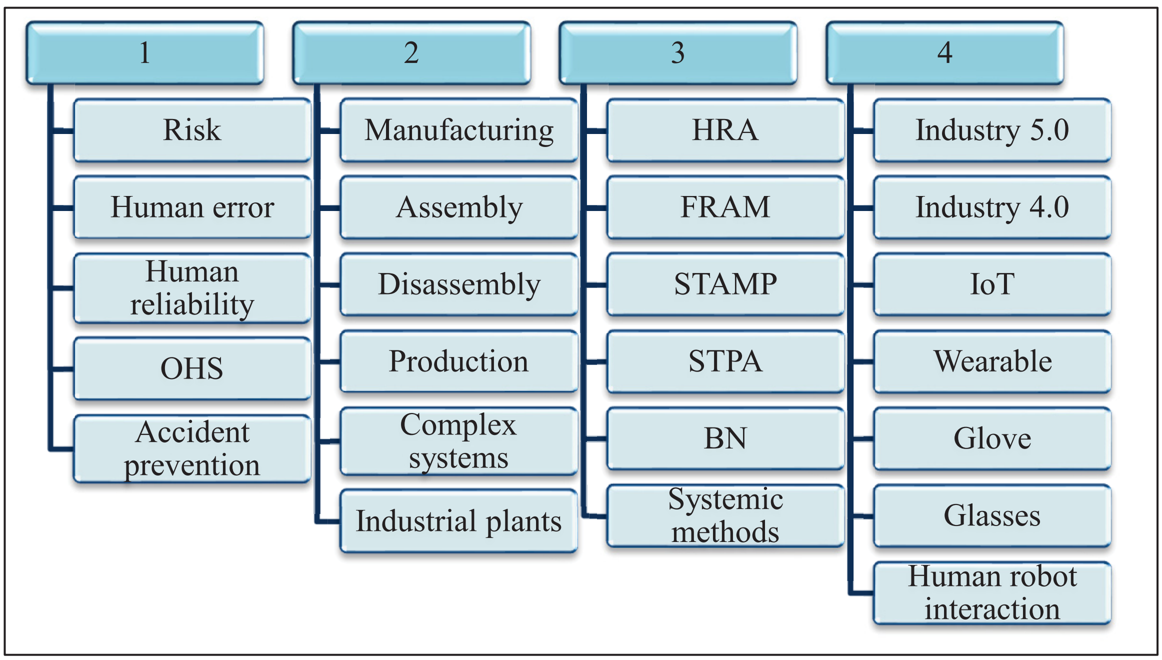

Figure 1.6 Keyword grouping adopted for the literature review

1.5.3 Inclusion and exclusion criteria

To ensure the quality and relevance of the sources, both exclusion and eligibility criteria were applied. Records were excluded if they were non-English, published before 2012, lacked full-text access, or were outside the study scope. Conversely, eligibility criteria were defined to guide inclusion. Publications were considered eligible if they focused on domains related to manufacturing (assembly, or disassembly processes); if they addressed risks such as human error or industrial equipment failure; and if they examined the use of IoT or wearable technologies. This systematic procedure ensured that only high-quality, relevant studies were included in the review, while minimizing the risk of overlooking significant contributions.

1.5.4 Analysis of the literature

The database searches identified 71 records. After removing duplicates and excluding non-English, non-peer-reviewed, out-of-scope, and non–full-text items, 23 studies remained for full-text assessment. These studies are summarized in Table 1.4 to support subsequent comparative analysis.

The integration of smart wearables—such as exoskeletons, data gloves, and augmented reality glasses—into manufacturing has opened transformative opportunities while simultaneously exposing new categories of risk (Devarajan et al., 2025). Equipped with IoT sensors for real-time monitoring and feedback, these wearable devices promise gains in productivity and safety, yet they also increase vulnerabilities in human–machine interaction, cybersecurity, and system reliability (Ioniță, Anghel, & Boudouh, 2025).

Human factors remain the most critical concern. While wearables are designed to reduce physical burdens, they can introduce ergonomic and cognitive strains if poorly integrated (Digiesi et al., 2023). For example, passive exoskeletons lower muscle activity by more than 20% in repetitive tasks, but extended use without ergonomic adaptation risks fatigue and discomfort (Coccia et al., 2024).

Data gloves in assembly reduce manual errors, yet systemic analyses using FRAM and STPA reveal new OHS hazards linked to sensor inaccuracies, interface misalignments, and unsafe control actions (Mofidi Naeini & Nadeau, 2022a, 2022c, 2023). Cognitive ergonomics research further suggests that wearable-based HMIs may elevate operator workload and error probability if interaction designs ignore human variability (Ioniță et al., 2025). In human–robot collaboration, taxonomies of performance-shaping factors show that IoT-enabled cobots can erode the operator's trust and escalate errors when sensor responses are delayed (Di Pasquale et al., 2023). These findings underline that wearables, while supportive, must be carefully designed and assessed to prevent unintended vulnerabilities.

Table 1.4 Included papers

Reference	**Main objective**	**Risk method**	**IoT / Wearabe**	**Industry**
(Devarajan et al., 2025)	Propose Bayesian-Fuzzy Inference for Risk Assessment (BFIRA) for cybersecurity risk assessment in smart manufacturing.	Quantitative -Bayesian-Fuzzy Inference	IoT in smart manufacturing	Smart manufacturing
(Ioniță et al., 2025)	Review HMI in Industry 5.0, focusing on cognitive ergonomics.	Qualitative-Ergonomic methods	Smart wearables, IoT in HMI	Smart manufacturing
(Mokhtarzadeh, Rodríguez-Echeverría, Semanjski, & Gautama, 2025)	Review failure analysis methods (FMEA, RCA, FTA) enhanced by I4.0 tech for reliability in manufacturing.	Qualitative with quantitative elements	IoT sensors and AI in I4.0	Manufacturing
(Veiga, Kudo, & Bulcão-Neto, 2024)	Links agile project planning with STPA-based safety & security analysis for critical IoT systems via the SafeSecIoT Canvas.	Qualitative-STPA	Critical IoT systems (Autonomous Driving System)	Autonomous Driving Systems
(Yuan, Yang, & Reniers, 2024)	Integrated safety and security risk assessment for ICPS in chemical plants.	Quantitative -Bow-tie with Bayesian networks	ICPS (cyber-physical systems implying IoT)	Chemical plants
(Bhaveshkumar N Pasi et al., 2024)	Design an Image Recognition-Based System (IRBS) using I4.0 to automate defect detection and improve accuracy.	Quantitative -Image processing and sampling risk analysis	Image-processing IoT	Manufacturing

Reference	Main objective	Risk method	IoT / Wearabe	Industry
(L. Qiao, Li, Wang, & Peng, 2024)	Propose a data space-based method using CNN and LSTM-OLS for fault diagnosis and propagation in industrial processes.	Quantitative -CNN for causal extraction, LSTM-OLS for propagation	IoT sensors	Manufacturing
(Coccia et al., 2024)	Evaluate biomechanical impacts (e.g., muscle activity reduction) of passive arm-support exoskeletons in tasks.	Quantitative - Electromyo graphy	Passive exoskeletons	Manufacturing
(D. Kumar et al., 2024)	Assess I4.0 tech (e.g., IoT) for decarbonization using Bayesian Networks to prioritize attributes.	Quantitative -Bayesian networks	IoT in I4.0	Manufacturing
(Digiesi et al., 2023)	Assessing human error's impact on the manufacturing system using PSFs for HEP.	Quantitative -PSF-based HEP estimation	Human-machine systems in Industry 4.0 (no specific IoT)	Manufacturing
(Mousavi, Shen, & Li, 2023)	Develop an online safety risk management system using IoT and BNs for underground environments.	Quantitative -Bayesian networks	IoT wireless sensors for environment al monitoring	Underground mining and construction
(Xiao, Li, Luo, & Liu, 2023)	Identify and assess public safety risks from UAVs using FTA and BN.	Quantitative -FTA-BN	UAV sensors and systems	Aviation

Reference	Main objective	Risk method	IoT / Wearabe	Industry
(Mofidi Naeini & Nadeau, 2023)	Integrate FRAM and STPA for risk analysis of data gloves in assembly 4.0.	Qualitative-integrated FRAM/ STPA	Data glove	Manufacturing
(Di Pasquale, De Simone, Giubileo, & Miranda, 2023)	Develop a PSF taxonomy for Human Error Probability in HRC, integrating I4.0 factors.	Qualitative-Performance-Shaping Factors	Collaborative robots (cobots)	Manufacturing
(Bhaveshkumar Nandanram Pasi, Mahajan, & Rane, 2023)	Classify I4.0 risks and develop mitigation strategies using DEMATEL for prioritization.	Quantitative - DEMATEL	IoT sensors and smart tech in I4.0	Manufacturing
(Mirabel, Yuliana, & Yahya, 2022)	Propose a framework for inbound supply chain analytics using I4.0 tech for visibility (automation, information, transformation) in developing countries.	Qualitative-KPI-based analytics dashboard	IoT sensors and cloud computing	Manufacturing
(Mofidi Naeini & Nadeau, 2022b)	Use FRAM for OHS and operational risk analysis of the data glove introduction in assembly.	Qualitative-FRAM	Data glove	Manufacturing

Reference	Main objective	Risk method	IoT / Wearabe	Industry
(Thekke Kanapram, Marcenaro, Martin Gomez, & Regazzoni, 2022)	Propose interpretable ML models for abnormality detection in IoT networks.	Quantitative -Markov jump particle filter, DBN	Data glove	Autonomous vehicles
(Mofidi Naeini & Nadeau, 2022c)	Analyze OHS and operational risks of the data glove in assembly 4.0 using STPA.	Qualitative-STPA	Data glove	Manufacturing
(Xue, 2021)	Build a Bayesian network model for reliability evaluation of Power IoT, integrating layers (perception, network, platform, application) to assess uncertainties and threats.	Quantitative -Bayesian networks	Power IoT (sensors for perception, interconnection of devices in power grids).	Energy
(Kaneko, Yoshioka, & Sasaki, 2020)	Propose a 5-layer STAMP model for hierarchical safety/security analysis of AI/IoT systems, generating specs/standards.	Qualitative-STAMP	AI/IoT systems	Automotive/Smart cities
(Adriaensen, Decré, & Pintelon, 2019)	Review safety methods for I4.0, assessing their handling of complexity (e.g., failure tractability, interaction coupling).	Qualitative-literature review of methods	IoT sensors and smart factories in I4.0	Manufacturing
(Z. Wang & Chiang, 2019)	Propose a sensor fusion scheme based on Bayesian inference for process monitoring.	Quantitative -Bayesian fusion	Multi-rate sensors in chemical processes	Chemical production

Reliability modeling highlights the methodological gap. Traditional safety tools struggle with the opacity and non-linearities introduced by wearables, leading scholars to advocate for resilience-oriented frameworks (Adriaensen et al., 2019). Agile-STPA demonstrates how systemic analysis can adapt to dynamic IoT environments, offering lessons for wearable-guided robotics in manufacturing (Veiga et al., 2024). At the operational level, wearable-enabled image recognition improves inspection accuracy, but sustained calibration and sensor integrity remain prerequisites (Bhaveshkumar N Pasi et al., 2024). Bayesian networks applied to sustainability contexts indicate that IoT sensors, including wearables, can support decarbonization, though interoperability challenges persist (A. Kumar, Upadhyay, Samanta, & Bhattacherjee, 2024). Risk prioritization studies further show that technical and economic vulnerabilities dominate Industry 4.0 adoption, while human and organizational factors follow closely (Bhaveshkumar Nandanram Pasi et al., 2023). Collectively, these results highlight a paradox: wearables enhance monitoring and control yet simultaneously create new dependencies vulnerable to environmental variability, technical faults, and human limitations (Mirabel et al., 2022).

Current literature demonstrates that smart wearables reshape the interaction between humans, machines, and networks, generating novel socio-technical failure modes that traditional tools cannot fully capture (Coccia et al., 2024; Naeini & Nadeau, 2023). While these technologies mitigate risks such as fatigue and inspection errors, they also introduce hazards related to cognitive overload, cyber intrusions, and fault propagation (Devarajan et al., 2025; Ioniță et al., 2025; Yuan et al., 2024). In complex manufacturing environments where small errors can escalate rapidly through interdependent systems, the absence of systematic, quantitative risk analysis leaves a critical blind spot. Addressing this gap is essential for safe and human-centered Industry 5.0 adoption (Adriaensen et al., 2019; Di Pasquale et al., 2023). Without robust methods, wearables may compromise both safety and trust; with them, they can evolve into enablers of smarter, safer, and more sustainable manufacturing.

CHAPTER 2

OBJECTIVES AND RESEARCH METHODOLOGY

Throughout this chapter, the research methodology for the study will be described. Four sections will make up the chapter:

- The first section describes the research problem and the objectives of the thesis.
- The second section contains the main research questions and scientific contributions.
- The third section contains the methodology to solve the research problem, including PSO, FRAM, STPA, and BN.
- And the final section contains the description of the case studies.

2.1 Research problem and objectives

Building on the literature review in Chapter 1, the central research gap concerns the absence of systematic and quantitative methods for analyzing the risks introduced by smart wearables, specifically smart glasses and smart gloves, in complex assembly and disassembly systems. Existing approaches highlight emerging vulnerabilities but cannot model, quantify, and prioritize risks in dynamic, human-centered environments. To address this gap, the objectives of this thesis are as follows:

- Develop systemic approaches to identify, analyze, quantify, and prioritize systemic risks, including those related to human error, arising from the use of smart wearables.
- Model the integration of multiple smart wearables (e.g., smart glasses and smart gloves) in hybrid assembly/disassembly systems, evaluate the associated risks, and propose mitigation strategies to support safer integration and decision-making.
- Incorporate sustainability dimensions (environmental, economic, and social) into risk management methods, and develop a sustainability-driven framework that not only evaluates risks but also guides the selection of optimal mitigation strategies.

- Establish probabilistic frameworks to quantify uncertainties, trace failure pathways, and support risk-informed decision-making.

As discussed in Chapter 1, several methods exist for analyzing risks. In this thesis, FRAM, STAMP-STPA, and BN are integrated with the PSO algorithm to enable quantitative evaluation and dynamic risk management. To ensure methodological robustness, three approaches—FRAM-PSO, STPA-PSO, and STPA-BN-PSO—are applied (Figure 2.1), allowing comparative analysis across multiple systemic perspectives. This strengthens the validity of the results and highlights the strengths and limitations of each method when applied to wearable-enabled manufacturing systems.

While FRAM and STAMP-STPA are originally qualitative, their integration with PSO—and the calibration of BN using PSO—enables quantitative risk assessment and management across all three approaches. To the best of our knowledge, no previous study has quantified the risks associated with introducing multiple intelligent devices (smart glasses and smart gloves) into hybrid manufacturing systems. The final step of this research is a comparative analysis of the three developed methods across case studies in manufacturing.

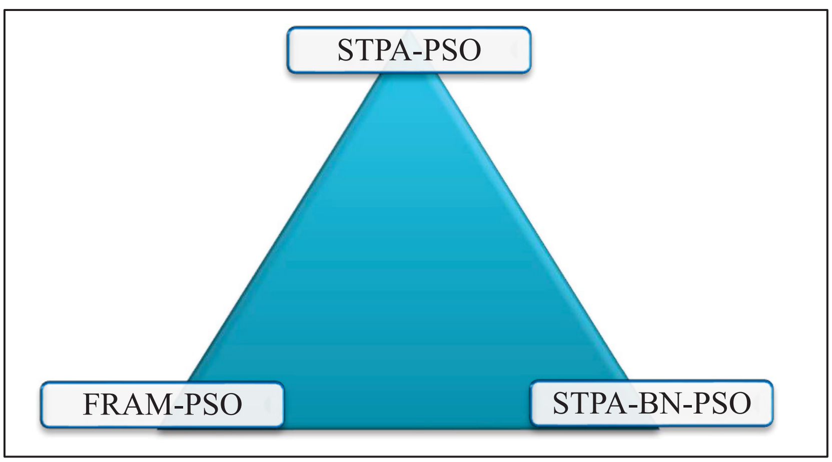

Figure 2.1 Overview of the proposed methodological approaches

2.2 Research questions and scientific contributions

Based on the objectives outlined in Section 2.1, the following research questions are formulated for further investigation:

- How can systemic risks, particularly those related to human error, be identified, quantified, and prioritized when integrating smart wearables such as smart glasses and smart gloves into assembly and disassembly systems?
- How can the simultaneous integration of multiple wearables be modeled, and what mitigation strategies can be proposed to support safer and more effective decision-making in wearable-enabled manufacturing?
- How can sustainability dimensions (environmental, economic, and social) be embedded into systemic risk analysis frameworks to guide the selection of mitigation strategies and ensure sustainable decision-making?
- To what extent can probabilistic and optimization-based frameworks trace failure pathways and provide decision support in wearable-enabled manufacturing systems?
- What are the comparative advantages and limitations of FRAM-PSO, STPA-PSO, and STPA-BN-PSO, and under what conditions should each be applied in real-world industrial contexts?

These research questions are addressed through a set of scientific contributions, illustrated in Figure 2.2, which map each question to a specific methodological advancement developed in this thesis. Moreover, this figure demonstrates the link between each scientific contribution and the resulting publications and presentations.

Development of an STPA-PSO method for quantifying systemic and human error risks associated with smart glasses.

- Journal paper (Heliyon, 2023): A comprehensive STPA-PSO framework for quantifying smart glasses risks in manufacturing
- Vulgarization activity (CAÉC, 2024): Wearables risks in manufacturing
- Vulgarization activity (IEA Resilience Engineering Committee, 2025): PSO-STPA model: case study of an Industry 4.0 plant using smart glasses
- Vulgarization activity (CAÉC, 2025): Risk of using smart glasses in an Industry 5.0 plant

Proposal of a multi-wearable systemic risk framework that models the simultaneous integration of smart glasses and smart gloves, incorporating a semi-automated mitigation loop to support safer decision-making.

- Journal paper (Robotics and Computer-Integrated Manufacturing, 2026): Integrating smart glasses and smart gloves in hybrid assembly/disassembly systems: an STPA-driven semi-automated risk management tool
- Conference paper (IEA, 2024): Fostering AI-human collaboration in Industry 5.0 manufacturing
- Vulgarization activity (3-minute thesis, 2025): Empowering humans, not replacing them

Introduction of a FRAM-PSO sustainability-driven method that integrates environmental, economic, and social criteria into systemic risk management, enabling the selection of mitigation strategies that are both effective and sustainable.

- Journal paper (Computers & Industrial Engineering, 2025): FRAM-PSO: A semi-quantitative framework integrating multi-dimensional sustainability criteria
- Conference paper (IISE, 2024): FRAM effectiveness in the era of Industry 4.0: A dual perspective review
- Vulgarization activity (Substance ÉTS, 2025): Making manufacturing smarter, safer and more sustainable

Development of a STPA-BN-PSO method that combines probabilistic reasoning with optimization to trace failure pathways, quantify uncertainties, and provide decision support in complex manufacturing contexts.

- Journal paper (Computers & Industrial Engineering, 2026): STPA-BN–PSO: a hybrid probabilistic framework for managing systemic risks in human-centric wearables-enabled manufacturing

Figure 2.2 Scientific contributions

2.3 Research methodology

This section presents the methodological foundations of the thesis. It introduces the core methods—namely Particle Swarm Optimization (PSO), Systems-Theoretic Process Analysis (STPA), the Functional Resonance Analysis Method (FRAM), and Bayesian Networks (BN)—and explains their integration into hybrid methods (STPA-PSO, FRAM-PSO, and STPA-BN-PSO). Each method is first described in its original form and then extended with PSO to enable quantitative evaluation and dynamic risk management. The structure of this research methodology, together with the main contributions of each method (shown as blue ellipses), is illustrated in Figure 2.3.

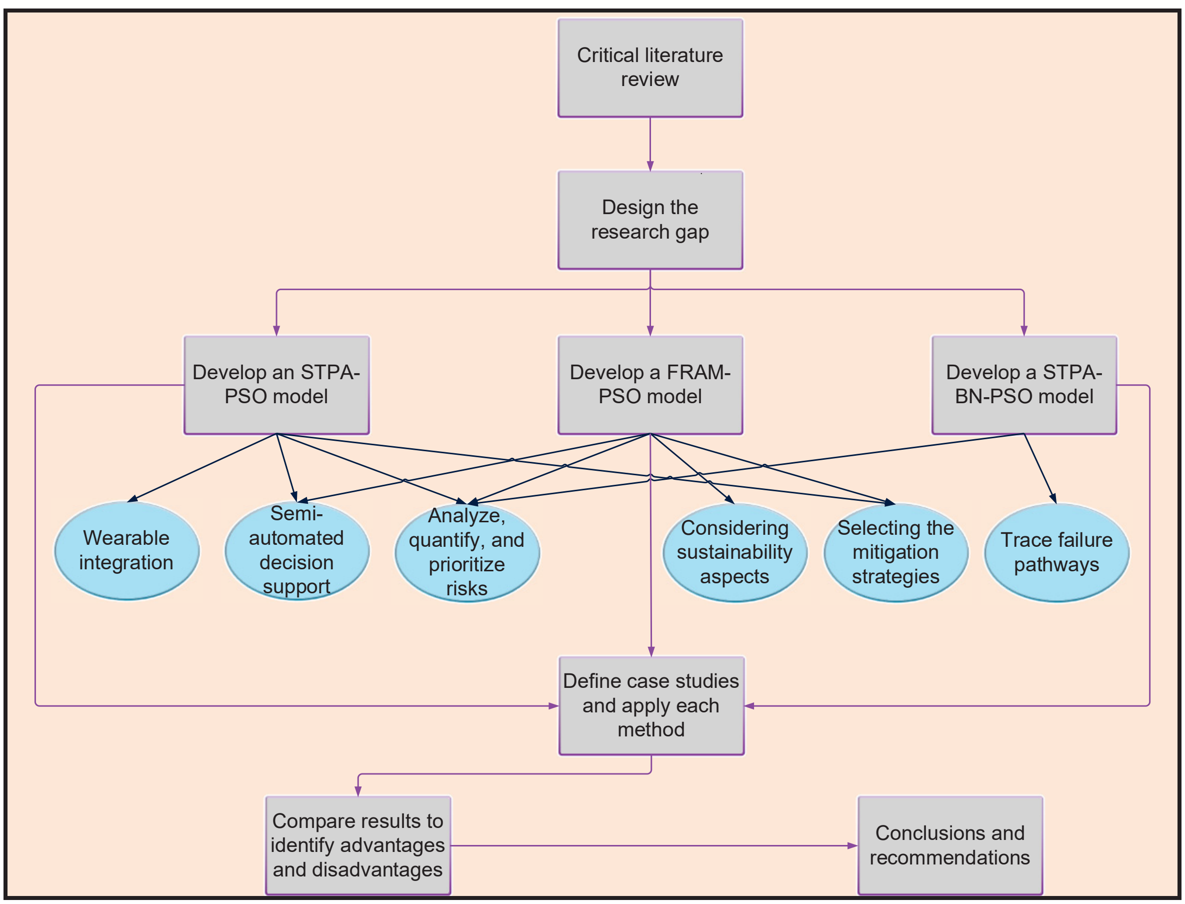

Figure 2.3 Research methodology structure

2.3.1 Introduction of PSO

Particle Swarm Optimization was introduced in 1995 by James Kennedy and Russell Eberhart, and is a well-known swarm-based optimization method (Jain et al., 2022). Its design was inspired by observing the collective behavior of animals during aggregation and aggression (Karevan & Vasili, 2018). As a tool for solving complex optimization problems, PSO has demonstrated excellent flexibility and practicality (Yang et al., 2020). Numerous optimization domains have successfully used PSO because of its ease of implementation (Lehre & Witt, 2013).

Unlike evolutionary algorithms that rely on explicit selection and replacement, PSO maintains a population of candidate solutions, called particles, that navigate a multidimensional search space. Each particle dynamically adjusts its trajectory by integrating its own best-found solution (self-experience) with the best solution discovered by the entire swarm (social experience). This dual-experience approach drives the swarm's convergence towards high-quality solutions (Jain et al., 2022).

As a heuristic algorithm, PSO iteratively improves candidate solutions through continuous updates of particle positions and velocities, though it does not guarantee the global optimum. Particles are never eliminated; instead, they continuously evolve from their initial random positions and velocity vectors (Wilson & Mantooth, 2013). PSO distinguishes itself from evolutionary algorithms by not using explicit selection and by manipulating individuals through guided updates rather than genetic operators. However, it cannot directly adapt velocity steps for space constraints (Yang et al., 2020).

In a *d-dimensional* search space, each particle is defined by its position X_i, velocity V_i, and personal best P_i (Jain et al., 2022; Lalwani, Singhal, Kumar, & Gupta, 2013). The algorithm's core mechanism for optimizing solutions involves regulating particle velocities. Based on equation 2.1, particle *k*'s velocity is updated in the $(i+1)^{th}$ iteration (Jain et al., 2022):

$$V_k(i+1) = V_k(i) + c_1 r_1 \left(P_{best,i}^{k} - X_k(i)\right) + c_2 r_2 \left(g_{best,i} - X_k(i)\right) \tag{2.1}$$

In the $(i+1)^{th}$ iteration, the velocity of the k^{th} particle is updated based on three components (Jain et al., 2022):

1. Momentum Part ($V_k(i)$): The inertia component, represented by the previous velocity, balances global exploration and local exploitation within the search space, acting as a memory of past movement.
2. Cognitive Part ($c_1r_1\left(P^k_{best,i} - X_k(i)\right)$): This part drives particles towards their own best-found positions, reflecting individual learning.
3. Social Part ($c_2r_2\left(g_{best,i} - X_k(i)\right)$): This component directs particles towards the swarm's global best position, embodying collective learning.

Subsequently, during iteration *(i+1)*, the position of each particle *k* depends on equation 2.2:

$$X_k(i+1) = X_k(i) + V_k(i+1) \tag{2.2}$$

Several control parameters influence the basic PSO:

- **Swarm size**: This refers to the total number of particles. Larger swarms increase computational complexity per iteration (Engelbrecht, 2007).
- **Neighborhood size**: This parameter dictates the extent of social interaction among swarm members. Smaller neighborhoods tend to converge slowly but reliably, whereas larger ones facilitate faster convergence due to increased interaction (Jain et al., 2022).
- **Acceleration coefficients**: These coefficients, along with random numbers *r1* and *r2*, control the influence of the cognitive and social components on particle velocity. Proper balancing of *c1* and *c2* is crucial, as inappropriate values can lead to divergent or cyclic swarm behavior (Jain et al., 2022).
- **Number of iterations**: The required number of iterations varies with the problem's complexity. Too few iterations can lead to premature termination, while too many unnecessarily increase computational time (Engelbrecht, 2007).
- **Velocity clamping**: Introduced to prevent swarm divergence, velocity clamping maintains velocities within defined boundary constraints. *Vmax* represents the maximum exploration rate and must be chosen carefully to balance global exploration with local exploitation, avoiding situations where the optimal solution is overshot or particles become trapped in local optima (Jain et al., 2022).
- **Weight of inertia**: Convergence performance of a particle is improved by increasing its inertia weight ‘ω’. Choosing a suitable value for ω will, in general, result in fewer

iterations to arrive at the optimal solution. A large adjustment of the inertia weight ω is essential for balancing global and local search and ensuring convergence to a sufficiently optimal solution in fewer iterations (Jain et al., 2022).

Figure 2.4 visually depicts particles within the swarm, showing their positions and velocities. It's important to note that PSO operates iteratively without utilizing gradient information during its search (Talbi, 2009).

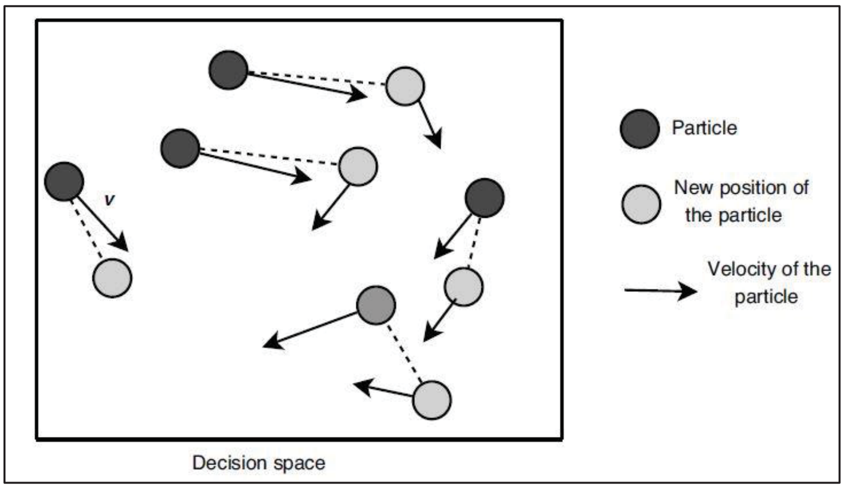

Figure 2.4 Positions and velocities of the particle swarm
Taken from Talbi (2009, p. 248)

2.3.2 STPA-PSO

2.3.2.1 Introduction of STAMP

Traditional accident analysis often struggles with complex systems, particularly when systems operate close to their stable limits. In such states, even minor parameter fluctuations can lead to catastrophic instability, a dynamic that classical approaches fail to capture (Alvarenga, e Melo, & Fonseca, 2014). Furthermore, complex system accidents are rarely attributable to a single 'root cause' and are instead understood as emerging from unexpected, uncontrolled interactions between system components. This necessitates a holistic view of systems rather than an isolated examination of their parts (Underwood, Waterson, & Braithwaite, 2016).

Based on these systems theory concepts, Nancy Leveson introduced STAMP in 2004 (Leveson, 2004). STAMP addresses the limitations of traditional accident analysis by framing safety as a dynamic control problem, emphasizing continuous control and constraint enforcement rather than solely focusing on failure prevention (Leveson & Thomas, 2018). It posits that accidents arise from inadequate control actions or uncontrolled disturbances rather than simply component failures (Ceylan, Akyuz, & Arslanoğlu, 2022). Its generic nature allows for both retrospective accident analysis and prospective safety assessment across diverse domains (Kazaras, Kirytopoulos, & Rentizelas, 2012; Underwood & Waterson, 2012). STAMP offers several distinct advantages over traditional safety methods (Allison, Revell, Sears, & Stanton, 2017):

- Providing the researcher with the opportunity to examine systemic feedback and actions taken in response to it.
- The analysis must encompass organizational and technological constraints at the same level.
- Its focus is on overall system improvement rather than identifying a single "root cause" of an accident.

This approach allows for the detection of various types of failures within dynamic and complex structures, often identifying accident causes more comprehensively than other system theory methods (Salmon, Cornelissen, & Trotter, 2012). STAMP is particularly effective at describing how inadequate control actions can violate safety constraints (Kazaras et al., 2012) by examining the safety control structure to identify why it failed to maintain safe operational limits (Leveson, 2004). It presents a robust alternative to classical safety methods such as FTA, ETA, HAZOP, and FMECA (Leveson & Thomas, 2018).

The STAMP framework conceptualizes socio-technical processes as systemic performances that are enabled by multilayered feedback loops between different stakeholders and are in a continuous state of dynamic equilibrium (Allison et al., 2017). Its primary purpose is to identify system components and characteristics that might lead to a violation of control mechanisms (Slim & Nadeau, 2020). STAMP functions by controlling restrictions at lower hierarchical levels through controllers and effective communication channels for transmitting and receiving feedback about those restrictions (Alvarenga et al., 2014). By evaluating both individual component failures and the interactions among components, STAMP's results often provide a more complete picture, effectively forming a superset of traditional safety analysis outcomes (Rising & Leveson, 2018). Further advantages of STAMP include (Leveson & Thomas, 2018):

- Its top-down design makes it suitable for analyzing highly complex systems.
- Its equitable consideration of software, human factors, organizational structures, and safety culture as causal factors.
- Its ability to serve as a foundation for various analytical tools, including System Theoretic Process Analysis (STPA) for hazard analysis, Causal Analysis based on STAMP (CAST) for accident investigation, risk identification and management, and organizational risk analysis.

Despite its powerful dynamic analysis capabilities rooted in systems theory, a primary disadvantage of STAMP is its qualitative nature, lacking quantitative metrics (Ceylan et al., 2022). Moreover, for those seeking to assign blame, a systemic accident model like STAMP might be unsatisfactory as it avoids identifying a single causal factor (Allison et al., 2017).

The STAMP model identifies situations where control actions are inadequate to maintain safety. These include when (Mofidi Naeini & Nadeau, 2022c):

- The controller cannot execute the safety constraints model.
- Control actions fail to impose safety constraints at any level of the socio-technical control structure.
- Control actions are performed at an inappropriate time (too soon, too late).
- Inappropriate control actions violate safety constraints.
- Suitable control actions, despite being considered, are not implemented properly.

In practice, STAMP manifests as STPA for prospective hazard analysis and CAST for retrospective accident and incident analysis (Pricop, Fattahi, Dutta, & Ibrahim, 2020).

2.3.2.2 Introduction of STPA

STPA is one of the most prominent STAMP-based proactive hazard analysis methods. Its purpose is to identify potential causes of accidents within a system, thereby enabling the elimination or control of hazards through systematic analysis (Andrews, Moulton, & Madnick, 2018). As a qualitative method, STPA offers a holistic view of the system and provides detailed insights into the relationships between system components regarding safety control actions (Mofidi Naeini & Nadeau, 2022c). To address the systemic focus offered by STAMP, the STPA method was developed, which included control types and factors not addressed by traditional techniques (Hulme et al., 2021).

STPA operates on the premise that accidents can occur not only from component failures but also from unsafe interactions among system components (Leveson & Thomas, 2018). It is uniquely capable of accounting for a wide range of loss-inducing factors, including design errors, software flaws, complex component interactions, cognitive human errors, and critical social, organizational, and management influences (Hulme et al., 2021). Crucially, STPA identifies potentially unsafe or inadequate control actions that could lead to hazards at any stage of the system lifecycle (Mofidi Naeini & Nadeau, 2022c). The structured approach of STPA typically involves four main steps (Bjerga, Aven, & Zio, 2016):

1. Defining accidents, system-level hazards, safety constraints, and functional requirements.
2. Developing a functional control model for the system.
3. Identifying unsafe control actions within the model.
4. Identifying loss scenarios for each unsafe control action identified in step 3.

While STPA aligns with model-based engineering (improving as design adjustments are made), its underlying model differs from those typically recommended for contemporary systems (Leveson & Thomas, 2018). Multiple studies have demonstrated STPA's effectiveness, particularly in complex operating environments characterized by multiple controllers managing the same process (Rising & Leveson, 2018). In STPA, a safety problem is fundamentally viewed as a control issue, not solely a reliability issue. This allows STPA to be applied at all stages of a system's standard engineering process, unlike many reliability-based tools (Rising & Leveson, 2018). Compared to traditional risk analysis techniques, STPA offers significant advantages (Leveson & Thomas, 2018; Rising & Leveson, 2018):

- It enables the analysis of highly complex systems.

- It effectively identifies safety requirements and constraints early in concept analysis, allowing for the detection of design flaws early in development or operation, thereby preventing costly rework.
- By integrating human and software operators into the hazard analysis, STPA ensures a comprehensive consideration of all potential loss events.
- It addresses the common issue of undocumented system functionality in large and complex systems by inherently building a functional model.
- It seamlessly integrates with model-based and system engineering practices.

Moreover, a major benefit of STPA is its ability to trace decisions and designs throughout the development process, which eliminates the need to redo prior analyses (Leveson & Thomas, 2018). It comprehensively considers all aspects of a system (humans, technology, and organizations) to identify hazards (Mofidi Naeini & Nadeau, 2022c). As development progresses and more information becomes available, these general requirements can be iteratively refined (Rising & Leveson, 2018).

2.3.2.3 STPA-PSO: A hybrid framework for quantitative risk assessment and mitigation

While STPA offers a robust qualitative framework for identifying hazards and unsafe control actions within complex socio-technical systems, its inherent qualitative nature presents limitations when precise risk quantification is required (Ceylan et al., 2022). Traditional STPA excels at identifying what could go wrong and how it could happen, but does not inherently provide metrics for the likelihood or severity of such events.

To address this gap, this thesis introduces STPA-PSO. This methodology extends STPA by integrating quantitative risk assessment techniques—impact and probability modeling—while leveraging the PSO algorithm to manage and prioritize risks. STPA-PSO thus moves beyond hazard identification toward the systematic calculation of risk, including human error, and supports the selection of optimal mitigation strategies in complex environments such as those involving smart wearables.

STPA-PSO systematically builds upon the four core steps of STPA (as described in Section 2.3.2.2). The first three steps—defining losses and hazards, developing the control model, and identifying unsafe control actions—follow standard STPA procedures. The contribution of STPA-PSO lies in its quantitative enhancements of these steps and the introduction of a risk mitigation phase, described in the following sections.

2.3.2.3.1 Consider losses, hazards, and system-level constraints

Consistent with foundational STPA, the initial phase involves clearly delineating the scope of the analysis by defining potential losses, system-level hazards, and the overarching safety constraints that the system must satisfy to prevent these hazards. This foundational step is critical for establishing the boundaries of the analysis and ensuring a common understanding of what constitutes an undesirable outcome. As defined by Leveson and Thomas (2018):

- Loss: "something of value to stakeholders. Losses may include a loss of human life or human injury, property damage, environmental pollution, loss of mission, loss of reputation, loss or leak of sensitive information, or any other loss that is unacceptable to the stakeholders."
- System-level Hazard: "A system state or set of conditions that, together with a particular set of worst-case environmental conditions, will lead to a loss."
- System-level Constraint: "System conditions or behaviors that need to be satisfied to prevent hazards (and ultimately prevent losses)."

2.3.2.3.2 Develop functional control model structure

The second step involves constructing a hierarchical control structure model of the system under analysis. This model visually represents the interactions between controllers (e.g., humans, software, automated systems), controlled processes, control actions, and feedback mechanisms. Unlike physical models, STPA control structures are conceptual representations of how safety is managed, focusing on control loops and communication pathways rather than physical components (Leveson & Thomas, 2018). Key components include:

- Controllers: Entities responsible for issuing control actions.
- Control actions: Commands or instructions issued by controllers to influence the controlled process.

- Feedback: Information flowing back to controllers about the state of the controlled process.
- Controlled process: The system or subsystem being managed.

2.3.2.3.3 Identification of unsafe control actions (UCAs)

Building upon the functional control model, this step systematically identifies UCAs. A UCA is defined as "a control action that, in a particular context and worst-case environment, will lead to a hazard" (Mofidi Naeini & Nadeau, 2022c). UCAs are categorized into four primary types:

- Not providing a required control action: A safety-critical action is omitted.
- Providing an unsafe control action: An action is performed that inherently leads to a hazard.
- Providing a safe control action at an inappropriate time or sequence: The action is correct but its timing (too early, too late) or order is wrong.
- A continuous safe control action applied for too long or stopped too soon: The duration of a continuous action is incorrect.

Each UCA becomes a candidate event for quantitative risk assessment in STPA-PSO.

2.3.2.3.4 Calculate the risk of each UCA using the PSO algorithm

This is where the STPA-PSO methodology diverges from traditional STPA, transforming qualitative insights into quantifiable risk metrics. After identifying the UCAs, the risk associated with each is calculated using a multi-criteria approach with PSO. The fundamental risk equation, adapted for multi-criteria assessment, is applied:

$$R_i = P_i * ((W_{IND\,i} * I_{IND\,i}) + (W_{OHS\,i} * I_{OHS\,i}) + (W_{FIN\,i} * I_{FIN\,i})) \tag{2.3}$$

Where:

- R_i is the risk of event i;
- P_i is the probability of event i;
- $W_{IND\,i}$, $W_{OHS\,i}$, $W_{FIN\,i}$ are the weight factor of industrial aspect, OHS aspect, and financial aspect of event i, respectively.

- $I_{IND\ i}$, $I_{OHS\ i}$, $I_{FIN\ i}$ are the impact grade of each industrial, OHS, and financial aspect, respectively.

Each component of this quantitative assessment is detailed below:

The impact of each UCA is assessed across multiple critical dimensions to provide a holistic view of potential consequences. This study considers three primary aspects: Industrial, Occupational Health and Safety (OHS), and Financial. Each aspect is graded on a five-point Likert scale (1=Very Low, 2=Low, 3=Medium, 4=High, 5=Very High), providing granularity beyond simple binary failure states.

- OHS Impact: Graded according to the severity of human injury or health impairment, aligning with established definitions from the Canadian Centre for Occupational Health and Safety. This ranges from minor first aid incidents to critical situations leading to severe injury or fatality.
- Industrial and Financial Impact: Recognizing the interconnection of these aspects, their impact is assessed based on scenarios that consider both time-related industrial disruptions (e.g., production delays, reassembly, and stop production) and corresponding cost implications. This comprehensive approach provides a more realistic representation of business and operational consequences.

To determine the relative importance (weights) of these different impact criteria ($W_{IND\ i}$, $W_{OHS\ i}$, $W_{FIN\ i}$), the Best Worst Method (BWM) is employed. BWM is a Multi-Criteria Decision Making (MCDM) technique selected for its computational efficiency and robust capability in establishing criteria weights based on expert judgment. This method involves identifying the best and worst criteria, followed by pairwise comparisons to derive the optimal weights, ensuring a systematic and transparent weighting process.

Determining the probability (P_i) of each UCA, especially in complex systems with uncertain failure modes (such as those involving wearables), is a critical step. Given the potential lack of reliable historical data, particularly during the design phase, random simulated data is employed to determine the probability of each UCA. This approach allows for the establishment and evaluation of a dependable framework even when empirical data is scarce, ensuring the methodology's functionality with varied scenarios. The PSO algorithm plays a role in generating and exploring these simulated probability scenarios.

The final part of the quantitative assessment in STPA-PSO involves the application of the PSO algorithm. Given the multi-variable nature of the risk calculation (involving probabilities, impact grades, and weights) and the need to identify the "worst-case scenarios" to prioritize risks, PSO provides a computational solution.

In the context of STPA-PSO, the algorithm is used to:

- Quantify risk: By iteratively evaluating the risk (Eq. 2.3) across various random simulated probabilities and impact scenarios.
- Identify high-risk scenarios: The PSO algorithm selects and prioritizes the top events (UCAs) that pose the highest risk levels, allowing for focused mitigation efforts.

The use of PSO ensures that the STPA-PSO methodology not only quantifies risk but also provides a reliable tool for identifying critical vulnerabilities and optimizing safety responses, particularly valuable when operating with simulated data during early design phases.

The final risk score combines probability and weighted impact. Based on the 1-5 impact scale and potential probabilities, the resulting risk scores are categorized into qualitative tiers for easier interpretation: very low risk ($R_i < 5$), low risk ($5 \leq R_i < 10$), medium risk ($10 \leq R_i < 15$), high risk ($15 \leq R_i < 20$), very high risk ($20 \leq R_i \leq 25$).

2.3.2.3.5 Identify loss scenarios

During this stage, the UCAs are ranked based on their calculated risk scores. The top-ranked scenarios (e.g., those falling into 'high' and 'very high' risk tiers) are identified for focused mitigation efforts in the next step. This prioritization is a key output of the quantitative assessment and guides subsequent decision-making.

2.3.2.3.6 Identify mitigation strategies (Human-AI collaboration)

In the final stage, improvement recommendations are generated for the identified loss scenarios in the previous step. In this final stage, improvement recommendations are generated for the identified loss scenarios. This step operationalizes a semi-automated mitigation tool, where AI assists human decision-making by prioritizing risks for each scenario. It transforms the methodology from purely analytical to include proactive risk reduction guidance during the design phase.

The initial steps (1, 2, and 3) are conducted through human analysis, while steps 4 and 5 are performed by the intelligent PSO algorithm. Step six, represents a collaboration between human expertise and AI capabilities. Here, the intelligent algorithm functions as a knowledge-based matching system, querying a predefined knowledge base to link identified unsafe control actions to relevant mitigation strategies. This human-AI collaboration enables iterative refinement, prompting recalculation of the model from step four after improvement recommendations are implemented, thereby completing the circular process of the model and continuously assessing the effectiveness of mitigations.

Therefore, by systematically identifying, quantifying, and mitigating risks, STPA-PSO provides a comprehensive framework for proactive risk management. It moves beyond theoretical hazard identification to deliver actionable safety improvements. Chapters 3 and 4 provide the detailed methodology and application of the model.

2.3.3 FRAM-PSO

2.3.3.1 Introduction of FRAM

In 2004, Erik Hollnagel introduced FRAM as a way to analyze and assess risks in complex sociotechnical systems (Hollnagel & Goteman, 2004). Since its introduction, FRAM has been widely applied in industries such as aviation, healthcare, and industrial processes, which together account for more than half of the published applications (Patriarca et al., 2020). It has also been applied in maritime safety (Salihoglu & Beşikçi, 2021), offshore drilling (França, Hollnagel, dos Santos, & Haddad, 2021), coal mine accidents (Wanguan Qiao, Li, & Liu, 2019), software engineering (E. A. de Carvalho, Gomes, Jatobá, da Silva, & de Carvalho, 2021), healthcare (Cheng et al., 2020), and increasingly in manufacturing (Melanson & Nadeau, 2019).

FRAM has proven effective both retrospectively (to analyze past accidents) and prospectively (to anticipate and prevent future risks), supporting resilience engineering by providing safety assurance in dynamic operational environments (Lundblad, Speziali, Woltjer, & Lundberg, 2008; Yousefi, Rodriguez Hernandez, & Lopez Peña, 2019; D. Smith, Veitch, Khan, & Taylor, 2017). Its main strength lies in modeling non-linear interactions and performance variability that arise during real operations, allowing analysts to understand how systems maintain safety despite complexity (Bellini, Coconea, & Nesi, 2019).

According to Hollnagel (2012), FRAM is based on four fundamental principles:

- There is no intrinsic difference between successes and failures—their causes are the same.
- Performance in sociotechnical systems is always adapted to match conditions.
- Many outcomes of a system are emergent, rather than the result of single components.
- Functional resonance describes how variability accumulates and combines, rather than following simple cause and effect chains.

FRAM derives its name from the idea that normal performance variability can resonate across functions, amplifying deviations until they result in an accident signal. FRAM represents systems in terms of functions rather than components. A function can be performed by humans, organizations, or technology. Each function is described using six aspects (Figure 2.5). The FRAM process typically follows four steps (Hulme, Stanton, Walker, Waterson, & Salmon, 2019):

- Identify system functions (human, technological, organizational).
- Identify functional variability based on observed and potential deviations.
- Model interactions by linking functions into a FRAM diagram, highlighting where variability may couple. The FRAM Model Visualizer (FMV) tool supports this stage.
- Visualize and evaluate variability across the model to propose monitoring to ensure the system continues to operate within safe boundaries.

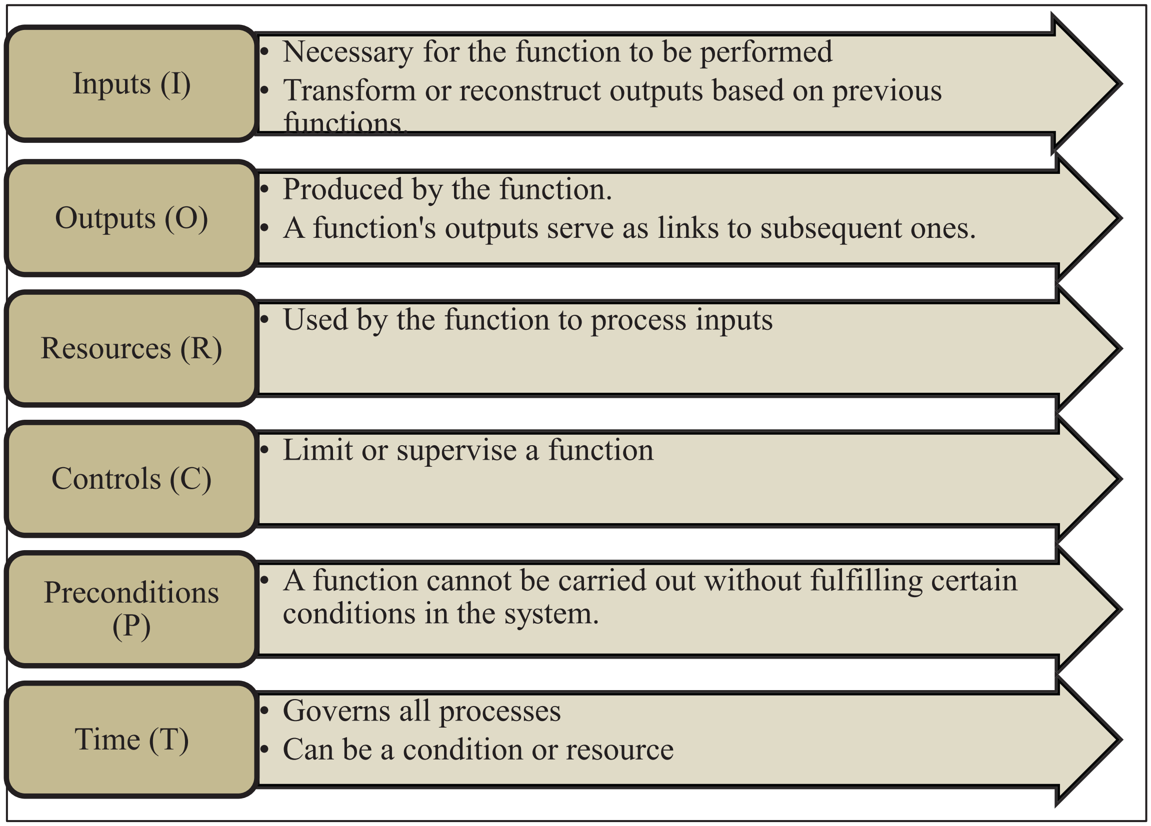

Figure 2.5 Six aspects of a function according to FRAM

Through this process, FRAM examines how everyday performance variability may combine to produce unexpected and undesirable outcomes, instead of simply tracing linear failure chains (Hulme et al., 2019). FRAM has been applied extensively in safety-critical domains. Its advantages over traditional techniques include:

- Capturing complex organizational and contextual influences.
- Modeling real-world work practices (work-as-done) instead of relying solely on procedures (work-as-imagined).
- Revealing functional couplings and emergent risks invisible to linear tools.

Table 2.1 summarizes how FRAM compares with traditional methods such as Fault Tree Analysis (FTA), Root-Cause Analysis (RCA), Failure Mode and Effect Analysis (FMEA), Event Tree Analysis (ETA), and Failure Mode, Effects and Criticality Analysis (FMECA) (Patriarca et al., 2020).

However, FRAM also presents challenges:

- High coupling complexity makes models difficult to construct and interpret (Nakajima, 2017; Praetorius, Graziano, Schröder-Hinrichs, & Baldauf, 2017).
- Analysis is time-consuming and heavily dependent on expert judgment (Bahoo Toroody, Talaee, Abaei, & Gholamnia, 2016).
- Results remain qualitative, limiting their direct use for quantitative decision-making (Guo et al., 2022).

Table 2.1 Advantages of FRAM over traditional methods

Method	Advantages of using FRAM over this method	Author, Year
FTA	• Prompts identification of organizational factors that may pose risks • Supports consideration of potential control measures	(Bahoo Toroody et al., 2016; Praetorius et al., 2017)
RCA	• Improves understanding of in-situ complex processes • Highlights emergent properties not captured by linear root-cause chains	(Nakajima, 2017)
FMEA	• Visualizes system design as a function of complexity • Considers different contextual influences on performance	(Das et al., 2018; Patriarca et al., 2020)
ETA / FMECA	• Improves understanding of composite causes of accidents • Reveals how accidents emerge from performance variability rather than linear sequences	(Melanson & Nadeau, 2019)

To overcome FRAM's qualitative limitations, researchers have attempted various quantification approaches (Table 2.2). These include Bayesian Networks (Bahoo Toroody, Bahoo Toroody, & De Carlo, 2017; Q. Wang, Jiang, Park, & Wang, 2023; Xinqi Zhang et al., 2022), Monte Carlo Simulation (Costantino, Di Gravio, & Tronci, 2018; Köpke, Schäfer-Frey, Engler, Wrede, & Mielniczek, 2020; Patriarca, Di Gravio, & Costantino, 2017; Peng, Zhen, & Huang, 2022; Zhou, Matsubara, & Takada, 2023), reinforcement learning (Salehi, Tran, Veitch, & Smith, 2022), fuzzy sets (Slim & Nadeau, 2019), analytic hierarchy process (P. de Carvalho, Villarinho, & Haddad, 2016; França, Hollnagel, dos Santos, & Haddad, 2020; Haddad & Rosa, 2015; Lucio Villarinho Rosa, Carvalho, & Haddad, 2020; Lucio V Rosa, França, Haddad, & Carvalho, 2017), and Genetic algorithm (Patriarca, Lovaglio, & Simone, 2025).

These efforts highlight that combining FRAM with complementary quantitative methods produces richer insights than applying them in isolation (Mofidi Naeini & Nadeau, 2022b). However, no prior work has integrated FRAM with PSO, and importantly, none of the quantification studies have specifically addressed wearable-enabled manufacturing systems. This gap motivates the development of FRAM-PSO, which will be introduced in the following section.

2.3.3.2 FRAM-PSO: A hybrid framework for sustainable risk assessment and mitigation

While FRAM provides a qualitative framework to model functional variability and explore how everyday performance deviations may resonate across a sociotechnical system, its descriptive nature limits its ability to support quantitative risk assessment. In particular, FRAM identifies how variability propagates but does not directly assign numerical measures to risk or offer systematic guidance for prioritizing mitigation strategies (Guo et al., 2022).

To address this limitation, this thesis introduces FRAM-PSO, a hybrid framework that integrates FRAM with PSO. The framework builds on FRAM's capacity to model variability while leveraging PSO to quantify risks, identify critical pathways, and propose sustainable mitigation strategies that explicitly account for economic, environmental, and social dimensions. The approach not only extends FRAM beyond descriptive modeling but also ensures that risk-reduction decisions are evaluated within a sustainability framework, aligning immediate safety improvements with long-term system resilience and sustainable development goals.

As illustrated in Figure 5.1, FRAM-PSO follows a structured process. The initial stages (Steps 1–4) are grounded in the established FRAM procedure, while later stages introduce quantitative enhancements and optimization routines through PSO. The framework distinguishes between tasks performed by the decision-making team (human analysis) and those automated through the intelligent algorithm.

Table 2.2 FRAM quantification efforts

Reference	**Method of quantifying**	**Industry**
(Q. Wang et al., 2023)	BN	Construction industry
(Bahoo Toroody et al., 2017)		Oil and gas industry
(Xinqi Zhang et al., 2022)	DBN	Gas pipeline industry
(Zhou et al., 2023)	Monte Carlo Simulation	Healthcare industry
(Peng et al., 2022)		Marine industry
(Köpke et al., 2020)		Offshore wind farms
(Costantino et al., 2018)		Manufacturing industry
(Patriarca, Di Gravio, & Costantino, 2017)		Aviation industry
(Patriarca et al., 2025)	Genetic Algorithm	Maintenance
(Lucio V Rosa et al., 2017)	AHP	Construction industry
(Haddad & Rosa, 2015)		Construction industry
(P. de Carvalho et al., 2016)		Socio-technical system
(França et al., 2020)		Oil and gas industry
(Lucio Villarinho Rosa et al., 2020)		Construction industry
(Salehi et al., 2022)	Reinforcement Learning	Healthcare industry
(Liu et al., 2021)	CREAM	Medical equipment
(Eljaoued, Yahia, & Saoud, 2020)	Resilience Measuring	Socio-technical system
(Slim & Nadeau, 2019)	Fuzzy Logic Rough Sets	Aviation industry
(J. Lee & Chung, 2018)	HIS Methodology	Marine industry
(Riccardo, Gianluca, Giulio, & Francesco, 2018)	Resilience Analysis Matrix	Aviation industry
(Bahoo Toroody et al., 2016)	Noisy OR-Gate Model	Marine industry
(Lopez de Obeso, Mock, & Zipper, 2016)	FMEA	Construction industry

2.3.3.2.1 Identification and description of the system's functions

The initial step in this methodology involves clearly articulating the primary objective of the study. This entails determining whether the focus is on accident investigation or a broader system risk assessment. For this research, the primary objective is a proactive system risk assessment, aiming to identify potential vulnerabilities and improve system resilience before incidents occur.

The next step involves identifying and categorizing system functions into foreground and background types. Foreground functions, central to the analysis, are characterized by six attributes: Input (what initiates the function), Output (the result), Precondition (requirements for execution), Resource (consumable elements), Control (guiding instructions), and Time (temporal constraints). Background functions, which play a supporting role, are defined by a single input or output to provide context. This distinction allows for focused analysis while acknowledging broader system interactions. The specifications of FRAM functions can be visually represented to enhance clarity.

2.3.3.2.2 Identification of performance variability

This step involves a detailed analysis of potential and actual performance variations inherent in each function, specifically within the context of various risk scenarios. Variability can originate from three main sources:

- Internal: Changes or fluctuations occurring within the function itself.
- External: Influences from the surrounding work environment or operational context.
- Coupling: Effects stemming from the outputs of upstream functions.

Understanding these sources is crucial for explaining discrepancies in function outputs. Variability can be categorized into several types based on characteristics such as timing, precision, speed, distance, sequence, object, force, duration, and direction (Zinetullina et al., 2021). However, most researchers simplify the approach by focusing primarily on timing and precision (A. Kumar et al., 2024), such as those by (Kaya & Hocaoglu, 2020; Kaya, Ozturk, &

Sariguzel, 2021; Mofidi Naeini & Nadeau, 2023; Patriarca, Di Gravio, & Costantino, 2017; Slim & Nadeau, 2019; Yu et al., 2025; Zinetullina et al., 2021). This study focuses on time, precision, force (exerted by the worker), and sequence, due to their direct relevance to manual assembly and disassembly operations and their impact on failure modes and performance with smart wearable technologies.

To quantify the collective influence of these variations on system outputs, the overall variability of an upstream output *j,* denoted as OV_j, is calculated using the following formula:

$$OV_j = V_j^T * V_j^P * V_j^F * V_j^S \tag{2.4}$$

Where V_j^T, V_j^P, and V_j^F represent the variability in timing, precision, and force, respectively, while V_j^S accounts for sequence variability.

To enhance the reliability of these quantifications, an occurrence probability vector is introduced for each output, considering the probability distribution across its timing, precision, force, and sequence characteristics. Since simulated data are used in this study, MCS will be used to estimate the probability distribution of the outputs, which is valuable during the design phase analysis. For running cases, historical data on these variabilities should be considered.

2.3.3.2.3 Aggregation of variability

This step investigates how variability propagates and interacts across interconnected system functions. FRAM's graphical modeling capabilities are utilized to illustrate the functional relationships and trace the flow of variability downstream. Variability in a function can arise from a combination of its inherent characteristics and the inputs it receives from upstream functions.

The aggregation process highlights the dual impact of variability: negative variability can resonate across interdependent functions, amplifying system risks and pinpointing critical areas such as accident precursors or key hazard contributors. Conversely, positive variability can act as a stabilizing influence, mitigating downstream variations and bolstering system resilience. A comprehensive understanding of these dynamics is essential for identifying critical couplings and assessing how variability disseminates through the system, ultimately informing improved risk management and system performance strategies.

To quantify the overall impact of timing, precision, force, and sequence from upstream function j on downstream function I (denoted as cumulative interaction effect (CI_{ij})), the equation 2.5 is used:

$$CI_{ijn} = \alpha_{ijn}^{T} * \alpha_{ijn}^{P} * \alpha_{ijn}^{F} * \ \alpha_{ijn}^{S} \tag{2.5}$$

Where, α_{ijn}^{T}, α_{ijn}^{P}, α_{ijn}^{F}, and α_{ijn}^{S} represent the damping or amplifying effect of output *n* from upstream function *j* on downstream function *i* in terms of time, precision, force, and sequence, respectively. In real cases, they should be determined by the decision-making team based on the real interactions between functions.

2.3.3.2.4 Management of variability

This step focuses on developing strategies to manage variability by amplifying positive outcomes and minimizing negative ones, particularly by addressing critical couplings identified during functional resonance analysis. Improvement measures are designed either to prevent accidents or to restore optimal system functionality following disruptions.

The influence of external operating conditions on system performance is integrated by defining a set of Scenario Performance Conditions (SPCs). These SPCs capture various internal and external factors—such as environmental conditions (e.g., temperature, lighting), equipment reliability, and workload fluctuations—that may affect overall system performance.

The overall effect of a scenario on a given function is determined by summing the weighted contributions of each SPC, as shown in Equation 2.6.

$$e_j^z = \sum_{k=1}^{m} SPC_z^k * b_j^k \tag{2.6}$$

Where, e_j^z is the conditional variability of function *j* under scenario *z*, SPC_z^k denotes the rating of the k^{th} condition in scenario *z*, and b_j^k represents the impact of the k^{th} condition on function *j*.

2.3.3.2.5 Quantifying the risk

At this step, a comprehensive index for each coupling, known as the Variability Propagation Number (VPN), is derived. This index integrates three critical elements: the inherent variability of the upstream function j (OV_j), the cumulative interaction effect between upstream and downstream functions (CI_{ij}), and the conditional variability e_j^z, which represents how external factors in scenario z influence the system's performance. The VPN provides a detailed and dynamic measure of a coupling's variability, capturing both internal performance fluctuations and the effects of external operating conditions.

The VPN for a coupling between function i and function j under scenario z is calculated as:

$$VPN_{ij}^z = OV_j * CI_{ij} * e_j^z \tag{2.7}$$

VPN is calculated for each function. The path VPN is then computed based on the summation of downstream functions for each function. The objective function for PSO is to minimize the path VPN, thereby minimizing the VPN for each function and identifying the critical path.

2.3.3.2.6 Sustainable mitigation strategies

After identifying the highest path VPN, the final step involves systematically mitigating this risk through the selection of sustainable strategies. These strategies are context-dependent, varying across case studies and industries, and must address the three pillars of sustainability: economic, environmental, and social.

Decision-making teams identify the functions and SPCs associated with each strategy, assess the difficulty of implementation (feasibility), and evaluate the strategy's impact on the system, considering its contribution to environmental, economic, and social sustainability. The algorithm then iteratively selects the most effective available sustainable mitigation strategy, applies its impact weight within the model, and recalculates the overall risk profile. This iterative process not only reduces high-risk outputs but also progressively transforms the model into a sustainable one, balancing risk reduction with long-term benefits. The process involves:

- Identifying the function with the maximum Path VPN.

- Selecting the most effective available sustainable mitigation strategy relevant to that function's associated SPCs (with a constraint preventing immediate re-selection of the same strategy for the same path if alternatives exist).
- Applying the chosen strategy's impact weight within the model.
- Recalculating all function VPNs and path VPNs.
- Repeating the process for a predetermined number of steps.

Chapters 5 provide the detailed methodology and application of the model.

2.3.4 STPA-BN-PSO

2.3.4.1 Introduction of BN

Bayesian Networks are probabilistic graphical models that represent dependencies between variables using a Directed Acyclic Graph (DAG). Nodes represent random variables, while arcs indicate probabilistic relationships between them. This structure enables reasoning under uncertainty that allows analysts to infer the likelihood of causes from observed effects and update prior beliefs when new evidence becomes available (Groth & Mosleh, 2011; Morais, Moura, Beer, & Patelli, 2020).

Each node (e.g., organizational, technological, personal, or cognitive factors) is connected by directed arcs that represent causal relationships. Conditional Probability Tables (CPTs) define the likelihood of each node's state, given the state of its parent nodes. The sum of probabilities across all possible states of a node must equal 1, ensuring a complete and consistent model (G. Li, Xing, & Chen, 2015).

BNs are grounded in Bayes' theorem (Eq. 2.8), which provides a mechanism for updating the probability of an event *A* given evidence *E* (Afenyo, Khan, Veitch, & Yang, 2017).

$$P(A|E) = \frac{P(E|A)P(A)}{P(E)} \tag{2.8}$$

The joint probability distribution of all variables in the network can be expressed through the chain rule (Eq. 2.9):

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P\big(X_i \big| parent\ (X_i)\big) \tag{2.9}$$

This combination of probability theory, graph theory, and decision theory makes BNs one of the most effective methods for modeling system behavior under uncertainty (Guo et al., 2022). Developing a BN typically involves the following steps (Weiliang Qiao et al., 2022):

- **Identification of nodes**: Depending on the application, nodes may be root, intermediate, or leaf nodes, modeled as random variables.
- **Identification of directed links**: Arcs indicate dependencies between nodes, defining the network's causal structure.
- **Specification of prior probabilities**: Root nodes are assigned marginal probabilities, derived from expert elicitation, historical data, or fuzzy evaluations.
- **Construction of CPTs**: Conditional probabilities for non-root nodes are established using data-driven approaches, expert judgment, or algorithms.

Also, BNs offer several advantages for risk analysis (Morais et al., 2020):

- Handle incomplete or uncertain data effectively.
- Capture causal relationships between variables.
- Integrate expert judgment with statistical data.
- Avoid the common but often incorrect assumption of independent factors.
- Support multidisciplinary communication using intuitive graphical models.
- Update probabilities dynamically as new evidence becomes available.
- Facilitate "what-if" analyses by fixing certain variables and propagating effects.

Despite these strengths, BNs have notable challenges (T. Du, Zhang, & Wang, 2005; Tao, 2005):

- Heavy reliance on expert judgment when data are scarce.
- Computational complexity increases rapidly for large networks.
- Learning BN structures from data is NP-hard, and heuristic algorithms such as hill-climbing, Simulated Annealing (SA), or Genetic Algorithms (GA) may converge prematurely to suboptimal solutions.

BNs have nevertheless been successfully applied in diverse industries. In aviation, they have been used for accident analysis and safety assessment (Mkrtchyan et al., 2015); in healthcare, they support diagnostic reasoning and patient safety modeling (Morais et al., 2020); in the construction industry, BNs model safety risks and project uncertainties (Q. Wang et al., 2023); in oil and gas, they evaluate equipment reliability and operational risks (Afenyo et al., 2017). More recently, they have been applied to manufacturing and human reliability analysis, where they estimate human error probabilities and unsafe behaviors in high-risk operations (Ghasemi, Ghasemi, & Kalatpour, 2022). Their flexibility allows them to represent complex dependencies, including common causes and hidden variables (Castillo et al., 2016).

2.3.4.2 STPA-BN-PSO: A hybrid framework for probabilistic risk assessment and optimization

The STPA-BN-PSO framework represents the third methodological pillar of this thesis and is explicitly conceived as a triangulation of STPA-PSO and FRAM-PSO. The approach integrates BN with PSO to calibrate CPTs, quantify systemic risks, and identify critical pathways in wearable-enabled manufacturing contexts. By embedding STPA outputs into a hierarchical BN structure and calibrating its conditional probabilities using PSO, this method extends the analysis to evaluate risk propagation and system sensitivity. As illustrated in Figure 6.1, the methodology follows a structured process from hierarchical BN formulation to optimization, quantification, and sensitivity analysis.

2.3.4.2.1 Hierarchical BN model formulation

The foundation of the STPA-BN-PSO methodology is a three-tiered hierarchical Bayesian Network (BN) designed to model the causal chain from root control failures to system-level losses. This structure is directly derived from the validated outputs of prior STPA work. This ensures that the model remains grounded in a systemic understanding of the system's dynamics. The tiers are constructed bottom-up, with directed arcs strictly following the STPA-defined adjacency: Control Actions influencing Hazards, Hazards influencing Losses, and

Losses contributing to a terminal Risk node. Acyclicity is rigorously enforced throughout the network structure.

- Tier 3 – Control Actions (CA): Root nodes representing unsafe control actions through which control of the system may be lost. Their prior probabilities are initialized by STPA scores.
- Tier 2 – Hazards (H): Intermediate nodes corresponding to system hazards, each linked to its contributing CAs. Their CPTs, initially unknown, are optimized during calibration.
- Tier 1 – Losses (L): Top-level nodes linked to hazards that may trigger unacceptable system outcomes.
- Tier 0 – Risk (R): The terminal node provides an aggregate measure of system risk.

2.3.4.2.2 BN optimization with PSO

Following the formulation of the BN structure based on STPA outputs (CA→H→L→Risk), the unknown parameters within the CPTs for all hazard and loss nodes are estimated using PSO. The PSO algorithm maintains a swarm of candidate CPT sets. After each velocity and position update for the particles, every CPT column is rigorously renormalized to satisfy the fundamental properties of a probability simplex. The fitness function balances two terms:

- Root-fit term: This term quantifies the mean-squared error between the marginal probabilities of the CA nodes sampled from the current BN model and their respective STPA-derived prior probabilities.
- Risk-fit term: The mean-squared error between the model’s sampled 5-level Risk distribution (generated by the probabilistic Risk node) and the target reference profile.

The fitness score for a candidate BN is then calculated as the inverse of this combined loss value. Consequently, a higher fitness score directly indicates a more accurate and plausible BN model. Marginal probabilities required for fitness evaluation are estimated through Monte Carlo sampling. An early stopping criterion is implemented to ensure efficient calibration, terminating the optimization when the global best fitness value shows no significant improvement over a defined number of iterations.

2.3.4.2.3 Model parameterization and risk quantification

Upon the successful construction and calibration of the BN, a single terminal 'risk' node is introduced to provide an aggregate measure of the system's overall risk. This node is characterized by five discrete states: Very Low, Low, Medium, High, and Very High. For practical decision-making, these five states are further categorized into 'Acceptable Risk' (encompassing Very Low, Low, and Medium states) and 'Unacceptable Risk' (comprising High and Very High states). This risk threshold can be dynamically adjusted based on the specific risk tolerance requirements of the application.

2.3.4.2.4 Risk analysis

With the BN model calibrated, a comprehensive, multi-faceted risk analysis is conducted to extract actionable insights.

- Baseline quantification: The initial step in the risk analysis involves establishing the system's baseline risk profile. This is achieved by performing a Monte Carlo inference on the calibrated network with no external evidence applied. The inference yields the probability distribution for the terminal 'risk' node, from which the cumulative probability of the 'High' and 'Very High' states is defined as the measure of unacceptable risk.

To pinpoint the most significant contributors to the overall system risk, two distinct forms of criticality are assessed:

- Node-Level Systemic Impact: This metric is calculated for every CA, Hazard, and Loss node. It involves programmatically forcing the state of a specific node to 'True' and then measuring the absolute increase in the system's baseline unacceptable risk.
- Path-Based CA Impact: This analysis quantifies the total risk propagated through all downstream pathways originating from each specific CA. It provides a measure of the cumulative influence of an individual CA on the ultimate risk profile.

2.3.4.2.5 Sensitivity analysis

To evaluate robustness, three forms of sensitivity are tested:

- CA evidence sensitivity: ±10% perturbations assess how evidence variations affect systemic risk.
- CPT sensitivity: ±10% perturbations identify the most influential probabilistic relationships.
- Structural sensitivity: Edge removals quantify the importance of causal links while preserving network acyclicity.

Chapters 6 provide the detailed methodology and application of the model.

2.4 Designing case studies

Case studies are widely recognized as a method for exploring complex systems where empirical data are scarce and experimentation in real industrial environments is impractical. They enable both qualitative and quantitative insights and provide a robust foundation for developing and testing emerging frameworks (Harrison, Birks, Franklin, & Mills, 2017; Rashid, Rashid, Warraich, Sabir, & Waseem, 2019).

In the methodological literature, there is a longstanding debate on the choice between single-case and multiple-case designs. Single-case studies are less costly and allow for deep analysis of one context, but they may limit generalizability. In contrast, multiple case studies strengthen analytical conclusions by allowing replication logic (Gustafsson, 2017; Yin, 2018). Each case can be viewed as a distinct experiment, and consistent findings across them significantly increase the robustness of results (Mofidi Naeini, 2022).

Given the objective of this thesis, three cases were chosen as a balance between depth and comparability without introducing excessive data management complexity (Dul & Hak, 2007). These three cases form a triangulation of industrial contexts: a sequential assembly line, a job shop assembly, and a disassembly line (Table 2.3). Together, they reflect complementary operational challenges in terms of efficiency, variability, safety, and sustainability. Importantly, in their baseline configuration, none of these cases involves the use of smart wearables. Smart glasses and smart gloves are therefore integrated into the scenarios, enabling the frameworks to analyze both their potential benefits and the systemic risks they may introduce. It is important to mention that, in this thesis, the analyses rely on simulated data, as access to real-world industrial data is not yet available.

2.4.1 Case Study 1 – Assembly line

The first case study focuses on a refrigerator manufacturing plant during its design phase. The analysis centers on the workstation responsible for assembling the fruit and vegetable box, drawers, and covering plates (W. Zhang, Gu, & Guo, 2019).

In the baseline configuration, one operator performs these tasks manually without wearable assistance. Three bins containing required parts are placed near the workstation. The operator retrieves components from these bins, assembles them according to the product map and supervisor's instructions, and transfers the partially completed unit to the next station. The warehouse is responsible for refilling the bins to avoid disruptions. The primary risks and challenges include:

- High manual dependency: Assembly precision and timing depend entirely on the operator's skills and physical condition.
- Potential bottlenecks: Delays occur if materials are missing or if instructions are misinterpreted.
- Error risks: Misplacement of drawers or incorrect installation of covering plates can compromise product quality.

This case study introduces smart glasses (to display real-time assembly instructions and highlight hazardous parts) and smart gloves (to provide haptic feedback for correct pressure application). The objective is to evaluate how these devices influence task precision, timing, and safety, as well as the new risks they may introduce (e.g., distraction, connectivity failures).

2.4.2 Case Study 2 – Job-Shop assembly

The second case study examines a hybrid job-shop environment, where operators handle multiple product types with frequent changeovers (Torres et al., 2021b). Compared to assembly lines, job-shop assembly is characterized by higher variability in task sequences and resource allocation. The primary risks and challenges include:

- Task variability: Increased cognitive load from frequent product switching.
- Manual complexity: Workers must interpret multiple product maps and specifications.
- Error propagation: Misassembly in one task can cascade across subsequent operations.

Here, wearable integration plays a more prominent role:

- Smart glasses provide context-specific product maps, guiding workers through diverse assembly sequences.
- Smart gloves deliver tactile signals to help control applied force, particularly for delicate components.

The analysis investigates how variability in sequence, force, and timing propagates through the system under wearable support. In this context, wearables are expected to reduce error rates and cognitive load, but the heterogeneity of tasks increases the likelihood of hazardous interactions (e.g., misprogramming or distraction when switching between products).

2.4.3 Case Study 3 – Disassembly line

The third case study focuses on a refrigerator disassembly line designed for recycling and end-of-life product recovery (Zeng, Zhang, Liang, & Zhang, 2023). Disassembly introduces risks distinct from assembly: workers must identify and separate hazardous and non-hazardous components, such as refrigerant-containing parts, under strict environmental and safety constraints.

In the baseline process, operators manually follow disassembly guides and sort components into bins. The primary risks and challenges include:

- Environmental risk: Improper handling of refrigerants or hazardous materials can cause environmental damage.

- Worker safety: Sharp edges, heavy lifting, and toxic exposure are recurring hazards.
- Sorting accuracy: Misclassification of hazardous vs. non-hazardous parts threatens both safety and regulatory compliance.

Table 2.3 Overview of case studies and wearable contributions

Case study	**Main risks**	**Smart glasses benefits**	**Smart gloves benefits**
Sequential assembly line	• High manual dependency • Bottlenecks if materials/instructions are missing • Misplacement or assembly errors reduce quality	• Display real-time assembly instructions • Highlight correct parts and hazards • Reduce misinterpretation errors	• Haptic feedback ensures correct pressure • Reduces risk of damaging components
Job-shop assembly	• High task variability and cognitive load • Manual complexity in interpreting product maps • Errors can propagate across operations	• Provide context-specific product maps • Guide workers dynamically across sequences • Reduce cognitive load in task switching	• Tactile cues regulate applied force • Support handling of delicate/variable components
Disassembly line	• Environmental risk from hazardous materials • Worker safety • Sorting errors threaten compliance and safety	• Highlight hazardous components in real time • Provide safe removal and sorting guidance • Improve regulatory compliance	• Assist with controlled disassembly force • Signal when unsafe pressure is applied • Reduce injury risk

Smart glasses are introduced to highlight hazardous components in real time and provide visual instructions for safe removal. Smart gloves are employed to assist with controlled force application and to signal when unsafe levels of pressure are applied. This case allows evaluation of wearable effectiveness in a safety-critical, environmentally sensitive context.

CHAPTER 3

A COMPREHENSIVE STPA-PSO FRAMEWORK FOR QUANTIFYING SMART GLASSES RISKS IN MANUFACTURING

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Abstract

The integration of cutting-edge technologies, such as wearables, in complex systems is crucial for enhancing collaboration between humans and machines in the era of Industry 5.0. However, this increased interaction also introduces new challenges and risks, including the potential for human errors. A thorough analysis of the literature reveals an absence of studies that have quantified these risks, underscoring the utmost importance of this research. To address the above gap, the present study introduces the STPA-PSO methodology, which aims to quantify the risks associated with the use of smart glasses in complex systems, with a specific focus on human error risks. The proposed methodology leverages the Systems-Theoretic Process Analysis (STPA) approach to proactively identify hazards, while harnessing the power of the Particle Swarm Optimization (PSO) algorithm to accurately calculate and optimize risks, including those related to human errors. To validate the effectiveness of the methodology, a case study involving the assembly of a refrigerator was conducted, encompassing various critical aspects, such as the Industrial, Financial, and Occupational Health and Safety (OHS) aspects. The results provide evidence of the efficacy of the STPA-PSO approach in assessing, quantifying, and managing risks during the design stage. By proposing a robust and comprehensive risk quantification framework, this study makes a significant contribution to the advancement of system safety analysis in complex environments, providing invaluable

insights for the seamless integration of wearables and ensuring safer interactions between humans and machines.

Keywords: Risk management; Systems-Theoretic Process Analysis (STPA); Particle Swarm Optimization (PSO); Industry 5.0; Smart Glasses; Manufacturing

3.1 Introduction

During the process of designing a new system or improving an existing one, engineers aim to anticipate potential patterns of system operation under various circumstances or uncertain situations (Zio, 2013). The concept of risk is rooted in the uncertainty of outcomes rather than their certainty (Gorrod, 2003).

In the realm of system design and improvement, engineers aim to anticipate potential patterns of system operation under various circumstances or uncertain situations (Zio, 2013). The concept of risk, deeply rooted in the uncertainty of outcomes rather than their certainty, underscores the dynamic nature of engineering endeavors (Gorrod, 2003). Moreover, emerging risks, characterized by their novelty, limited data, and absence of verifiable information, pose unique obstacles in decision-making processes (ISO, 2023). These risks carry the potential for substantial threats and opportunities, emphasizing the essential need for their thorough management within organizational risk frameworks. This management approach should be flexible, adjusting to shifts in external conditions and considering their impacts on internal operations (ISO, 2023).

Considering the inherent fallibility of human beings, it becomes evident that a spectrum of occupational hazards and risks emanates from human error, especially in the context of system design (Wiegmann & Shappell, 2001). Factors such as insufficient operator qualifications, inaccuracies during work, and misunderstandings of instructions contribute to this risk landscape (Stojiljkovic et al., 2018). To mitigate the occurrence of accidents, a deeper understanding of human error and its causes is imperative (Wiegmann & Shappell, 2001). An interesting observation is that a significant proportion, ranging from 50% to 90%, of reported incidents in industry can be attributed to human errors (Castiglia & Giardina, 2013). Given the preceding, extensive research has therefore been carried out on improving human reliability and reducing human errors (Calixto, 2016; Emami-Mehrgani, Neumann, Nadeau, & Bazrafshan, 2016).

In product manufacturing, human behavior is influenced by situations involving machines, systems, and organizations (Bubb, 2005). Human variability makes errors inevitable and cannot be eliminated entirely (Torres et al., 2021b). Therefore, it is crucial and of utmost priority to put forth solutions that facilitate the reduction of human errors. However, achieving this goal requires not only appropriate qualifications but also effective quantification methods to accurately assess and address the issue (Karevan & Nadeau, 2023).

By employing sensors to regulate multiple parameters, the Internet of Things (IoT) has the capacity to mitigate the risk of injuries and hazards in the workplace, thereby fostering a healthier work environment (Riso, 2021); more evaluative work is needed to determine this, though. Industry 5.0 seeks to facilitate the restoration of factories to peak productivity while leveraging the benefits of modern technology in an effective manner (Nahavandi, 2019). In the current landscape, there exists a demand not only for intelligent machines but also for humans to possess the necessary skills to effectively utilize the underlying technologies (Reiman et al., 2021). In contrast to previous industrial revolutions, Industry 5.0 aims to intricately blend the precision of technology with human creativity and intelligence, acknowledging that these elements are interdependent rather than separate entities (Raya, 2022). The fifth industrial revolution places significant emphasis on reintegrating humans into the production process by harnessing the power of intelligent, precise, and efficient machines, while simultaneously leveraging human intelligence and creativity. This unique combination of human and machine capabilities forms a fundamental aspect of the fifth industrial revolution (I. Sharma et al., 2020). Through the use of IoTs, humans can optimize their efficiency in performing critical tasks and responsibilities, resulting in enhanced safety, productivity, and overall performance (Gaiardelli et al., 2021).

While new technologies have the potential to reduce human errors, it is important to recognize that they cannot completely eliminate them. Indeed, the introduction of these technologies may bring about new threats to the system, among others, industrial and occupational risks (Brocal, González, Komljenovic, Katina, & Sebastián, 2019), such as the possibility of workers being unable to make optimal use of machinery. It is crucial to strike a balance between technological advancements and providing adequate training and support to ensure that workers can effectively use machinery to minimize potential risks and optimize performance (Reiman et al., 2021). Thus, the risks associated with their integration into complex systems must be considered (Karevan & Nadeau, 2023; Mofidi Naeini & Nadeau, 2023). A literature review conducted by Karevan and Nadeau (2023) revealed a notable dearth of research related to the risks associated with the implementation of IoTs in manufacturing and complex systems. Specifically, few studies have thoroughly examined these risks, and, to the best of our knowledge, no quantitative studies have thus far been identified. This highlights the significance and novelty of the present study, as it aims to address this research gap by quantifying and analyzing the risks associated with wearables implementation in manufacturing and complex systems (Karevan & Nadeau, 2023).

In the light of this stated gap, this study will propose a novel quantitative approach to identify and quantify risks, including that of human error associated with using smart glasses (In a manufacturing setting, smart glasses are categorized among the various wearable devices available, which include smart gloves, smart mechanical tools, smartwatches, and smartphones, all designed to provide information assistance (Nadeau et al., 2021)) in a complex system with the STPA method. To evaluate the practical implications of our research, a comprehensive case study focusing on a specific component of a refrigerator assembly was conducted. The primary objective here is to assess the effectiveness of the model and the usability of the novel methodology by using simulated data. The findings highlight that this approach successfully identifies and evaluates the risks associated with individual scenarios, while also providing a quantified assessment of the overall risk for the entire model.

The paper is organized as follows: Section two presents the state of the art, encompassing an overview of various topics such as Complex Systems, Human Reliability Analysis techniques, STAMP-STPA, PSO, and wearables in the manufacturing domain. Section three details the methodology employed in this study. Section four is dedicated to presenting the comprehensive case study conducted. The obtained results are elaborated upon in section five, followed by an in-depth discussion in section six. The study's conclusion is presented in section seven, summarizing the key findings and their implications.

3.2 State of the art

3.2.1 Complex systems

There are two main types of systems: simple and complex (Slim, 2020). A complex system consists of numerous interconnected components whose behavior cannot be simply inferred from the behavior of the individual components (J. B. Smith, 2003). The crucial aspect in understanding complexity isn't the quantity of units involved. Complex systems may consist of only two units yet remain intricate due to relationships that aren't apparent at the unit level (A. Jensen & Aven, 2018). Complex systems are more than the sum of their components (Kane & Higham, 2015). It is impossible to predict the behavior of a system as a whole, despite knowing the functions of its individual components (Slim, 2020). Interconnected systems and networked risks created by humans lead to systemic failures and could lead to extreme events. When networks depend on each other, they become more vulnerable to sudden failures, establishing heightened risks termed "hyper-risks" in the extensively connected world (Helbing, 2013).

In sociotechnical systems, social and technical elements are integrated into a defined objective (Hettinger et al., 2015). Individuals and organizations represent the social dimensions of sociotechnical systems. Any technology employed to carry out a function or address a technical aspect, be it a machine, tool, or resource, can be considered within this framework (Slim, 2020). Based on the above-mentioned characteristics, sociotechnical systems include a wide range of complex systems. It is possible to consider sociotechnical systems like the economy, manufacturing, healthcare, education, etc. (Mofidi Naeini, 2022). Simulation and modeling can reduce unintended consequences and unforeseen, negative interactions in sociotechnical systems (Hettinger et al., 2015). It is imperative to consider both technical and human factors when designing or assessing an application. In other words, from the perspective of sociotechnical resilience, humans need to be considered as a system component that interacts with technical components, not as an individual component (Mofidi Naeini, 2022). As a result of the fact that sociotechnical systems have many determinants and consequences associated with their emergent properties and phenomena, they are formally considered complex.

3.2.2 Human Reliability Analysis techniques

In the field of human reliability analysis, a combination of qualitative and quantitative methods is used to assess and comprehend the extent of human contribution to risks. These methods help in evaluating the impact of human factors on the overall reliability and safety of systems and processes (Bell & Holroyd, 2009). Multiple methodologies have been developed that enable the estimation of human error probability (Kirwan, 1992; Torres et al., 2021a). Human reliability analysis (HRA) focuses on identifying errors, identifying reasons for faults, and reducing the likelihood of human error (A. M. Kumar et al., 2017). It aims to optimize safety, reliability, and productivity by predicting and mitigating errors (Torres et al., 2021b).

The HRA process involves identifying essential functions, analyzing relevant tasks, and quantifying the risk of human error (Aliabadi, 2021). Table 3.1 presents a variety of main methods that have been introduced in this regard (Mkrtchyan et al., 2015). The probability of human error can be quantified if a variety of groups of professionals are involved, such as operators, conductors, Probabilistic Risk Assessment (PRA) experts, statisticians, etc. (Castillo et al., 2016). To avoid costly late-stage design modifications and rework, it is essential to tackle hazards and potential issues early in the design process. Taking proactive measures during the initial stages of design helps identify and address potential problems, leading to a smoother and more efficient development process. This can be achieved by identifying and prioritizing potential fault scenarios, incorporating mitigation strategies into the early design stages, and quantifying the interplay between component failures and human error. By taking these proactive measures, the negative impact of hazards can be minimized, leading to more efficient and effective design processes (Irshad et al., 2021).

PRA is a traditional risk assessment method used by engineers to quantify failure probabilities and severity (Stamatelatos et al., 2011). Failure Modes and Effects Analysis (FMEA) (Baig & Prasanthi, 2013), Fault Tree Analysis (FTA) (Vesely et al., 1981), and Event Tree Analysis (ETA) (Ericson, 2015) are some of the main traditional methods. Human error risk and severity can be quantified using various methods, such as the Systematic Human Error Reduction and Prediction Approach (SHERPA) (Torres et al., 2021a) and the Technique for Human Error Rate Prediction (THERP) (Boring, 2012). The Cognitive Reliability Error Analysis Method

(CREAM) is considered a human reliability analysis method. It is focused on cognitive aspects, hierarchical task analysis, and comprehensive error analysis. Moreover, along with other quantitative methods such as HEART, THERP, SHERPA, SPAR-H, etc., it is a quantitative method for measuring human error probability (Guo et al., 2022). By using these approaches, one can identify a hazardous scenario that involves failures of components or human errors. Since detailed system/component models are required, they are not appropriate for early design stages (Irshad et al., 2021).

The Functional Resonance Analysis Method (FRAM) and Systems-Theoretic Accident Model and Processes (STAMP) methods are the most cited in the field of complex systems risk management (Underwood & Waterson, 2012). It was also previously found that these two methods can be used in identifying risks, especially human error risks of using wearables in complex systems (Karevan & Nadeau, 2023). However, these two methods are qualitative. The STAMP method was chosen for evaluation in the present study due to its emphasis on dynamic control rather than solely focusing on failure prevention. Safety is viewed as a dynamic control problem within this method. STAMP considers a broader range of causes and shifts the focus towards constraining the behavior of the system. By adopting this approach, a more comprehensive understanding of the system's behavior and its constraints can be achieved, leading to effective safety management and control measures (Leveson & Thomas, 2018). Further, it has the ability to compare its usage in both research and practice contexts, and the availability of detailed instructions for applying it, allowing participants to be trained (Underwood et al., 2016). A powerful detection ability makes STAMP one of the most innovative analytical methods available. It can analyze human, organizational, hardware, software, and external factors, as well as their interactions within its structure to identify patterns and problems (Ceylan et al., 2022). The STAMP-STPA approach can play an important role in improving systemic safety (Allison et al., 2017). However, the application of STAMP can be intricate and demanding, particularly for individuals inexperienced in systems thinking and system safety analysis. It entails comprehending and representing intricate relationships and interdependencies among components of a system, which can be time-consuming and necessitate a thorough understanding of system theory (Underwood et al., 2016). By combining qualitative and quantitative methods, researchers are attempting to assess human error risks in a way that is more reliable and effective (Karevan & Nadeau, 2023).

3.2.3 STAMP-STPA

Based on the concept of system theory, STAMP was developed in 2004 by Nancy Leveson to deal with complex systems (Leveson, 2004; Mofidi Naeini & Nadeau, 2022c). It addresses the limitations of traditional accident analysis by incorporating system complexity, multicausality, human factors, system resilience and adaptation, and a forward-looking approach to proactive accident prevention (Leveson & Thomas, 2018). STAMP allows for the detection of failures of every type of component in a dynamic and complex structure. The method is likely to identify root causes of accidents more comprehensively than other system theory methods (Salmon et al., 2012), and can describe how inadequate control actions can violate safety constraints (Kazaras et al., 2012). STAMP examines the safety control structure in order to determine the cause of its failure to maintain safe behavior limits (Leveson, 2004). The STAMP framework conceptualizes socio-technical processes as systemic performances that are enabled by multilayered feedback loops between different stakeholders and that are in a continuous state of dynamic equilibrium (Allison et al., 2017). The selection of the STAMP method for evaluation is primarily driven by its emphasis on dynamic control rather than a sole focus on failure prevention. Within the STAMP framework, safety is regarded as a dynamic control problem. This approach considers a broader range of causes and expands the focus to encompass constraining the behavior of the system. By adopting the STAMP method, a comprehensive perspective is gained, enabling a deeper understanding of the system's behavior and facilitating effective control and management of safety measures (Leveson & Thomas, 2018).

In the context of hazard analysis, STAMP is known as STPA (System Theoretic Process Analysis), while in accident and incident analysis, it is known as CAST (Causal Analysis based on STAMP) (Pricop et al., 2020).

Table 3.1 Main HRA and risk management methods

Method	Reference	School of thought	Model (Qualitative/ Quantitative)
Functional Resonance Analysis Method (FRAM)	(Hollnagel & Goteman, 2004)	Resilience Engineering	Qualitative
Systems Theoretic Accident Model and Processes (STAMP)	(Leveson, 2004)	System Theory	
Failure Modes and Effects Analysis (FMEA)	(Military, 1949)	Safety Engineering	
Fault Tree Analysis (FTA)	(Watson, 1961)		
Technique for Human Error Rate Prediction (THERP)	(Kirwan, 1983; Swain, 1964)	Reliability Engineering	Quantitative
Human Error Assessment and Reduction Technique (HEART)	(Williams, 1986)		
Systematic Human Error Reduction and Prediction Approach (SHERPA)	(Embrey, 1986)		
Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H)	(Gertman et al., 2005)		
Cognitive Reliability and Error Analysis Method (CREAM)	(Hollnagel, 1998)	Cognitive Engineering	
A Technique for Human Error Analysis (ATHEANA)	(Cooper et al., 1996)		
Successive Likelihood Index Method (SLIM)	(Embrey et al., 1984)	Safety Engineering	
Bayesian Network (BN)	(Pearl, 1985)	Artificial Intelligence	

To address the systemic focus offered by STAMP, the STPA method was developed, and included control types and factors not addressed by traditional techniques (Hulme et al., 2021).

This method is one of the most popular STAMP-based proactive analysis methods. Analyzing the system can aid in identifying potential causes of accidents, thus enabling the elimination or control of hazards (Andrews et al., 2018). This qualitative method offers a comprehensive perspective of the system and facilitates a detailed analysis of the interrelationships among system components in terms of safety control actions (Mofidi Naeini & Nadeau, 2022c). In order to avoid or control hazards during development, STPA analyzes the potential causes of accidents (Leveson & Thomas, 2018).

Despite a component functioning correctly, STPA assumes that failure can occur due to unsafe interactions among components (Leveson & Thomas, 2018). In addition to accident analysis, STPA can successfully be used to lead a safety assessment process as well (Kazaras et al., 2012). STPA assumes that system components may have failed but that accidents can still occur due to unsafe interactions within them (Leveson & Thomas, 2018).

It is capable of considering various factors that can lead to loss events, including design errors, software flaws, interactions among components, complex human errors, as well as social, organizational, and management factors (Hulme et al., 2021). By employing STPA, it becomes feasible to detect control actions that could be unsafe or insufficient, potentially resulting in hazards at any point in the system's lifecycle (Mofidi Naeini & Nadeau, 2022c). Several studies have shown that this method is effective in complex operating environments with multiple controllers controlling the same process (Rising & Leveson, 2018).

One notable drawback of STAMP-STPA, despite its foundation in system theory and dynamic analysis capabilities, is that it focuses primarily on qualitative analysis rather than quantitative analysis (Ceylan et al., 2022). Some researchers have attempted to quantify human error probability (HEP), but it remains to be seen if more studies can be conducted to improve and develop more efficient methods (Bahoo Toroody et al., 2017). The reader is invited to consult the methodology section for more details.

3.2.4 PSO

Metaheuristics algorithms help determine what to do when faced with a problem (Luke, 2013). Metaheuristics are employed in the fields of science and engineering to effectively tackle intricate and complex problems within a reasonable timeframe (Talbi, 2009). A problem can be solved using two resources: time and space. In algorithmic terms, time complexity refers to the number of steps required to solve an n-dimensional problem (Talbi, 2009).

Metaheuristic algorithms are instrumental in addressing complex optimization problems by enhancing calculation accuracy, reducing the computational burden, and generating high-quality optimal solutions (Nesmachnow, 2014). It may be challenging to find an optimal solution in a principled manner when the level of knowledge of the solution is insufficient and heuristic information is limited. A potential solution to the problem can be tested and its effectiveness determined to decide whether it will work (Luke, 2013).

In addition to ensuring relative accuracy, AI and metaheuristics can be used to observe, test, or verify the reliability of a theoretical model, thus providing an effective means of assessment (Zhu, Qi, & Jiang, 2020). However, there are drawbacks associated with the use of AI and metaheuristics in this context. Firstly, AI models rely heavily on data, and if the data used for training is biased, incomplete, or unrepresentative, it can lead to inaccurate or biased results. Additionally, the complexity of AI algorithms and metaheuristic optimization techniques can make it difficult to interpret and understand the underlying decision-making process, thus limiting transparency and accountability. Moreover, ethical concerns such as privacy and security need to be carefully considered and addressed when deploying AI and metaheuristics in real-world scenarios (Khanzode & Sarode, 2020).

The PSO method was introduced in 1995 by James Kennedy and Russell Eberhart. In modeling this algorithm, they were inspired by observing the behavior of animals during aggression and aggregation (Karevan & Vasili, 2018). It is one of the well-known swarm-based optimization methods (Jain et al., 2022). Instead of producing new samples, PSO saves a significant statistical population. The members of that population are optimized based on discoveries. Its functions are similar to differential evolution in terms of multidimensional space and actual distances (Karevan, Tee, & Vasili, 2020).

As PSO relies on a heuristic approach, it does not guarantee the optimal result, which is determined by analyzing the movement of the population rather than a single movement. While particles move randomly, their best positions are taken into account in this algorithm (Wilson & Mantooth, 2013). Since the PSO algorithm is based on swarms and uses real spaces to solve problems, candidate answers are described as swarms of particles. There will never be a death of any of these particles. In contrast, mutations occur within the surrounding space and involve the replacement of particles. Each particle begins at a random location with its associated velocity vector (Karevan & Vasili, 2018).

As a tool for solving complex optimization problems, PSO has demonstrated excellent flexibility and practicality (Yang et al., 2020). Numerous optimization domains have successfully used PSO because of its ease of implementation (Lehre & Witt, 2013). Complex problems can be solved with PSO, which is a population-based metaheuristic algorithm. Since it is straightforward, capable of finding global optimums, and has a high convergence level, it is recognized as one of the most effective swarm intelligence algorithms (Jain et al., 2022). Also, it can be used with other methods to quantify the risk probability (Karevan & Vasili, 2018).

3.2.5 Wearables in manufacturing

IoT finds applications in various fields and products, and wearables are just one example of its implementation (Mofidi Naeini & Nadeau, 2022a). Wearable devices offer the opportunity to extend the functionality of mobile operating systems (OS) by running applications specifically designed for these devices. This integration enables users to access additional features and services beyond health- and fashion-related applications (D. Kim & Choi, 2021).

Wearable computers should be mobile and provide context-sensitive information (Billinghurst & Starner, 1999). Using wearables equipped with IoT sensors in manufacturing or healthcare can trigger automated alerts in the event of hazardous conditions (Riso, 2021). With wearables, users can now perform tasks such as aircraft maintenance, navigation, and vehicle inspection much more efficiently (Billinghurst & Starner, 1999). Even though wearable technology holds great potential in the manufacturing industry, the challenge lies in figuring out how to seamlessly integrate these devices into the manufacturing system and how they can effectively enhance productivity (Hao & Helo, 2017).

The connectivity between manufacturing resources and IoT allows the comprehensive monitoring and optimization of the complete production process. Wearable devices play a significant role in augmenting and extending the capabilities of IoT in industrial settings, unlocking new possibilities for enhancing productivity and efficiency (Hao & Helo, 2017). The aim of integrating wearable technology in the workplace is to provide employees with pertinent information based on their context, thereby empowering them to enhance their performance. Simultaneously, wearable devices gather and transmit data to the company's IT systems. These wearables act as interfaces, delivering relevant information to employees while enabling them to work efficiently with both hands free (Krzywdzinski et al., 2022). Wearable technologies, a key component of IoTs, have demonstrated their ability to boost employee productivity by 8.5% and enhance overall life and job satisfaction by 3.5% (Hao & Helo, 2017; Nadeau et al., 2021).

3.2.5.1 Smart glasses

Wearable devices known as smart glasses allow wearers to connect to computing facilities and clients to handle complex tasks with ease (N. M. Kumar et al., 2018). As well as displaying visual information (such as text messages, videos, and pictures), smart glasses can also provide audio content and positional information in real time and run mobile applications (Khodammohammadi, Ngô, & Nadeau, 2023; Nadeau et al., 2021).
Smart glasses offer user interaction through touch buttons or natural language command processing, leveraging voice recognition technology. These devices are equipped with a front-mounted camera that enables real-time capture of images and videos of the surrounding environment (D. Kim & Choi, 2021). These devices can pose new risks, which need to be analyzed and reduced (Khoddammohammadi, 2023), such as user interface challenges, interaction challenges, calibration challenges, social acceptance challenges, eye fatigue challenges, and data security challenges (Due, 2014; L.-H. Lee & Hui, 2018).

3.3 Methodology

This study introduces and evaluates a novel approach for quantifying risks, including human error risks, associated with the use of IoTs in complex systems. The methodology employed in this research involves the application of STPA to identify and assess the associated risks. By using STPA, it becomes possible to identify potentially unsafe or inadequate control actions that could give rise to hazards at any stage of the system lifecycle (Mofidi Naeini & Nadeau, 2022c). The STPA analysis has four main steps (Bjerga et al., 2016). Figure 3.1 shows the proposed methodology of this study. Based on its algorithm, the steps of this methodology are structured as follows:

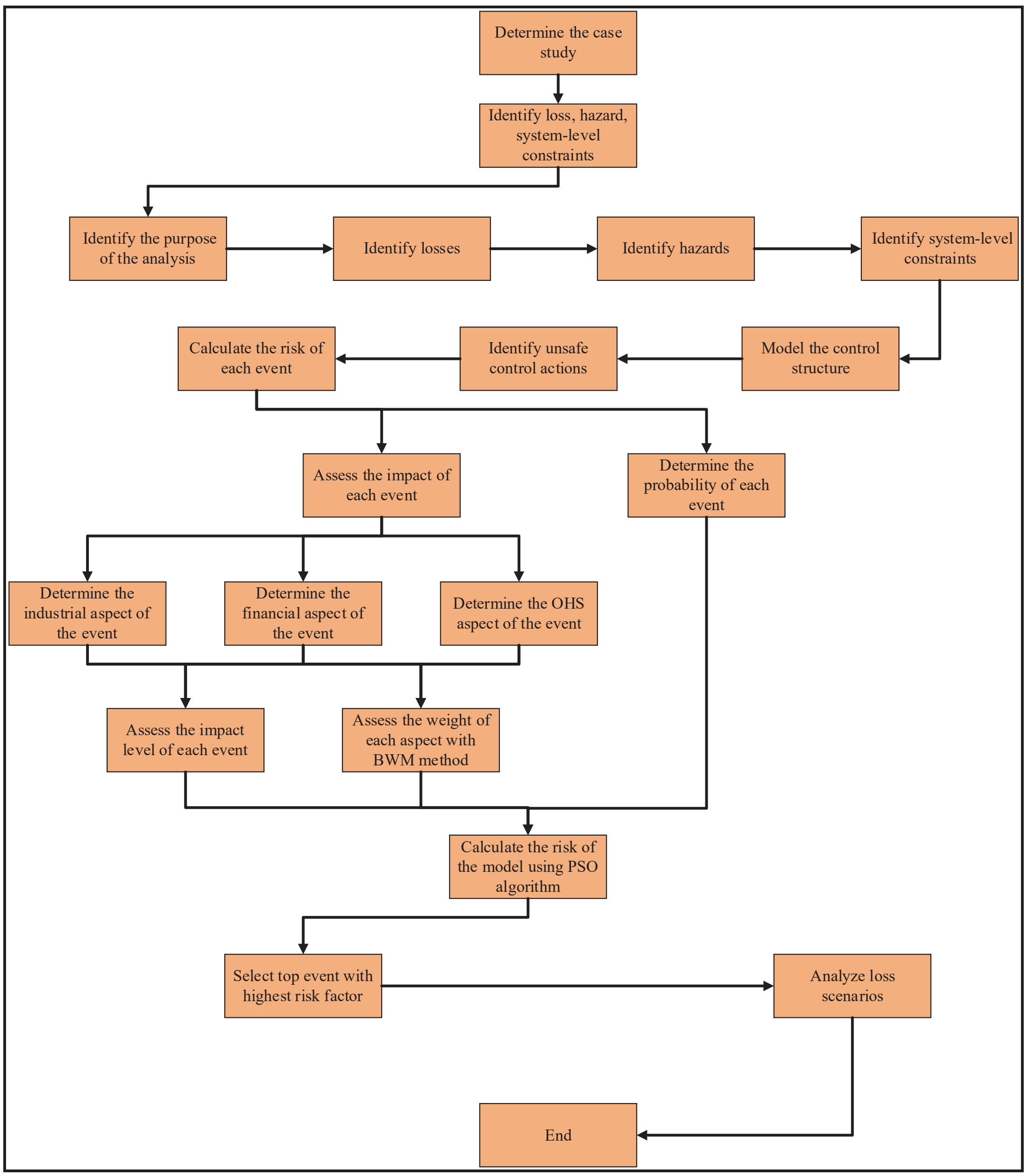

Figure 3.1 STPA-PSO methodology

3.3.1 Consider all losses, system-level hazards, constraints related to safety, and requirements related to the system's functionality

Whenever an analysis method is used, the first step is to define its purpose (Leveson & Thomas, 2018). To better understand the concept of loss, system-level hazards, and system-level constraints, we used Leveson's (2018) main definition for these basic concepts:

Loss: "A loss involves something of value to stakeholders. Losses may include a loss of human life or human injury, property damage, environmental pollution, loss of mission, loss of reputation, loss or leak of sensitive information, or any other loss that is unacceptable to the stakeholders" (Leveson & Thomas, 2018).

System-level hazard: "A hazard is a system state or set of conditions that, together with a particular set of worst-case environmental conditions, will lead to a loss" (Leveson & Thomas, 2018).

System-level constraints: "A system-level constraint specifies system conditions or behaviors that need to be satisfied to prevent hazards (and ultimately prevent losses)" (Leveson & Thomas, 2018).

3.3.2 Develop a functional control model for the system

The person who analyzes the system must explain the structure of the control system and find out which variables are involved in the study (Mofidi Naeini & Nadeau, 2022c). Hierarchical control structures typically encompass five essential components: controllers, control actions, feedback, other inputs and outputs from components, and processes controlled by the controllers (Leveson & Thomas, 2018).

In this step, there are several points of misunderstanding (Leveson & Thomas, 2018):

- Control structures are not physical models.
- Control structures are not executable models.
- Control structures do not assume obedience.
- Complexity can be managed by abstraction.

3.3.3 Identification of hazardous (unsafe) control actions

The definition of the unsafe control action provided by Leveson (2018) is: "An Unsafe Control Action (UCA) is a control action that, in a particular context and worst-case environment, will lead to a hazard" (Leveson & Thomas, 2018).

The first step is to identify the control actions obtained from the functional model. Then, explain different scenarios for controlling actions, and finally, identify each control action's unsafe behavior based on the scenarios (Mofidi Naeini & Nadeau, 2022c). The following four scenarios can make control actions unsafe (Leveson & Thomas, 2018):

- A hazard results from not providing the control action.
- A hazard results from providing the control action.
- Giving an action that may be safe, but it is done too early, too late, or in the wrong order.
- The control action lasts too long or ends too soon.
- Each controller's behavior can be constrained once UCAs have been identified (Leveson & Thomas, 2018).

3.3.4 Calculate the risk of the model

After determining the UCAs, the risk of the model is calculated based on the research objective. First, Eq.3.1 shows the standard formula for calculating the risk (Baranoff et al., 2009):

$$\textit{Risk (i)} = \textit{Impact (i)} * \textit{Probability (i)} \tag{3.1}$$

3.3.4.1 Impact

In this formula, the risk of event (i) is assessed by the impact of event (i) if it occurs, and the likelihood of event (i) (Baranoff et al., 2009). Researchers have used various methods to determine the impact of an event, and almost all of them are based on the judgment of experts in each field. For example, (Badri, Nadeau, & Gbodossou, 2011) used a three-scale method (minor (1,2,3), average (4,5,6), and major (7,8,9)) in their work.

In OHS problems, some injury typologies consider three groups (Canadian Centre for Occupational Health and Safety, 2017):

- High: Contains broken bones, intoxication, excessive bleeding, an injury to the head, or an illness that leads to death.
- Medium: Contains sprain, strain, burns, skin conditions, asthma, and injuries requiring time off from work.
- Low: Contains temporary pain, swelling, or dizziness.

Qureshi (2023) used a comprehensive six-level approach that analyzes different categories, such as health and safety, environmental impact, financial loss, and reputation. (Qureshi, 2023). La Fata et al. (2023) used five-level incidents: no incidence, low incidence, medium incidence, high incidence, and very high incidence (La Fata, Adelfio, Micale, & La Scalia, 2023). (Yazdi, Nedjati, Zarei, & Abbassi, 2020) used a seven-point scale method: very low, low, moderately low, average, moderately high, high, very high. (Kraidi, Shah, Matipa, & Borthwick, 2021) used a five-scale method: very low (0-1), low (1-2), moderate (2-3), high (3-4), and very high (4-5).

From the literature, it is demonstrated that each study could have a different impact definition. Based on a comprehensive analysis of different types of Likert scale points done by Ngô et al. (2020), the 4-7 point-scale is appropriate in terms of both validity and reliability of results (Ngô, Nadeau, & Hallé, 2020), and thus, a five scale is used in this study. Using the results of (Qureshi, 2023), different categories will be investigated based on the OHS, financial, and industrial aspects to gain a better result.

Each of these aspects is graded on a scale of five levels: "very low impact," "low impact," "medium impact," "high impact," and "very high impact.". For the Occupational Health and Safety (OHS) aspect, the grading aligns with the definitions provided by the Canadian Centre for Occupational Health and Safety as follows:

- "Very low impact" indicates that the event has no impact related to OHS.
- "Low impact" signifies an injury that requires first aid only, resulting in short-term pain, irritation, or dizziness.

- "Medium impact" indicates conditions like sprains, strains, burns, skin conditions, asthma, and injuries requiring time off from work.
- "High impact" denotes severe conditions such as broken bones or intoxication.
- "Very high impact" represents critical situations involving excessive bleeding, head injuries, or an illness that leads to death.

Indeed, it is evident that the Industrial and Financial aspects are interconnected and cannot be considered in isolation (Badri et al., 2011). To address this relationship and its impact on risk assessment, we have proposed several scenarios in Table 3.2, where we consider the time impact for the Industrial aspect and the cost impact for the financial aspect.

In this study, a comprehensive approach will be employed to quantify the risks obtained using the STPA method. Instead of solely analyzing one aspect of impact, a combination of the industrial, Occupational Health and Safety (OHS), and financial aspects will be considered. Each of these aspects will be weighted to provide a more accurate estimation of the risk associated with the event. By integrating multiple dimensions of risk assessment, this comprehensive approach aims to provide a more holistic and robust evaluation of potential risks in the analyzed system or process.

Criterion weighting is a crucial element in the decision-making process, accomplished through the criteria weighting method. Criterion weighting is a critical aspect of decision-making processes, as it determines the relative importance of different criteria in evaluating alternatives. This study employs Multi-Criteria Decision Making (MCDM) techniques to address the complexity of decision-making scenarios. MCDM methods enable the assessment of multiple alternatives across various criteria, facilitating the identification of the most suitable option (M. Singh & Pant, 2021).

In the realm of decision-making theory, MCDM plays a pivotal role, offering a range of methodologies tailored to different decision contexts (Rezaei, 2015). These include the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), ELECTRE (ELimination Et Choix Traduisant la REalité), PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), SWARA (Step-wise Weight Assessment Ratio Analysis), BWM (Best Worst Method), and others (Rezaei, 2015). It's important to note the distinctions among these methods. For instance, AHP relies on independent expert input to determine criteria weights, whereas ANP considers interdependency effects among criteria (M. Singh & Pant, 2021). ELECTRE and PROMETHEE are recognized for their ability to yield more refined outcomes, especially in complex decision scenarios. On the other hand, BWM offers computational efficiency and ease of use, making it suitable for scenarios where extensive comparison data may be lacking (Rezaei, 2015; M. Singh & Pant, 2021).

Table 3.2 Impact level of industrial and financial aspects

Scenario	**Industrial aspect (regarding time)**	**Financial aspect (regarding cost)**
No Economic/industrial loss	Very Low	Very Low
Delay in production (Breakage of some parts, or material, equipment, not receiving material, etc.)	Low	Medium
Reassembly	Medium	Low
Major damage to the product, equipment	High	High
Stop production	Very High	Very High

In this study, we have opted for the BWM method due to its practical advantages in our specific context. While more sophisticated methods like ANP may offer comprehensive treatment of interdependencies, we believe that, for the scope and nature of our study, BWM provides a pragmatic balance between accuracy and feasibility. By selecting BWM, we aim to streamline the decision-making process while ensuring robust and reliable results.

BWM was introduced by (Rezaei, 2015). The technique has five steps:

- Create a list of criteria for making decisions ($c_1, c_2, \ldots, c_n$).
- Determine the best and worst criteria.
- A Best-to-Others (BO) vector is formed by determining the preferred criterion over all the other criteria by using a number between 1 and 9 (It is possible to use other scaling methods), as demonstrated in Eq.3.2:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{3.2}$$

where a_{Bj} indicates that criterion B is preferred over criterion j.

- To calculate the Others-to-Worst (OW) vector, use a number between 1 and 9 to indicate all criteria' preference over the worst criterion (Eq.3.3):

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T \tag{3.3}$$

where a_{Jw} indicates that criterion j is preferred over the worst criterion W.

- Calculate the optimal weights ($w^*_1, w^*_2, \dots, w^*_n$) by using Eq.3.4 to Eq.3.6:

$$\min \max j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \tag{3.4}$$

$$s.t.$$

$$\textstyle\sum_j w_j = 1 \tag{3.5}$$

$$w_j \geq 0, for\ all\ j \tag{3.6}$$

3.3.4.2 Probability

To proceed, it is crucial to determine the probability of each event occurring. Table 3.3 shows some of the ranges of occurrence in different industries. As can be seen in the table, most of the authors who used 5-point scale systems used 1-5 grading points, with 1 being the lowest grade, and 5 being the highest one. Thus, in this study, we used a 5-point scale system. Herein, five categories of probability are considered: very low (1), low (2), medium (3), high (4), and very high (5). A probability of occurrence is assigned to each UCA.

For analyzing uncertain scenarios and calculating probabilities, the Monte Carlo simulation (MCS) is an extremely helpful mathematical technique (Raychaudhuri, 2008). Due to its ability to achieve a closer adherence to reality, MCS represents an effective method of analyzing complex systems (Zio, 2013), and with it, input variables that are risky can be investigated methodically (Raychaudhuri, 2008). By employing the Monte Carlo Simulation (MCS) approach, it becomes possible to realistically account for all possible phenomena that may occur without requiring any additional complexities in modeling or solution methods (Zio, 2013).

MCS has been used in different industries and for different purposes, including finance, reliability analysis and six sigma, mathematics and statistical physics, engineering, etc. (Raychaudhuri, 2008). Analyzing potential mechanisms of failure and assessing their probability is essential for complex systems consisting of several components. In many cases, failure data cannot be collected for identical systems, so a statistical analysis of failures cannot be conducted. Using Monte Carlo Simulation procedures, occurrences of system failures and success state transitions can be simulated stochastically using models of process evolution and operator behavior (Zio, 2013). Monte Carlo simulation uses the repeated random sampling and statistical analysis method to compute the results (Raychaudhuri, 2008).

3.3.4.3 Risk calculation

Eq.3.7 is used to assess the risk of each UCA:

$$R_i = P_i * ((W_{IND\,i} * I_{IND\,i}) + (W_{OHS\,i} * I_{OHS\,i}) + (W_{FIN\,i} * I_{FIN\,i})) \tag{3.7}$$

where R_i is the risk of event *i*; P_i is the probability of event *i*; and $W_{IND\,i}$, $W_{OHS\,i}$, $W_{FIN\,i}$ are the weight factors of the industrial aspect, OHS aspect, and financial aspect of event *i*, respectively. As mentioned before, BWM will be used to assess these weights. Also, $I_{IND\,i}$, $I_{OHS\,i}$, $I_{FIN\,i}$ are the impact grades of each industrial, OHS, and financial aspect, respectively.

It has been illustrated above that several variables need to be simulated, meaning that solving the problem is not straightforward and involves a substantial amount of time and effort, as well as a high risk of calculation errors. Therefore, the PSO algorithm is used to seek a solution.

Since the PSO algorithm is based on swarms and uses real spaces to solve problems, candidate answers are described as swarms of particles. Mutations, on the other hand, occur in the vicinity and replace particles. Each particle initiates at a random position with its velocity vector (Karevan & Vasili, 2018).

The PSO parallel space represents a *d-dimensional* space, with each candidate solution termed a “particle” (Marini & Walczak, 2015). In describing a particle, a group of vectors is identified as (X_i, V_i, P_i) in a *d-dimensional* search space. Particles modify their positions based on their current positions, current velocities, distance between the current position and *pbest*, and the distance between the current position and *gbest* (Lalwani et al., 2013), which are shown in Eq.3.8 to Eq.3.10.

Table 3.3 Range of occurrence

Reference	Industry	Range of occurrence				
(D. Li et al., 2021)	Healthcare	Low [<0.2]		Medium [0.2-0.8]		High [>0.8]
(Sreenath, Sudhakar, & Yusop, 2020)	Aviation	Exceptional [1]	Unlikely [2]	Possible [3]	Likely [4]	Certain [5]
(Cristaldi, Khalil, & Soulatintork, 2017)	Power plant	Unlikely [1]	Low [2-3]	Moderate [4-6]	High [7-8]	Very high [9]
(Mostafa, Aleem, & Zobaa, 2016)	Aviation	Extremely improbable [1]	Extremely remote [2]	Remote [3]	Reasonably probable [4]	Frequent [5]
(Wirawan & Garniwa, 2018)	Power plant	Insignificant [<0.2]	Minor [0.2-0.4]	Moderate [0.4-0.6]	Major [0.6-0.8]	Catastrophic [>0.8]
(Seňová, Pavolová, & Škvareková, 2023)	Mining	Rare [1]	Unlikely [2]	Possible [3]	Likely [4]	Almost certain [5]
(Noman, Alqahtani, Alharkan, Alabdulkarim, & Alasim, 2023)	Maintenance	Non expected [1]	Very unlikely [2]	Unlikely [3]	Possible [4]	Expected [5]
(Richert & Dudek, 2023)	Supply Chain	Very small [1]	Small [2]	Medium [3]	High [4]	Catastrophic [5]
(Virdi & Pamnani, 2023)	LPG unloading operation	Highly unlikely [0-2]	Rare [1-4]	Occasional [3-6]	Repeated [5-8]	Unavoidable [7-10]

$$X_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \quad for\ i = 1,2, \ldots, N \tag{3.8}$$

$$V_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \quad for\ i = 1,2, \ldots, N \tag{3.9}$$

$$P_i = (p_{i1}, p_{i2}, \ldots, p_{id}) \quad for\ i = 1,2, \ldots, N \tag{3.10}$$

In order to optimize the solution in the search space, this algorithm regulates the velocity of particles as a major feature. Based on Eq.3.11, particle *k*'s velocity is updated in the *(i+1)*th iteration (Jain et al., 2022):

$$V_k(i+1) = V_k(i) + c_1 r_1 \left(P^k_{best,i} - X_k(i)\right) + c_2 r_2 \left(g_{best,i} - X_k(i)\right) \tag{3.11}$$

In the *(i+1)*th iteration, the velocity of the *k*th particle is updated based on three components (Jain et al., 2022):

- Momentum part ($V_k(i)$): The inertia component provides a balance between exploring and exploiting every particle in the search space, using the previous velocity as a memory.
- Cognitive part ($c_1 r_1 \left(P^k_{best,i} - X_k(i)\right)$): The particle is driven to its best position by this cognitive part, which equals the particle's distance from its best position.
- Social part ($c_2 r_2 \left(g_{best,i} - X_k(i)\right)$): By determining the best position based on the swarm, this social component drives the particle to the best position.

During iteration *(i+1)*, the position of each particle *k* depends on Eq.3.12:

$$X_k(i+1) = X_k(i) + V_k(i+1) \tag{3.12}$$

Several control parameters influence the basic PSO, including the swarm size, the acceleration coefficient, the weight of inertia, the neighborhood size, the number of iterations, and the velocity clamping (Engelbrecht, 2007). The PSO flowchart is shown in Figure 3.2.

Thus, in this study, the PSO is used to quantify the STPA and calculate the model's risks, including human error risks. The PSO algorithm analyzes the model's risk after determining the impact of each event (UCA). The simulation of each event's probability is performed to produce a reliable prediction with this algorithm. Every time the algorithm runs, the worst scenarios are selected, and the model's risk is determined. In the final stage of STPA, loss scenarios were identified by selecting the top events that posed the highest risk levels.

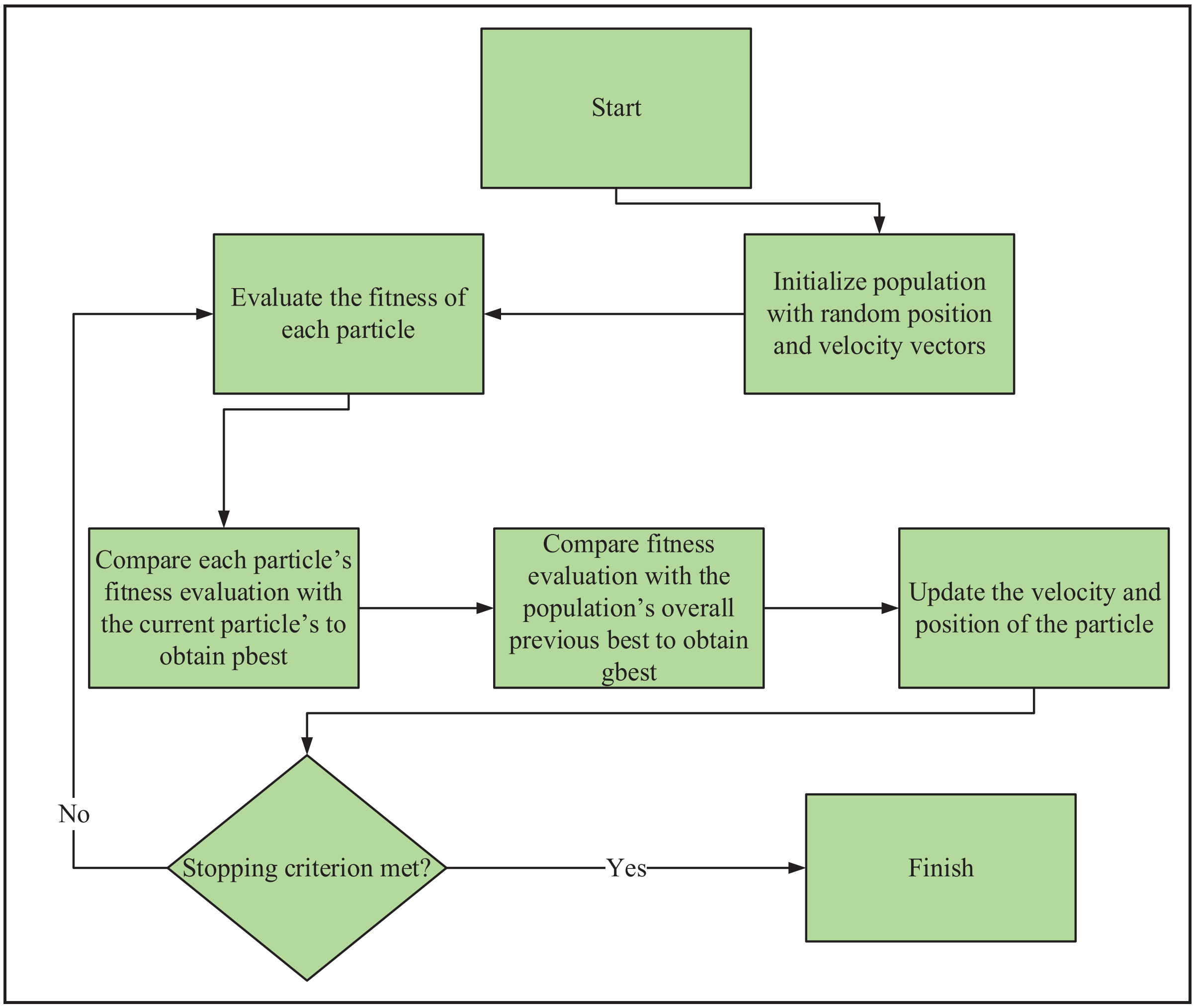

Figure 3.2 PSO algorithm

Now at the design stage of the implementation of IoT in this assembly section, we are faced with a lack of reliable data. To address this challenge, we will be using the Monte Carlo Simulation to assess the probability of each event and determine the best and worst criteria. The purpose of this study is to test the effectiveness of this model and the usability of this novel methodology using simulated data. However, it is important to note that we have a clear plan to incorporate real data into our work. The simulated data in the algorithm can seamlessly be replaced with actual data when it becomes available.

3.3.5 Identify loss scenarios

An unsafe control action or hazard is the result of the causal factors described in a loss scenario (Leveson & Thomas, 2018). In this step, the system analyst must examine the potential causes that might contribute to unsafe control actions or control actions that might cause hazards if not implemented properly. Then, by applying scenario recommendations, they will minimize or eliminate hazards (Mofidi Naeini & Nadeau, 2022c).

3.3.6 Case study

For the first level validation of the proposed methodology in this paper, a case study was used. As the purpose of this study was to investigate the risks associated with using smart glasses in the assembly operations of a manufacturing plant, a small part of the assembly operations of a refrigerator manufacturing plant was examined. The refrigerator manufacturing process is demonstrated in Figure 3.3.

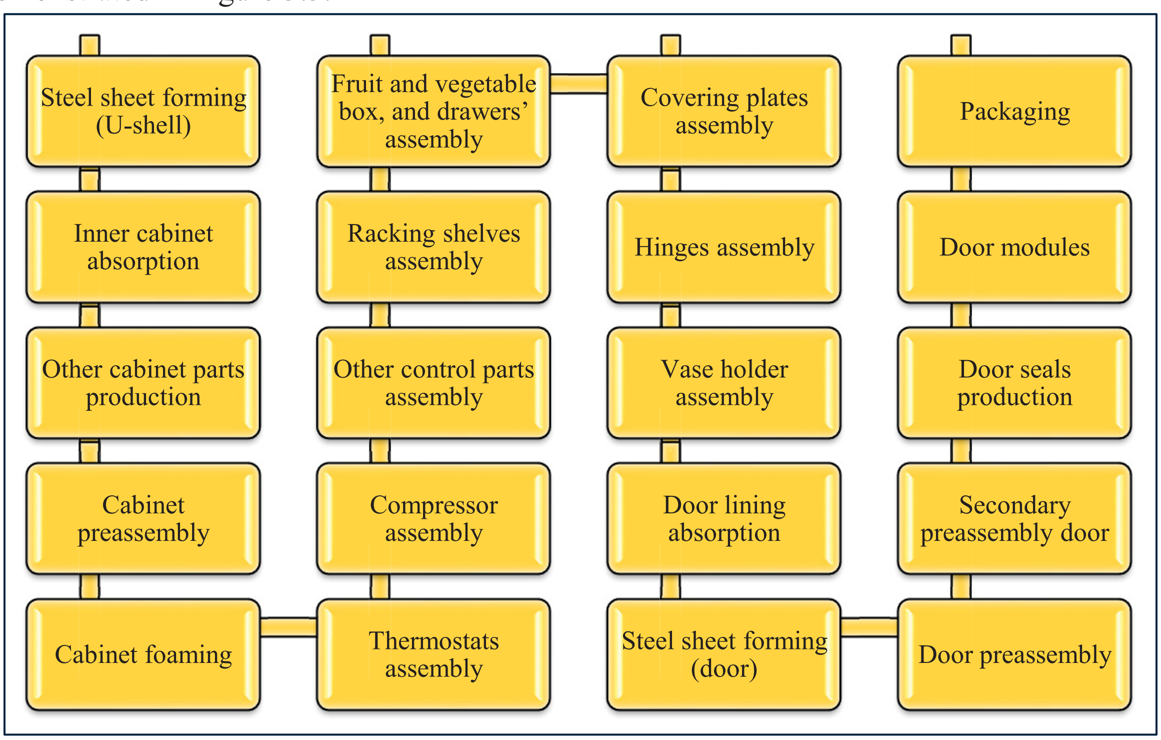

Figure 3.3 Refrigerator manufacturing process

In this study, we focus on “Fruit and vegetable box assembling, Drawers assembly, covering plates assembly”. The process for producing the refrigerator is demonstrated at How It’s Made Fridge (How_It's_Made_Show, 2016). There is one worker who works in this workstation and must assemble the Fruit box, Vegetable box, and drawers, based on the model of the refrigerator. There are three big bins located near the worker. Each bin contains numbers of each part, and the worker must use each of the bins to assemble the product. Figure 3.4 shows this section of the assembly line.

This work has the following process:

- First, sales orders and market demand are checked by the production planning unit.
- Next, the production plan is developed based on the parameters available.
- A detailed production plan is sent to all units involved (production, quality control, warehouse, sales, maintenance, etc.).
- The warehouse department provides the necessary materials and parts according to the production plan.
- Production personnel receive workshop planning from the supervisor with product maps, technical specifications, and required instructions for each station.
- Assembly is performed according to the supervisor’s orders and the production schedule and requirements.
- According to the type of product, it may be necessary to assemble a certain number of each part in the refrigerator, which is specified in the product map.
- The assembler must correctly place the required parts of the “Fruit and vegetable box, drawer, and covering plates” in the correct places.
- Consequently, the worker must take each part from different bins next to him/her.
- In addition, the warehouse department is responsible for completing these parts to prevent interruptions at the assembly line.
- Upon assembly of all the items in the refrigerator, the product is sent to the next workstation, and another product from the previous station is replaced.

In this assembly section, the worker assembles the parts manually and does not use smart glasses. This study aims to investigate the introduction of smart glasses in this section. The STPA can be used during the design and development stage (Leveson & Thomas, 2018). We intend to analyze the risks associated with the introduction of the IoT (smart glasses) in this assembly area.

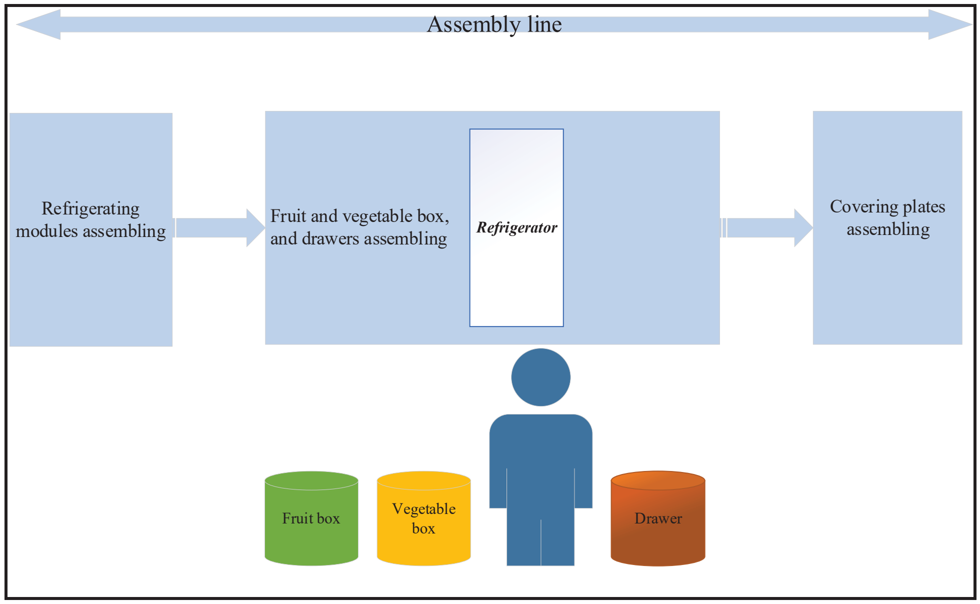

Figure 3.4 Assembly of fruit box, vegetable box, and drawers

3.4 Results

The results of introducing smart glasses to the assembly section are presented below:

3.4.1 Consider all losses, system-level hazards, constraints related to safety, and requirements related to the system's functionality

3.4.1.1 Identify the purpose of the analysis

This analysis aims to identify the risks connected to introducing a pair of smart glasses to the assembly section.

3.4.1.2 Identify losses

In this case study, different types of loss may occur:

L1: Injury to the worker

L2: Unacceptable damage to the product

L3: Unacceptable damage to the component and equipment

L4: Financial loss resulting from delayed operations

3.4.1.3 Identify hazards

The study categorizes hazards and provides descriptions along with their respective codes, along with the associated losses:

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

3.4.1.4 Identify system-level constraints

System-level constraints are shown in Table 3.4.

Table 3.4 System-level constraints

Code	System-level Constraint	Hazard
SC1	Workers must be trained before starting their jobs to prevent harmful activities in the workplace	H1
SC2	Supervisor must check the workers to ensure that they do not do harmful activities	H1
SC3	Workers must be cautious to avoid doing harmful activities	H1
SC4	Supervisor must prepare safety instructions for workers	H1
SC5	Workers must be trained to use smart glasses properly	H2
SC6	Supervisor must check the workers work periodically to ensure that they know how to do their tasks	H1, H2
SC7	Consider sensor positioning and glasses fit based on the workers during design phase	H1
SC8	Calibrate the smart glasses based on the manufacturer's instructions	H1, H2, H4, H5
SC9	Program the smart glasses to transfer reliable data	H3, H4, H5
SC10	Ensure effective and reliable communication channels between the supervisor and production planning department to ensure the reliability of the data	H3, H4, H5
SC11	Ensure effective and reliable communication channels between the logistic and warehouse department and production planning department to ensure the reliability of the data	H3, H4, H5
SC12	Ensure effective and reliable communication channels between the logistic and warehouse department and assembly line to ensure the reliability of the data	H3, H4, H5
SC13	Ensure effective and reliable communication channels between the supervisor and assembly line to ensure the reliability of the data	H3, H4, H5
SC14	IT department must apply proper instructions to ensure the proper and reliable feedback of the smart glasses	H3, H4, H5
SC15	Check connection between receiver and processor and smart glasses	H3, H4, H5
SC16	Workers should know to report any errors or late feedback from smart glasses	H3, H4, H5

3.4.2 Develop a functional control model for the system

A hierarchical control structure consists of control loops. Control actions may be provided by controllers to enforce constraints on the behavior of a process (Leveson & Thomas, 2018). Figure 3.5 shows the smart glasses control structure model.

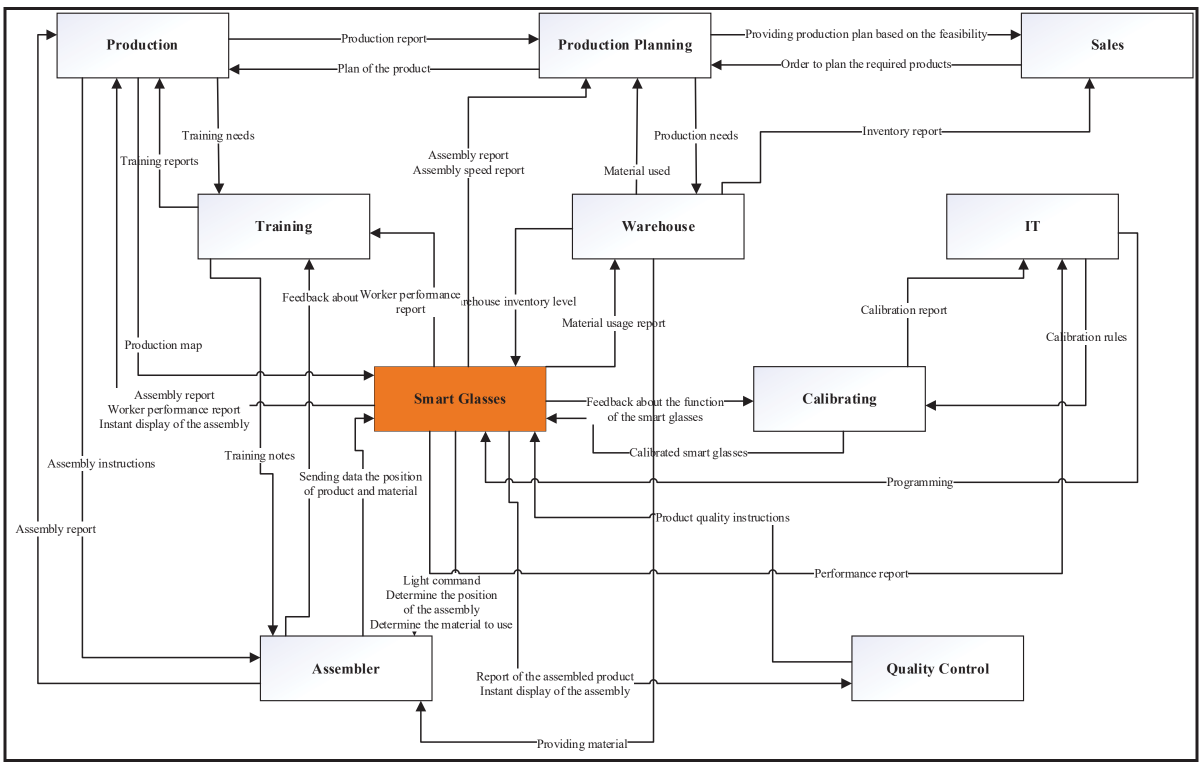

Figure 3.5 Control structure model of smart glasses

3.4.3 Identification of hazardous (unsafe) control actions

UCAs are control actions that could lead to a hazard in particular contexts and worst-case environments (Leveson & Thomas, 2018). By demonstrating where safety constraints may be violated or insufficiently enforced, the STPA aims to eliminate unsafe conditions (Mofidi Naeini & Nadeau, 2022c).

A UCA contains five parts:

- The controller, which can provide the control action.
- A definition of the type of unsafe control action (provided, not provided, too early or too late, stopped too soon, or applied too long).
- The command itself, which comes from the control structure.
- UCA construction often incorporates words such as “when”, “while”, or “during” to develop context.
- Finally, linking each UCA to hazards (Leveson & Thomas, 2018).

Table 3.5 shows the unsafe control actions for the present case study. Once all the unsafe control actions (UCAs) have been identified, it is essential to illustrate the consequences that may arise from their occurrence. This step involves assessing and describing the potential impacts and outcomes associated with each UCA.

Table 3.6 shows the result of each UCA in terms of their OHS, industrial, and financial impact. From the table above, it can be seen that L4 (Financial losses from delayed operation) is the most connected to each UCA, with all 20 scenarios, while L1 (Injury to the worker) is the least connected, with only 10 scenarios. L2 (Unacceptable damage to the product) and L3 (Unacceptable damage to the component and equipment) have the same number of connections, with 17 scenarios.

3.4.4 Calculate the risk of the model

Initially, the BWM solver, as developed by its founder (Rezaei, 2015), was employed to ascertain the weight of each impact. Priority was given to the Occupational Health and Safety (OHS) aspect, followed by the financial and industrial aspects, resulting in respective weights of 0.65, 0.25, and 0.10. Due to the unavailability of real-world data for risk probability evaluation, simulation techniques were employed. Subsequently, with these parameters in hand, we implemented PSO-STPA in MATLAB. A key objective of this study was to evaluate and quantify the risk associated with each UCA (Unsafe Control Action) and the entire model. The PSO parameters used in the study are detailed in Table 3.7. As the primary aim was to test the model's effectiveness and the usability of this innovative methodology with simulated data, a sensitivity analysis for the PSO parameters was not conducted.

After the STPA-PSO code is run using the stated parameters, the risk of each UCA is determined and is shown in Figure 3.6. It is obvious that UCA 20, 11, 10, and 17 have the highest risk, while UCA 2, 12, 6, and 5 have the lowest risk. Also, the risk of the model is 14.8513, which is considered a medium risk factor.

Table 3.5 Unsafe control actions (UCAs)

Control action	**Not providing causes hazard**	**Providing causes hazard**	**Providing too early, too late, or out of sequence**	**Stopped too soon, applied too long**
Plan of the product	UCA-1: The production planning department does not provide the production plan	UCA-2: The production planning department provides a wrong production plan	UCA-3: The production planning department provides a plan too late	UCA-4: The production planning department stopped the previous plan too soon
Training notes	UCA-5: The training department does not provide training for workers	UCA-6: The training department provides insufficient training for workers	UCA-7: The training department provides training late for workers	UCA-8: The training department stopped the training sessions too soon
Feedback about the place of the assembly	UCA-9: The smart glasses not provide feedback about the place of assembly to the worker	UCA-10: Smart glasses provide wrong feedback to the worker	UCA-11: Smart glasses provide feedback to the worker too late	N/A
Calibrated smart glasses	UCA-12: Smart glasses not calibrated before use	UCA-13: Smart glasses calibrated incorrectly before use	N/A	N/A
Turn off/on the light command	UCA-14: The receiver and processor do not provide light commands	UCA-15: The receiver and processor provide wrong light commands	UCA-16: The receiver and processor provide light commands too late	UCA-17: The receiver and processor provide light commands very quickly
Programming	UCA-18: The IT department does not provide programming for the receiver and processor	UCA-19: The IT department provides wrong programming for the receiver and processor	UCA-20: The IT department provides programming for the receiver and processor too late	N/A

Table 3.6 Consequences of unsafe control actions

#UCA	Consequence of UCA (Industrial and Financial impact)	Consequence of UCA (OHS impact)	#Loss			
			L1	L2	L3	L4
UCA1	Delay in production	The event has no impact related to OHS				*
UCA2	Reassembly	The event has no impact related to OHS		*		*
UCA3	Stop production	The event has no impact related to OHS				*
UCA4	Stop production	The event has no impact related to OHS			*	*
UCA5	Major damage to product	Broken bones, intoxication	*	*	*	*
UCA6	Delay in production	Sprain, strain, burns, skin conditions, asthma, and injuries requiring time off from work	*	*	*	*
UCA7	Reassembly	Sprain, strain, burns, skin conditions, asthma, and injuries requiring time off from work	*	*	*	*
UCA8	Major damage to product	An injury that requires first aid only, short-term pain, irritation, or dizziness	*	*	*	*
UCA9	Stop production	An injury that requires first aid only, short-term pain, irritation, or dizziness		*	*	*
UCA10	Major damage to product	The event has no impact related to OHS		*	*	*
UCA11	Delay in production	An injury that requires first aid only, short-term pain, irritation, or dizziness	*	*	*	*
UCA12	Major damage to product	An injury that requires first aid only, short-term pain, irritation, or dizziness	*	*	*	*
UCA13	Major damage to product	An injury that requires first aid only, short-term pain, irritation, or dizziness	*	*	*	*
UCA14	Stop production	An injury that requires first aid only, short-term pain, irritation, or dizziness	*	*	*	*
UCA15	Major damage to product	An injury that requires first aid only, short-term pain, irritation, or dizziness	*	*	*	*
UCA16	Delay in production	An injury that requires first aid only, short-term pain, irritation, or dizziness	*	*	*	*
UCA17	Reassembly	The event has no impact related to OHS		*	*	*
UCA18	Major damage to product	The event has no impact related to OHS		*	*	*
UCA19	Major damage to product	The event has no impact related to OHS		*	*	*
UCA20	Major damage to product	The event has no impact related to OHS		*	*	*

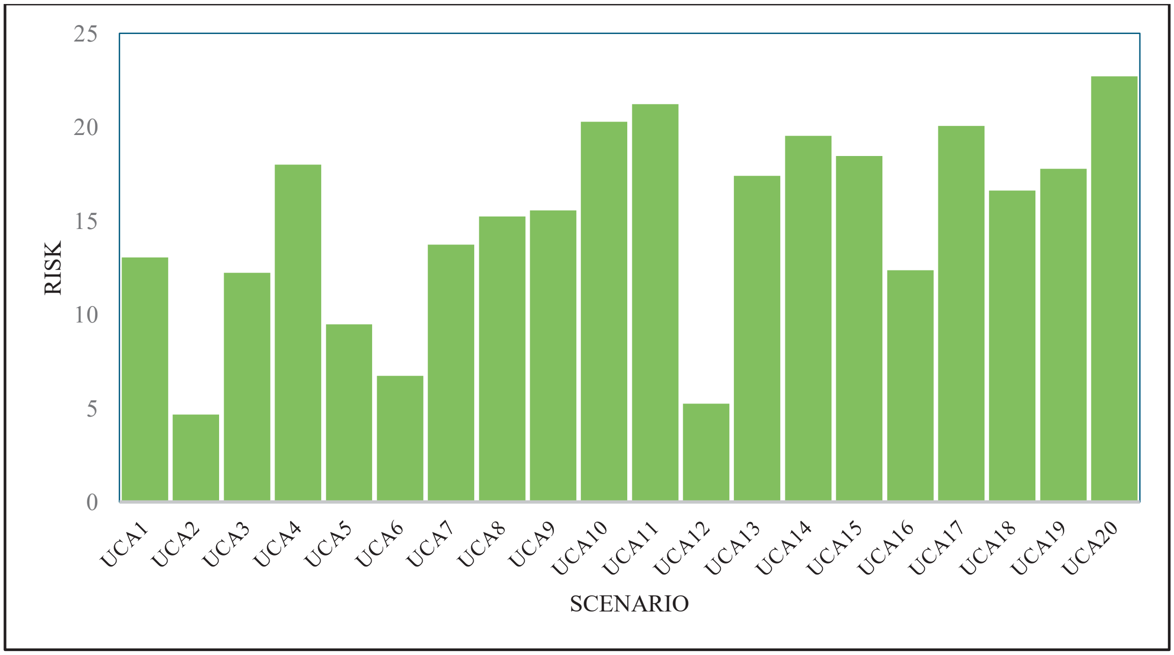

Figure 3.6 Risk of each scenario

Table 3.7 PSO parameters

Parameters	Value
Number of particles	50
Number of iterations	1,000
Inertia weight	0.5
Cognitive weight	0.9
Social weight	1.5
Number of links	3

3.4.5 Identify loss scenarios

In this section, in order to better concentrate on the identified risks, it divided the risk values into five categories, given that a 5-scale method was used (Table 3.8): Very low [1-5), Low: [5-10), Medium: [10-15), High: [15-20), Very high: [20-25]. The Pareto chart of the risk of each scenario is demonstrated in Figure 3.7. Herein, we focused on the scenarios with ‘high’ and ‘very high’ risk values (higher than 15). These scenarios are shown in Table 3.9.

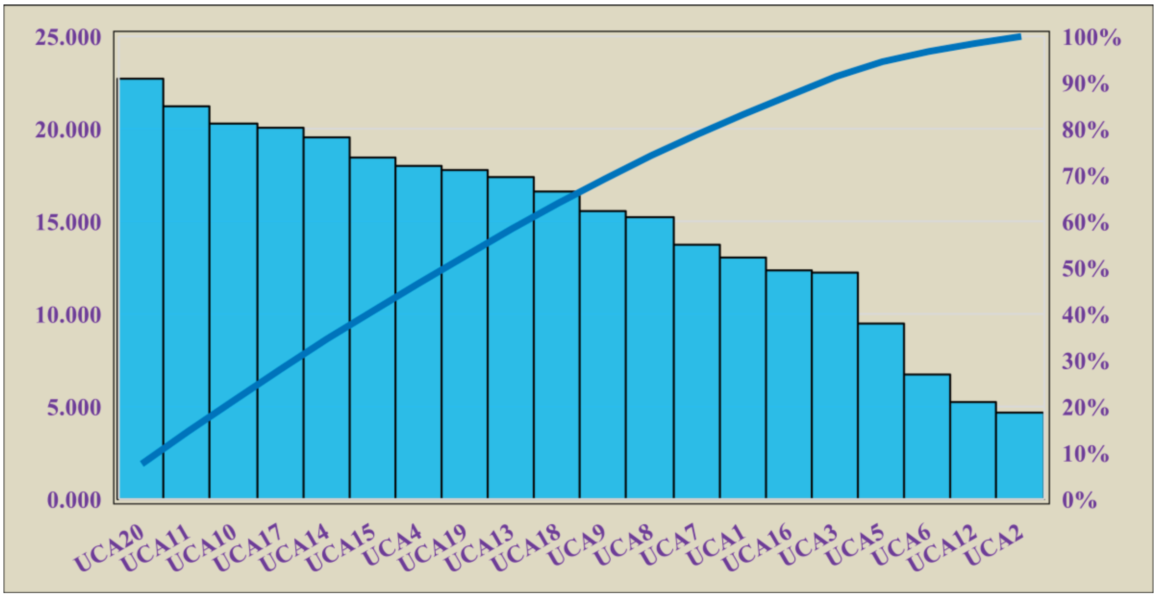

Figure 3.7 UCA Pareto chart

Table 3.8 Risk matrix

Risk		**Probability**				
		Very Low (1)	Low (2)	Medium (3)	High (4)	Very High (5)
	Very Low (1)	1	2	3	4	5
Impact	Low (2)	2	4	6	8	10
	Medium (3)	3	6	9	12	15
	High (4)	4	8	12	16	20
	Very High (5)	5	10	15	20	25

Table 3.9 Scenarios with ‘high’ and ‘very high’ risks

#UCA	Description	Risk
UCA20	The IT department provides programming for the receiver and processor too late	22.699
UCA11	Smart glasses provide feedback to the worker too late	21.226
UCA10	Smart glasses provide wrong feedback to the worker	20.278
UCA17	The receiver and processor provide light commands very quickly	20.066
UCA14	The receiver and processor do not provide light commands	19.534
UCA15	The receiver and processor provide wrong light commands	18.454
UCA4	The production planning department stopped the previous plan too soon	18.003
UCA19	The IT department provides wrong programming for the receiver and processor	17.781
UCA13	Smart glasses calibrated incorrectly before use	17.397
UCA18	The IT department does not provide programming for the receiver and processor	16.608
UCA9	The smart glasses not provide feedback about the place of assembly to the worker	15.549

3.5 Discussion

While STPA falls under the model-based engineering concept (which is enhanced as design adjustments are made), its model is different from the model-based engineering approach normally recommended for today’s systems (Leveson & Thomas, 2018). Several studies have shown that this method is effective in complex operating environments with multiple controllers controlling the same process (Rising & Leveson, 2018). STPA, based on the STAMP technology that attributes accidents to inadequate control, exhibits the following characteristics (Mofidi Naeini & Nadeau, 2022c):

- The model utilizes a functional control diagram.

- "Guide words" are primarily derived from the absence of complete assurance of analysis due to insufficient control in most cases.
- Apart from aiding in guiding design proofs, it proves beneficial even before the actual design phase.
- Its applicability extends throughout the entire life cycle of any system.

A safety problem in STPA is viewed as more of a control issue than a reliability issue. Unlike reliability-based tools, the STPA can be used at all stages of a system's standard engineering process (Rising & Leveson, 2018). As compared to traditional risk analysis techniques, STPA has the following advantages (Leveson & Thomas, 2018):

- It allows the possibility of analyzing very complex systems.
- It is an effective method for identifying safety requirements and constraints in early concept analysis. Consequently, design flaws can be detected early in development or operation, preventing costly rework.
- By incorporating human and software operators into the hazard analysis, STPA ensures that all potential losses can be considered.
- Often, in large and complex systems, when there is no documentation for system functionality, STPA steps in and fills the gap.
- Model-based and system engineering can easily be integrated with STPA.

One notable advantage of STPA is its ability to track decisions and designs throughout the development process, eliminating the need for redundant analyses (Leveson & Thomas, 2018). By considering all aspects of the system, including humans, technology, and organizations, STPA enables the identification of hazards (Mofidi Naeini & Nadeau, 2022c). During the concept development phase, STPA can generate high-level safety requirements that inform architectural decisions, which can later be refined as development progresses and more information is obtained (Rising & Leveson, 2018). The STAMP-STPA approach plays a crucial role in enhancing systemic safety (Allison et al., 2017).

However, a major drawback of STPA is its qualitative nature (Karevan & Nadeau, 2023). In light of the advantages and this limitation, this study presents a novel approach that quantifies STPA using a metaheuristic algorithm called PSO. The STPA-PSO methodology introduced assesses and reduces risks, including human error risks, associated with using smart glasses in a complex system such as refrigerator assembly.

While the use of IoTs and wearables in complex systems has increased, there is a lack of studies quantifying their risks (Karevan & Nadeau, 2023). The methodology presented in this study is straightforward and applicable to real cases, as demonstrated above. It assesses the risk of unsafe control actions (UCAs) and uses a metaheuristic algorithm. The results indicate the effectiveness of the proposed methodology in identifying worst-case scenarios and determining their associated risks, including human error risks.

However, there are limitations to this study, including the assessment of probability using the Monte-Carlo Simulation (MCS) due to the absence of real data. Also, effective risk management decisions cannot solely rely on ordered categorical ratings of frequency and severity, as other quantitative factors like costs of risk reduction measures, budget constraints, legal imperatives, scientific consensus, and interactions among risks are crucial. Additionally, if consequence severities vary widely, higher ratings in a risk matrix may not always indicate greater risks. Therefore, risk matrices may not consistently support optimal risk management decisions or efficient resource allocation (Cox, 2008). On the other hand, as BWM is based on the decision-makers and their judgment, in order to avoid motivational and cognitive biases, it is recommended to use debiasing techniques, which are provided by (Montibeller & Von Winterfeldt, 2015).

Additionally, only one wearable device was utilized, and the study focused on three impact factors (Industrial, OHS, and Financial), while the inclusion of other relevant impact factors based on particular situations could be interesting to explore. Furthermore, it is worth mentioning that the model could be further enhanced by exploring and testing other PSO parameters. Conducting such tests would allow a deeper understanding of how these parameters influence the performance and outcomes of the model.

3.6 Conclusion

In conclusion, as Industry 5.0 is being ushered in, there is a pressing need to enhance the collaboration between humans and machines. Equipping humans with new technologies, such as wearables in complex systems, is crucial to improving their efficiency and effectiveness. However, this increased interaction introduces the potential for new forms of human error risks. Hence, it becomes imperative to define, assess, and mitigate these risks. Despite an extensive literature analysis, no existing studies were found that quantified these specific risks. To bridge this research gap, we have proposed a novel methodology called STPA-PSO, designed to quantify and mitigate the risks associated with using smart glasses in complex systems, including human error risks.

In this study, we first identified a suitable case study, focusing on a particular assembly part of a refrigerator assembly. Employing the STPA approach, we proceeded to identify all potential losses, hazards, and system-level constraints within the given context. Subsequently, a functional control model was constructed to represent the system. By analyzing the functional control model, we identified all the unsafe control actions that could occur. The risk associated with each UCA was then calculated using the proposed PSO algorithm. To determine the probability of each UCA, we employed the Monte-Carlo Simulation, while considering three impact aspects: Industrial, Financial, and OHS. The weighting of each aspect was assessed using BWM (Best Worst Method). Through this comprehensive analysis, the overall risk of the model was identified and subsequently quantified. Ultimately, this approach facilitated the identification of loss scenarios.

The results obtained from this methodology clearly demonstrate its effectiveness in identifying, assessing, and quantifying the risks associated with each unsafe control action at the design stage. The findings underscore the model’s potential to enhance safety and assess the occurrence of human errors in complex systems.

CHAPTER 4

INTEGRATING SMART GLASSES AND SMART GLOVES IN HYBRID ASSEMBLY/DISASSEMBLY SYSTEMS: AN STPA-DRIVEN SEMI-AUTOMATED RISK MANAGEMENT TOOL

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Abstract

With the rise of Industry 5.0, wearables have become increasingly common in manufacturing, making effective risk management more critical than ever. Despite this trend, there remains a gap in research regarding the risks associated with the simultaneous use of multiple wearables, particularly in complex hybrid systems involving human operators. This study addresses this gap by using an improved Systems-Theoretic Process Analysis combined with Particle Swarm Optimization (STPA-PSO) methodology. Moreover, it introduces a circular, semi-automated methodology (incorporating mitigation measures) that can systematically identify, analyze, quantify, and mitigate risks, including those arising from human error, in the integration of multiple wearables. Three case studies, two assembly lines and one disassembly line, were tested to check the effectiveness of this method. The findings indicate that increased interactions among system components can lead to elevated risk levels. It demonstrates that highlighting the hazardous areas, calibration regulations, and training of workers are high-risk control action scenarios that need to be reduced. This methodology can provide a safer and more efficient integration of wearable technologies in human-centered manufacturing environments.

Keywords: *STAMP-STPA, Hybrid assembly/disassembly systems, Wearables, Risk management*

4.1 Introduction

As we transition from Industry 4.0 to Industry 5.0, modern manufacturing increasingly integrates advanced technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) to create smarter manufacturing environments (T. Wang, Liu, Wang, Li, & Wang, 2024). These technologies aim to enhance operational efficiency while supporting human workers in reducing errors and mitigating risks (Karevan & Nadeau, 2023). Understanding and addressing workplace risks is crucial, especially since human error often contributes significantly to operational safety (Sezer, Akyuz, & Gardoni, 2023) and quality (Torres et al., 2021b). For example, AI, robots, and real-time data can improve product quality, robustness (X. V. Wang, Xu, Cui, Yu, & Wang, 2024), cycle time (Y. Zhang et al., 2024), as well as sustainability and energy efficiency (Billey & Wuest, 2024). Among the significant applications of IoT are wearable technologies, which are being adopted across diverse sectors (Mofidi Naeini & Nadeau, 2022a). Aligned with the principles of Industry 5.0, production and assembly processes must prioritize human-centric design (Xu et al., 2021). This paradigm reinforces the concept of 'human-in-the-loop' smart manufacturing, which explores the significant opportunities and addresses the inherent challenges at the interface between human operators and intelligent technologies (Jwo, Lin, & Lee, 2021). By working alongside machines and technology, human workers can achieve greater productivity across various manufacturing tasks (e.g., inspections, diagnostics, assembly, disassembly, maintenance, and logistics), yielding better results than relying solely on manual labor or automation (B. Wang et al., 2024). Recent work explores interactive frameworks for human-robot collaboration to increase sustainability, resilience, and human-centeredness (Makris, Michalos, Dimitropoulos, Krueger, & Haninger, 2024) and specific AR-based assistance systems that can support workers in assembly lines (Aivaliotis et al., 2024).

As we explore the intersection of human-centric design and technology in Industry 5.0, wearable technology emerges as a pivotal element that can further enhance this collaboration.

Wearable technology is designed to provide employees with context-specific information, enhancing their performance while also collecting and transmitting company data (Krzywdzinski et al., 2022). These smart devices (e.g., smart glasses, smart gloves, smartwatches) are capable of processing, storing, and communicating data, facilitating their integration into existing systems (Pavón et al., 2018). They have emerged as tools for improving worker health, safety, and motivation within cyber-physical production systems (Romero et al., 2018). However, despite their potential to boost productivity and decrease errors, the importance of sociotechnical interactions is often overlooked (Ulmer, Braun, Cheng, Dowey, & Wollert, 2023). Moreover, there is a significant gap in comprehensive strategies to address potential risks during implementation (Karevan & Nadeau, 2023; Mutual, 2017; Yuen, Choy, Lam, & Tsang, 2019), particularly when multiple wearables are used concurrently within complex systems (Marino, Barbieri, Bruno, & Muzzupappa, 2024). This is especially important as Industry 5.0 and the reliance on wearable devices continue to grow, making effective risk management essential. To minimize human-system error risks, work system designers and managers must carefully identify and quantify these risks (Setayesh, Di Pasquale, & Neumann, 2022). Additionally, industrial workers and occupational health and safety (OHS) professionals have expressed concerns about wearables, citing issues like discomfort, distraction, and the extra burden these devices may impose (Xuanxuan Zhang et al., 2022). For instance, while smart glasses in logistics and assembly lines are recognized for improving productivity and safety (Tenholt et al., 2023), worries regarding the potential hazards linked to this emerging technology persist (Khoddammohammadi, 2023; Sedighi, Rashedi, & Nussbaum, 2020).

In this context, there are two primary avenues for advancement. The initial option involves improving wearable devices themselves, while the alternative focuses on integrating wearable devices into various systems and assessing their performance. This study concentrates on the latter path and addresses the specific challenge of managing risks associated with the simultaneous integration of multiple wearable devices (smart glasses and smart gloves) into complex hybrid assembly/disassembly systems. Notably, to the best of our knowledge, no studies have explored the risks associated with the simultaneous use of two wearables within a complex system (e.g., assembly or disassembly), including potential human error risks, underscoring the significance and originality of this study. In the other hand, the increasing prevalence of such multi-wearable setups in Industry 5.0 introduces novel complexities (Karevan & Nadeau, 2024a). Existing risk assessment methods often struggle to capture these systemic interactions holistically or provide the quantitative prioritization needed for effective decision-making in the design and operational phases (Read, Shorrock, Walker, & Salmon, 2021).

To tackle this challenge, we propose an improved STPA-PSO methodology. STPA (Leveson, 2004) is chosen for its strength in analyzing complex socio-technical systems by focusing on unsafe control actions and systemic flaws, rather than just component failures. It effectively models interactions between technical components, humans, and organizational factors (Ab Rahim, Reniers, Yang, & Bajpai, 2024; Hulme et al., 2021). However, STPA in its original form has limitations: it can be time-consuming, requires detailed system knowledge, and does not inherently provide risk quantification or prioritization (Carniel, Bezerra, & Hirata, 2023; Karevan & Nadeau, 2024a). This makes it difficult for decision-makers to focus resources on the most critical risks, especially when many potential unsafe scenarios are identified.

To overcome these limitations, we integrate PSO as a robust metaheuristic algorithm capable of solving complex optimization problems (Yang et al., 2020) and can be adapted for risk quantification (Karevan & Vasili, 2018). By combining STPA with PSO, we leverage STPA's systemic hazard identification capabilities with PSO's power to quantify and prioritize the identified unsafe control actions based on multiple criteria (e.g., OHS, industrial, financial impacts) and estimated probabilities, even with limited empirical data. This addresses the need for a structured, quantitative risk assessment tool tailored to the complexities of multi-wearable integration. Furthermore, this work extends the original STPA-PSO framework (Karevan & Nadeau, 2024a) by introducing a mitigation step, creating a circular, semi-automated risk management tool.

The remainder of the paper is structured as follows: Section two outlines the methodology, covering the literature on STPA, PSO, and the introduction of the improved STPA-PSO. Section three presents the three case studies. Section four discusses the study's findings, while section five includes a discussion that compares the results along with relevant literature. Finally, the last section provides the conclusions.

4.2 Methodology

4.2.1 STPA (System-Theoretic Process Analysis)

The STAMP (Systems Theoretic Accident Model and Processes) methodology was introduced by Nancy Leveson (Leveson, 2004) as a method of handling complex systems (H. Sun, Wang, Yang, & Reniers, 2022). Generally speaking, STAMP is known as STPA when used in hazard analysis and CAST (Causal Analysis based on STAMP) when used for accident and incident analysis (Patriarca, Chatzimichailidou, Karanikas, & Di Gravio, 2022; Pricop et al., 2020). STPA was created to tackle the systemic perspective offered by STAMP, integrating control types and factors not typically covered by conventional techniques (Hulme et al., 2021; L. Sun, Li, & Zio, 2022). Moreover, it is one of the most widely used methods in proactive analysis (Karevan & Nadeau, 2024a) that could help to eliminate or control hazards by analyzing the system (Andrews et al., 2018).

Wearables introduce new complexities and potential points of failure in manufacturing processes (Karevan & Nadeau, 2023), and STPA is particularly well-suited to assess the potential risks of these workstations. Additionally, by analyzing the interactions between human operators and wearable devices, a thorough assessment of potential risks and human errors associated with the use of wearables can be conducted (Karevan & Nadeau, 2024a, 2024c). The original STPA analysis is structured as follows (Leveson & Thomas, 2018):

- “Define the Purpose of the Analysis”: Consider all losses, hazards, safety limitations, and system-level constraints
- “Model the control structure”: Create a functional control model for the system
- “Identify unsafe control actions (UCAs)”
- “Identify loss scenarios”: Identify each potential safety control action from step 3

The structured analysis process facilitates a systematic exploration of accidents, system-level hazards, safety constraints, and functional requirements related to the use of wearables (Bjerga et al., 2016). This approach ensures a holistic view of the potential risks associated with human-technology interactions, identifying not only technical failures but also human-related factors contributing to errors (Karevan & Nadeau, 2024a). An important benefit of STPA is its ability

to track decisions and designs across the development process, reducing the necessity for repeating earlier analyses (Leveson & Thomas, 2018). Furthermore, STPA's proactive approach is well-suited to the objective of identifying potential risks before they lead to accidents. This capability is particularly valuable in the fast-paced environments of manufacturing and assembly/disassembly processes, where early detection of safety issues can prevent expensive disruptions and promote a safer workplace (Rising & Leveson, 2018).
This method offers a complementary approach to traditional techniques by identifying causes of workplace incidents and accidents (Carniel et al., 2023; Karevan & Nadeau, 2024d). It can be applied both retrospectively and prospectively, effectively maps structural complexity, and incorporates qualitative data (Hulme et al., 2021). Its validation across various sectors highlights its versatility and effectiveness (Hulme et al., 2021; Karevan & Nadeau, 2024a; Leveson & Thomas, 2018; Mofidi Naeini & Nadeau, 2022a). Recent developments have further enhanced its capabilities, including the creation of an ontology (Carniel et al., 2023), quantification techniques (Karevan & Nadeau, 2024a), and considerations for the dynamic aspects of digital systems (Karevan & Nadeau, 2024a; Mofidi Naeini & Nadeau, 2022a). Additionally, a new validation framework has been introduced (Sadeghi & Goerlandt, 2023).

4.2.2 PSO (Particle Swarm Optimization)

PSO has proven highly flexible and practical as a tool for tackling complex optimization problems (Yang et al., 2020). As a population-based metaheuristic algorithm, PSO excels in solving intricate problems by its ability to straightforwardly navigate towards global optima with high convergence rates (Jain et al., 2022). Additionally, PSO can be combined with other methods to assess risk probability (Karevan et al., 2020). The PSO algorithm operates with a population (swarm) of candidate solutions (particles) moving through the problem space. Each particle's movement is influenced by its own best-known position and the best-known position of the entire swarm (or a local neighborhood). Key control parameters govern this behavior (Engelbrecht, 2007):

- Swarm size: The number of particles in the population.

- Acceleration coefficients (cognitive and social): Weights influencing the pull towards the particle's personal best position and the global/neighborhood best position, respectively.
- Inertia weight: Controls the influence of the particle's previous velocity on its current velocity, balancing global exploration and local exploitation.
- Neighborhood size: Defines the subset of the swarm influencing a particle's movement in local best PSO variants.
- Number of iterations: The maximum number of cycles the algorithm runs.
- Velocity clamping: Limits the maximum step size a particle can take in one iteration to prevent divergence.

In the context of this study, PSO facilitates the STPA analysis by providing an optimization engine to quantify and prioritize the numerous UCAs. Given the UCAs and the multi-faceted impact assessment (Industrial, OHS, Financial), PSO simulates potential risk scenarios. It searches the solution space (defined by potential probabilities and impact levels for each UCA) to identify the combinations representing the highest overall risk scores.

4.2.3 Improved STPA-PSO

Karevan and Nadeau (2024) introduced and applied the STPA-PSO method for the identification and quantification of the risks of using smart glasses in an assembly process (Karevan & Nadeau, 2024a). However, this model needs to be further validated as it only analyzed one case study, and more studies are needed to validate this method (Gustafsson, 2017; Yin, 2018). Meanwhile, industries face the challenge of integrating multiple wearables simultaneously. They need a systemic risk management decision-making tool for these complex systems. Therefore, the model needs to be improved and extended with a mitigation decision-making capability. The initial STPA-PSO comprises five primary stages (Karevan & Nadeau, 2024a).

- Define Losses, Hazards, and Constraints (STPA Step 1).
- Develop the Functional Control Model (STPA Step 2).

- Identify Unsafe Control Actions (UCAs) (STPA Step 3).
- Calculate Risk for each UCA
- Identify High-Risk Loss Scenarios (Prioritization based on calculated risk, STPA Step 4).

However, this paper introduces an additional step focusing on identifying mitigation strategies. This step transforms the methodology from analytical to include proactive risk reduction guidance during the design phase. It should be noted that this is a semi-automated mitigation tool where AI helps humans to make better decisions by providing the prioritization of risks for each scenario, which respects the European guidelines (Schneider & Weber, 2024). The novelty lies in formalizing this mitigation feedback loop within the STPA-PSO framework, making it a more actionable tool for risk management. The entire procedure is outlined below and illustrated in Figure 4.1.

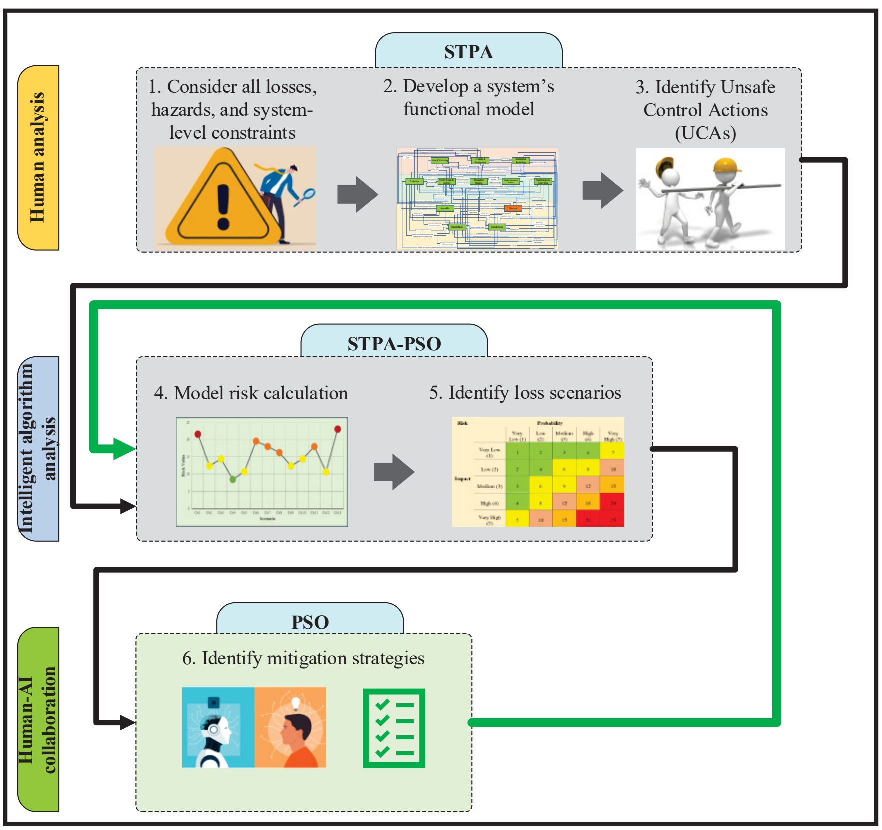

Figure 4.1 Methodology process

This figure shows that the first three steps are completed through human analysis, while the next two steps are performed by the meta-heuristic algorithm (PSO). Step six involves collaboration between humans, who prepare the strategies, and the algorithm, which selects the strategy, as well as recalculating the model from step four, as demonstrated by the thick green arrow.

4.2.3.1 Consider all losses, hazards, and system-level constraints

In the first step, after determining the problem and the case studies, all the losses, hazards, and system-level constraints must be determined.

4.2.3.2 Develop a system's functional control model

Then, a functional control model of the system should be developed. Hierarchical control structures generally consist of five crucial elements: controllers, control actions, feedback loops, additional inputs and outputs from components, and the processes controlled by the controllers (Leveson & Thomas, 2018).

4.2.3.3 UCA identification

In the third step, based on the functional model, all the unsafe and hazardous control actions in different scenarios will be identified. According to Leveson and Thomas (2018), four scenarios make a control action unsafe (Leveson & Thomas, 2018; H. Sun, Wang, Yang, & Reniers, 2024), as follows:

- Not providing control action.
- Providing the wrong control action.
- Providing a potentially safe control action at the wrong time or in the wrong order.
- Providing a control action for too long or stopping it too soon.

4.2.3.4 Risk calculation

Step four contains the calculation of the risk of each control action. With equation 4.1, the risk of each CA will be determined.

$$R_i = P_i * ((W_{IND\,i} * I_{IND\,i}) + (W_{OHS\,i} * I_{OHS\,i}) + (W_{FIN\,i} * I_{FIN\,i})) \quad (4.1)$$

In this equation, the impact of each UCA is assessed across three dimensions (Industrial, OHS, Financial) using a five-point scale (1=Very Low, 2=Low, 3=Medium, 4=High, 5=Very High). Table 4.2 provides qualitative descriptions for these levels.

Table 4.1 Symbol definition

Symbol	**Definition**	**Symbol**	**Definition**
R_i	Risk of event i	P_i	Probability of event i
$W_{IND\,i}$	Weight factor of industrial aspect of event i	$I_{IND\,i}$	Impact of industrial aspect of event i
$W_{OHS\,i}$	Weight factor of OHS aspect of event i	$I_{OHS\,i}$	Impact of OHS aspect of event i
$W_{FIN\,i}$	Weight factor of financial aspect of event i	$I_{FIN\,i}$	Impact of financial aspect of event i

The weighting factors reflect the relative importance of each impact dimension. For weighing each of the aspects, BWM (Rezaei, 2015) is used as one of the most robust methods, which is justified in different papers (Karevan & Nadeau, 2024a; H. Sharma, Sohani, & Yadav, 2022). For this study, focusing on methodological demonstration in a design phase context without an available expert panel, equal weights ($W_{IND} = W_{OHS} = W_{FIN} = 1/3$) were assigned arbitrarily; however, a sensitivity analysis is performed to show how different weights can affect the risk of each identified UCA.

As we are analyzing the integration of two smart wearables in hybrid assembly/disassembly systems, and the empirical data is unavailable, the probability (P_i) for each UCA was estimated using the PSO simulation by random numbers. This study aims to establish a dependable framework and evaluate it with random data to ensure functionality.

Table 4.2 Impact aspects

Scenario	**Industrial aspect (regarding time)**	**Financial aspect (regarding cost)**	**Scenario**	**OHS aspect**
No Economic/Industrial loss	Very Low (VL)	Very Low (VL)	No OHS impact	Very Low (VL)
Delay in production (Breakage of some parts, or material, equipment, not receiving material, etc.)	Low (L)	Medium (M)	Injuries that require first aid only	Low (L)
Redoing the process	Medium (M)	Low (L)	Injuries requiring time off from work	Medium (M)
Major damage to the product, equipment	High (H)	High (H)	Broken bones or intoxication	High (H)
Stop production	Very High (VH)	Very High (VH)	Critical situations	Very High (VH)

The final risk score combines probability and weighted impact. Based on the 1-5 impact scale and potential probabilities, the resulting risk scores are categorized into qualitative tiers for easier interpretation: Ver Low Risk ($R_i < 5$), Low Risk ($5 \leq R_i < 10$), Medium Risk ($10 \leq R_i < 15$), High Risk ($15 \leq R_i < 20$), Very High Risk ($R_i \geq 20$).

4.2.3.5 Identify loss scenarios

During this stage, the UCAs are ranked based on their calculated risk scores. The top-ranked scenarios (e.g., those falling into 'High' and 'Very High' risk tiers) are identified for focused mitigation efforts in the next step.

4.2.3.6 Identify mitigation strategies

In the final stage, improvement recommendations are generated for the high-risk loss scenarios identified in Step 5. This step operationalizes the semi-automated, human-AI collaboration. Implementing these suggestions helps to reduce the likelihood of unsafe control actions, ultimately increasing the reliability of the STPA-PSO model. This step completes the circular process of the model. Following the implementation of these improvements, the risk associated with each control action should be recalculated, as outlined in step 4.

As mentioned earlier, this is a semi-automated mitigation tool. To elaborate, the initial steps (1, 2, and 3) are conducted through human analysis, while steps 4 and 5 are performed by the intelligent PSO algorithm. The last step represents a collaboration between human expertise and AI capabilities (as demonstrated in Figure 4.1). Here, the intelligent algorithm is not a learning-based AI but rather a knowledge-based matching system. Its function is to query a predefined knowledge base—represented by the improvement recommendations in Table 4.7—which links known unsafe control actions to mitigation strategies.

Humans are responsible for decision-making and actions (Rick et al., 2024), with AI assisting by providing risk assessments, classification, and quantification. This collaboration ensures a comprehensive and effective evaluation process.

The process involves:

- The PSO algorithm first provides a prioritization by identifying and ranking the UCAs based on their calculated risk scores.
- The human decision-maker (e.g., a safety engineer or manager) proposes the mitigation strategies list.
- The knowledge-based algorithm then assists the human by parsing the description of the selected UCA, and uses the best relevant mitigation strategies from the knowledge base (Table 4.7).
- Implementing these suggestions aims to reduce the risk of the targeted UCAs.
- The model encourages recalculating the risk to assess the effectiveness of the implemented mitigations, completing the circular process. Figure 4.2 shows this process.

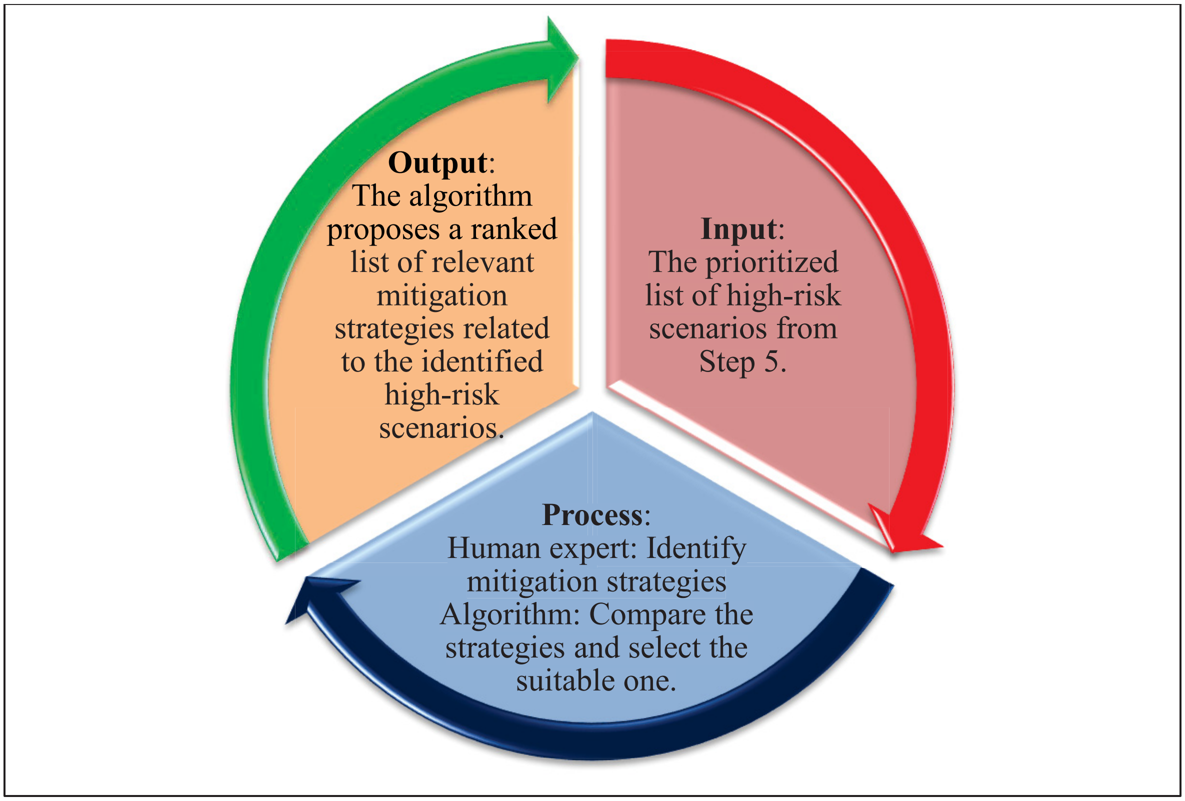

Figure 4.2 The process of step 6 (identify mitigation strategies)

4.3 Case studies

Case studies are invaluable when delving into subjects with limited existing knowledge. They facilitate qualitative exploration of intricate systems, especially in cases where real-world analysis is unfeasible (Rashid et al., 2019). By employing case studies, one establishes a sturdy groundwork, particularly during the initial phases of the research, setting the stage for future development (Harrison et al., 2017). Furthermore, multiple case studies enable comparisons between different settings. By analyzing processes (e.g., assembly or disassembly) in varied environments, one can draw comparisons and identify patterns, trends, and nuances that may not be apparent from a single case. This approach supports the exploration of similarities and differences, enhancing theoretical generalization (Eisenhardt, 1989). Also, triangulating results across multiple cases contributes to the robustness and validity of the findings (Stake, 1995).

In this paper, three case studies are employed to validate the proposed methodology. To have a more comprehensive perspective, the first one is an assembly line, the second one is a job shop assembly, and the third one is a disassembly line. In the next paragraphs, these case studies will be presented.

The first case study is an assembly section named “Fruit and vegetable box, and drawers assembling” in a refrigerator manufacturing plant, which was studied by Karevan and Nadeau (2024), integrating only smart glasses. Here, the refrigerator moves along an assembly line (conveyor), and the required assembly tasks are completed at each section. In the 'Fruit and Vegetable Box and Drawers Assembling' section, the assembler must assemble three parts from three bins following the assembly instructions and the product map with the use of smart glasses (Karevan & Nadeau, 2024a). However, in this paper, we have retained the use of smart glasses while introducing an additional wearable, smart gloves, into the same operational context.

The second case study is from a fieldwork presented by Torres et al (2021). Unlike the first case study, this one focuses on a job shop assembly process that does not use wearable devices. In this workstation, the assembler has a tool cabinet that contains the required tools for the assembly operation. Also, 7 bins of required parts to assemble are placed in front of the assembler. The assembly structure is transferred by a dolly (Torres et al., 2021b). In the original case study, as mentioned, the assembler is not equipped with any wearables and has access to a computer to read the work instructions. However, based on the results and findings of that paper, the authors discussed the errors that can arise from the work conditions. By using wearables, many of the identified errors could be reduced and mitigated. Figure 4.3 shows the layout of the workstation with the assembler equipped with smart glasses and smart gloves for our modelling purposes.

The third case study involves a refrigerator disassembly operation, presented by Zeng et al. (2023). In this case, the manufacturing company operates a disassembly line for three different refrigerator models. Based on the optimal disassembly sequence provided by the authors, the process is divided into five workstations. Each station is responsible for removing specific parts according to disassembly instructions (Zeng et al., 2023). For this study, we focus on the second workstation from the fourth sequence, which has been identified as the most economically profitable sequence by the authors (Zeng et al., 2023). At this station, the worker disassembles the refrigerant for recycling, the freezer door, the process pipe, and the dry filter. The worker is equipped with a tool cabinet and storage bins for sorting the disassembled components. In the original study, the worker is not equipped with any wearables. However, herein, we introduce smart glasses and smart gloves to enhance the worker's efficiency. The smart glasses display real-time disassembly instructions and highlight the exact parts to be removed, while the smart gloves guide the worker with precise pressure requirements. Additionally, the wearables help the worker identify potentially hazardous components, allowing for safer handling. Also, the worker can communicate with supervisors and manage the disassembled parts more effectively, sorting them based on their material properties. The basic layout of this workstation is illustrated in Figure 4.4.

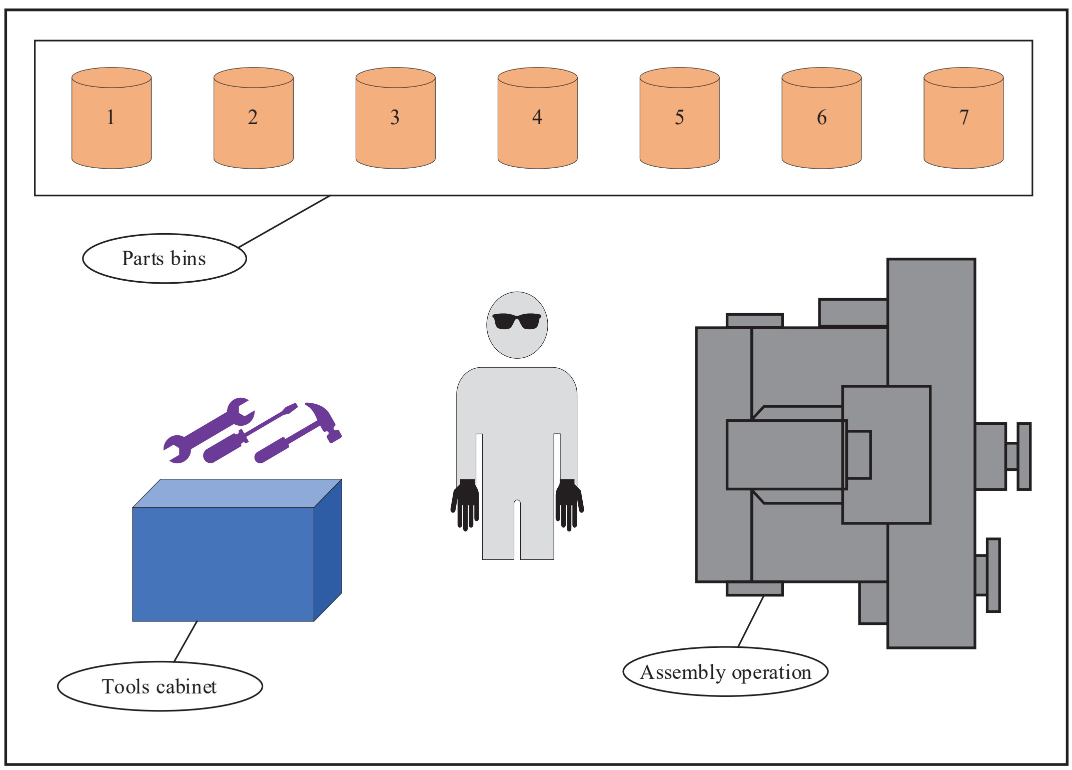

Figure 4.3 Layout of the job shop workstation

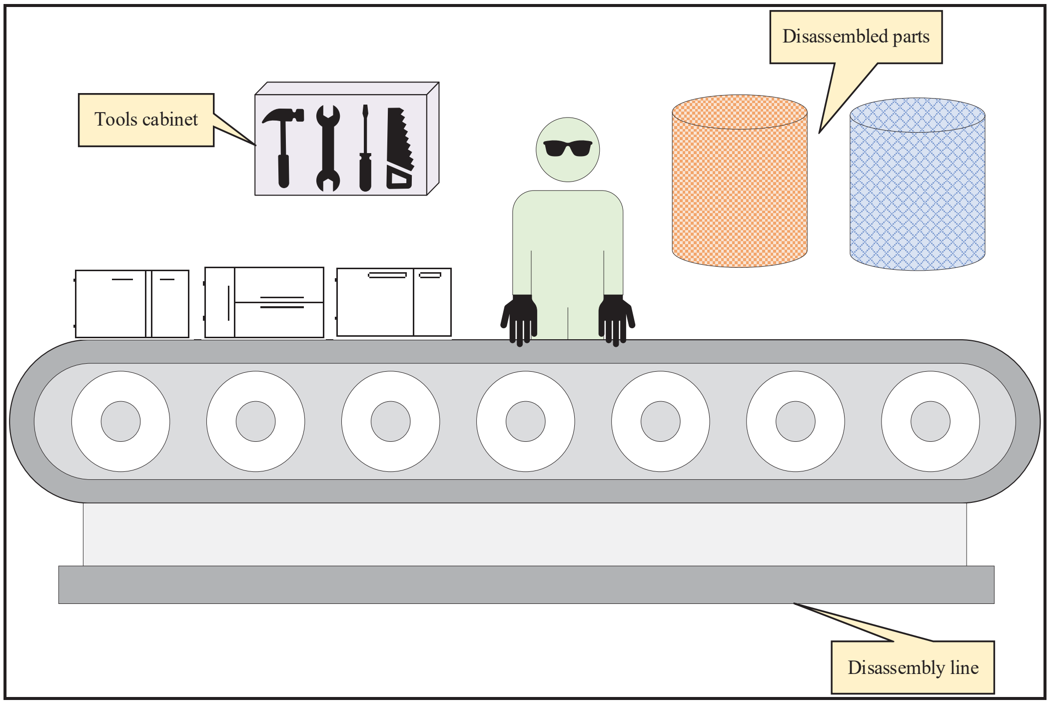

Figure 4.4 Layout of a refrigerator disassembly workstation

4.4 Results

4.4.1 Consider all losses, hazards, and system-level constraints

The primary step is to identify the purpose of the analysis. For this study, the main objective is to investigate the risks associated with the integration of smart glasses and smart gloves into complex systems (assembly/disassembly). Six losses were identified for these case studies, and they are presented in Figure 4.5. Ten identified hazards are shown in Table 4.3. Also, system-level constraints are shown in Table 4.4.

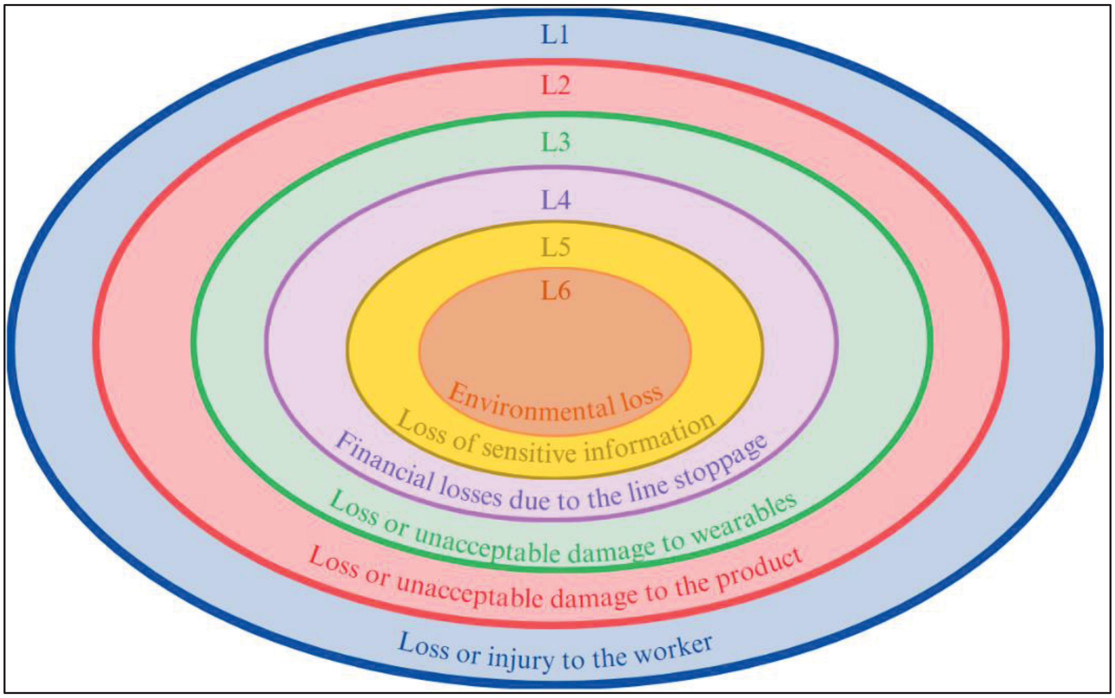

Figure 4.5 System-level losses

4.4.2 Develop a system's functional control model

Controllers provide control actions to regulate a process's behavior within a hierarchical control structure (Leveson & Thomas, 2018). In this context, we first present the macro-level control structure of an assembly/disassembly company (Figure 4.6) to provide a holistic view of the system. This figure is designed to illustrate the inherent hierarchical levels within the STPA model, progressing from higher-level organizational control and decision-making at the top, down through various management and supervisory functions, to the physical processes and equipment at the lowest level. This hierarchical representation is crucial for a comprehensive STPA analysis, as it enables the identification of unsafe control actions and feedback loops across various levels of abstraction within the system. Additionally, Figure 4.6 illustrates the interconnections between various departments, workstations, and the integration of smart wearables. By comparing this model to the one with a single wearable (Karevan & Nadeau, 2024a), it becomes clear that the current model involves more interactions and communications, potentially leading to increased control complexity and unsafe control actions if not properly managed.

For a more in-depth analysis of specific operational contexts, we then derive and focus on detailed control structure models for the individual workstations involved in the three case studies. Figure 4.7 provides a work-system level control structure focused specifically on assembly operations, relevant to Case 1 and Case 2. This model details the interactions and control loops pertinent to the assembly process, highlighting the direct control exercised by the Supervisor over the Assembler, the crucial role of Maintenance & Calibration in ensuring equipment readiness, and the operational interplay between the Assembler, Smart Glasses, Smart Gloves, and the Conveyer/Dolly system.

Similarly, Figure 4.8 presents another work-system level control structure, this time focused on disassembly operations, which is central to Case 3. This model outlines the specific interactions involved in the disassembling process, mirroring the level of detail provided for assembly. Key elements include the Supervisor's oversight of the Disassembler, the continued importance of Maintenance & Calibration, and the specialized functions of the Smart Glasses and Smart Gloves in guiding disassembly tasks, detecting components, and monitoring environmental factors. The inclusion of Disassembled Parts Bins emphasizes the different material flow and handling requirements compared to assembly.

4.4.3 UCA identification

Through the STPA, unsafe conditions are identified and eliminated (Mofidi Naeini & Nadeau, 2022a). After developing the system's functional model and identifying the control actions, this step determines the unsafe control actions for each and presents them in Table 4.5. A total of thirteen control actions were identified, resulting in the determination of thirty-four unsafe control actions. Each control action corresponds to one or more system-level hazards, as presented in the Table 4.5. The last column indicates which control actions correspond to each of the case studies.

Table 4.3 System-level hazards

Code	Description	Associated losses
H1	Harmful activities that may lead to a worker’s injury or death	(L1, L2, L3, L4)
H2	Insufficient training of workers to work with wearables	(L1, L2, L3, L4, L5)
H3	Not providing the required materials and structure on time	(L4)
H4	Not providing precise and real-time data	(L2, L3, L4)
H5	Connection problem between wearables	(L2, L3, L4, L5)
H6	Communication problem between departments	(L3, L4, L5)
H7	Data security problem	(L3, L5)
H8	Damage to the product during the process	(L2)
H9	Release of harmful refrigerants due to improper disassembly	(L6, L1)
H10	Incorrect sorting of hazardous and non-hazardous components, leading to environmental or safety risks	(L6)

Table 4.4 System-level constraints

Code	System-level constraints	Associated hazards
SC1	Workers must comply with OHS rules	(H1)
SC2	Workers must not be exposed to hazardous materials (e.g., refrigerants or sharp components) without adequate safety measures.	(H1, H9)
SC3	Supervisors must train workers on OHS rules and regularly check them	(H1)
SC4	The workstation must be inspected for safety compliance before the start of work	(H1)
SC5	Supervisors must regularly check the safety of both the workers and the workstation	(H1, H9, H10)
SC6	Workers should be careful to avoid engaging in activities that could be harmful	(H1)
SC7	Workers need to be trained and evaluated before using smart wearables	(H1, H2)
SC8	Workers need to be trained and evaluated regularly for using smart wearables	(H1, H2)
SC9	Supervisors must assess the efficiency of workers	(H1, H2)
SC10	Consider the positioning of sensors and ensure that the smart glasses are comfortable for workers to wear	(H1, H4, H5)
SC11	Consider the positioning of sensors and ensure that the smart gloves are comfortable for workers to wear	(H1, H4, H5)
SC12	Establish effective and reliable communication channels between departments to ensure data accuracy and reliability	(H3, H4, H6, H7)
SC13	Implement procedures to ensure that feedback from the smart glasses is accurate	(H4, H6, H7)
SC14	Implement procedures to ensure that feedback from the smart gloves is accurate and reliable	(H4, H6, H7)
SC15	Configure and program the smart glasses to transmit reliable data	(H4, H5, H6, H7)
SC16	Configure and program the smart gloves to transmit reliable data	(H4, H5, H6, H7)
SC17	Verify the communication between departments and wearable devices	(H4, H6, H7)
SC18	Regularly verify the reliability of the information	(H4, H6, H7)
SC19	Smart glasses must be calibrated according to the manufacturer's instructions	(H4, H5, H6, H7)
SC20	Smart gloves must be calibrated according to the manufacturer's instructions	(H4, H5, H6, H7)
SC21	Verify the connectivity between the receiver, processor, and smart glasses	(H4, H5, H6, H7)
SC22	Verify the connectivity between the receiver, processor, and smart gloves	(H4, H5, H6, H7)
SC23	The connection between smart glasses and smart gloves must be tested regularly	(H4, H5)
SC24	The structure must be delivered on time by the dolly (Case study 2)	(H3, H7)
SC25	The structure must be delivered on time by the conveyor (Case study 1 & 3)	(H3, H7)
SC26	Smart glasses must provide accurate, real-time instructions	(H4, H5)
SC27	Establish rules to address data security issues	(H7)
SC28	Smart gloves must provide accurate feedback on the force/pressure needed for disassembly	(H4, H5, H8)
SC29	Hazardous components must be disassembled with specific safety protocols, and must be detected by smart wearables	(H1, H8, H9)
SC30	Disassembled components must be stored in appropriate bins without damage	(H10)
SC31	The disassembly process must not release harmful refrigerant gases into the environment	(H9)

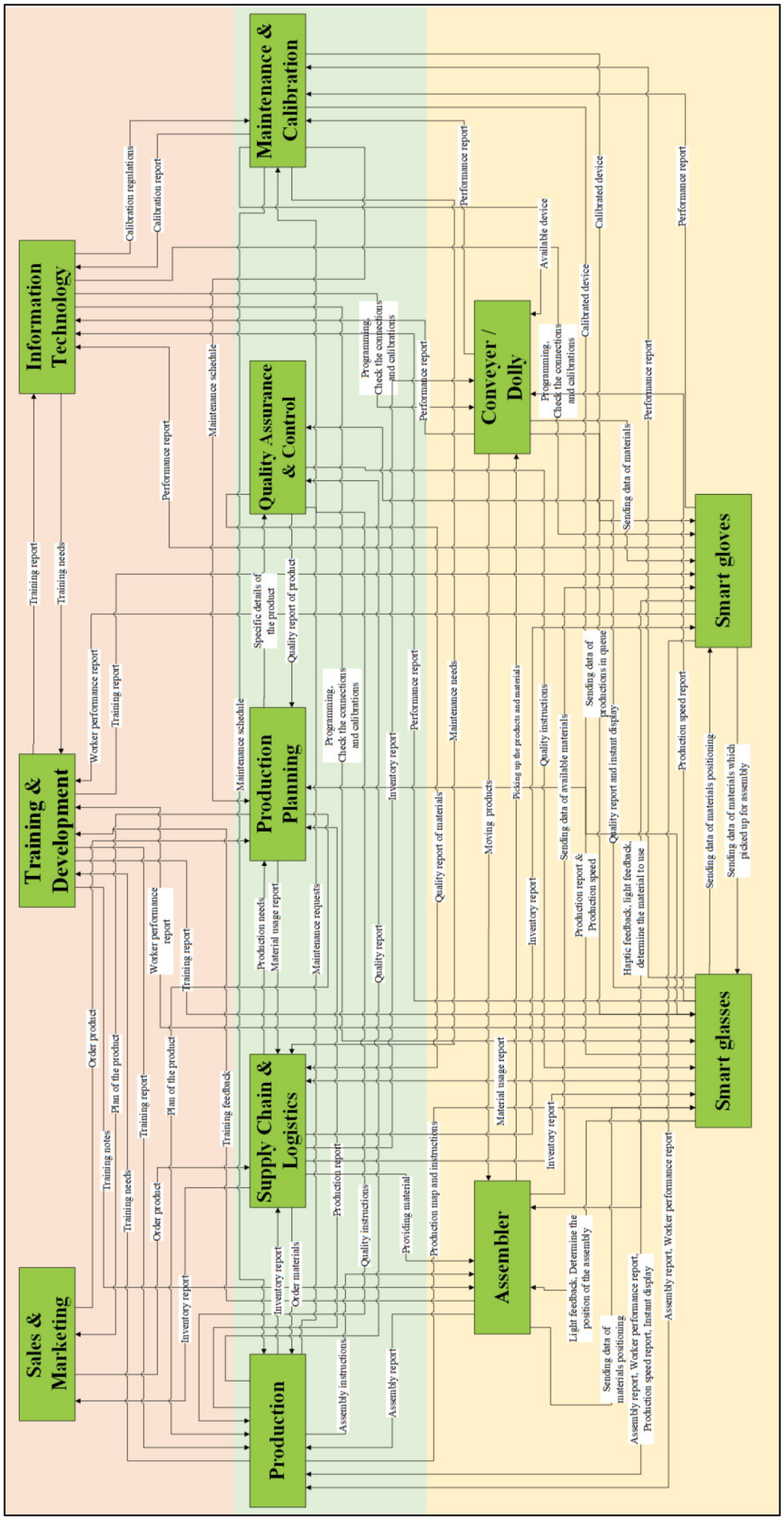

Figure 4.6 Macro-level control structure model

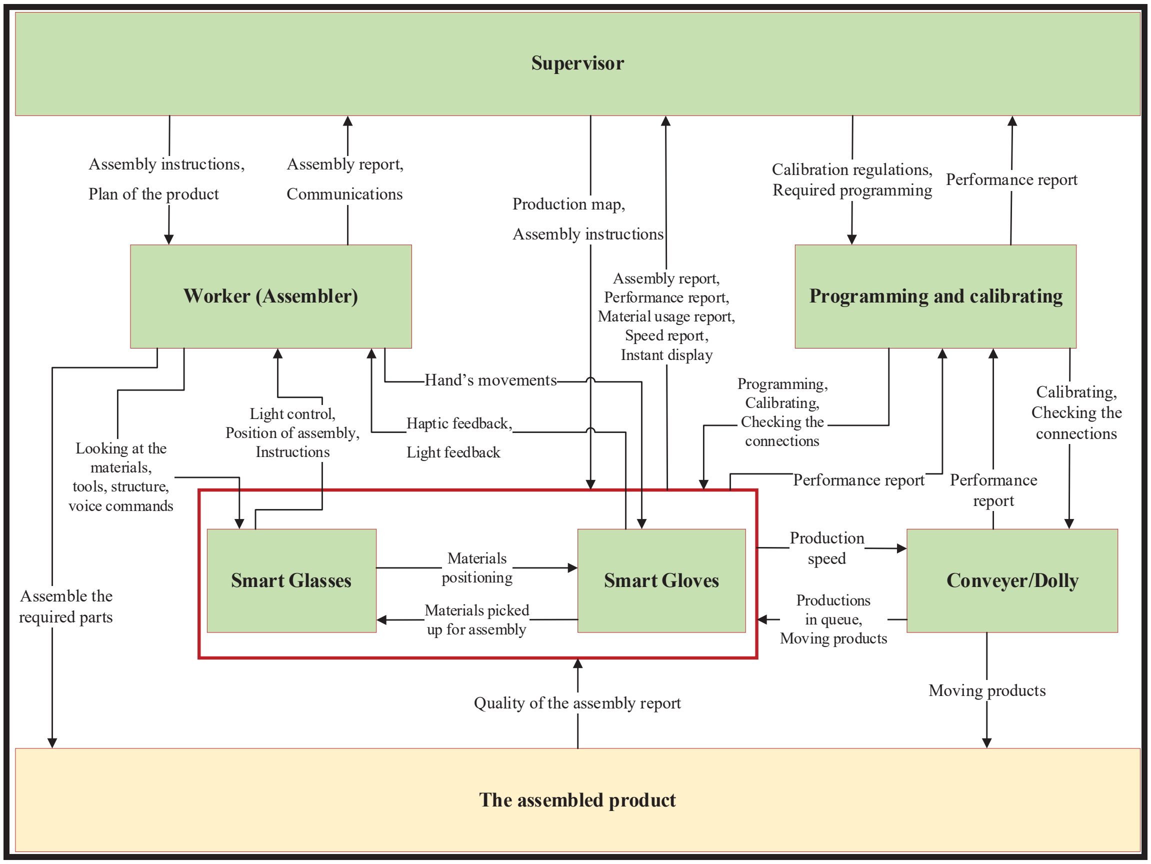

Figure 4.7 Assembly control structure model (work-system level)

4.4.4 Risk calculation

After identifying the control actions and evaluating their potential impact, in this step, the risk associated with each control action was calculated using Equation 1. In this analysis, as noted previously, we have assigned, arbitrarily, equal weight to each factor; however, these weights can be adjusted according to the decision-maker's priorities. Given that this research focuses on the design phase and actual data is unavailable, simulated data will be used to estimate the probability of each event. For this study, arbitrarily, the PSO algorithm was configured with 50 particles, 500 iterations, a cognitive weight of 0.9, a social weight of 1.5, and an inertia weight of 0.9.

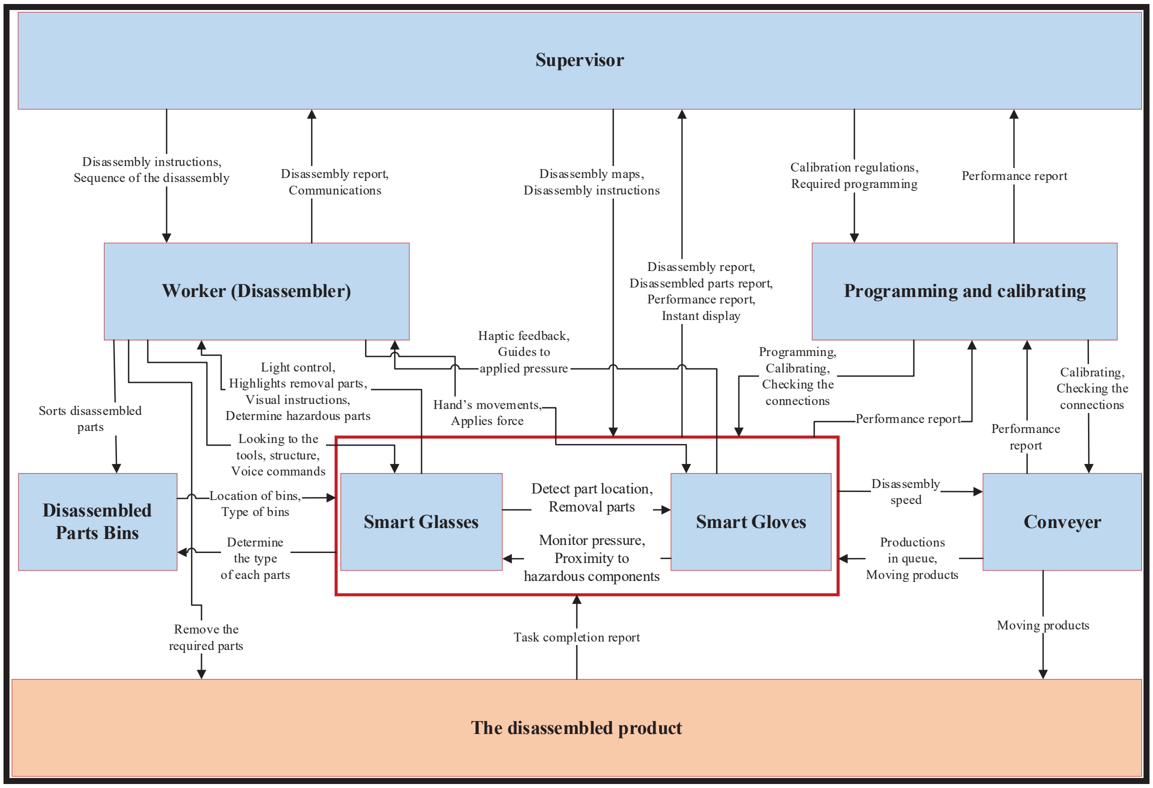

Figure 4.8 Disassembly control structure model (work-system level)

The algorithm begins by determining random probabilities and impacts, as illustrated in Figure 4.9, to test the algorithm's performance. This figure represents a line plot where four distinct factors are tracked across multiple control action scenarios: Financial Impact (red line), Industrial Impact (black dashed line), OHS Impact (blue dashed line), and Probabilities (green line). The plot highlights the variation of each factor across 13 different control action scenarios.

Following this, the risk for each scenario is calculated as shown in Figure 4.10. This figure shows the risk values for control action scenarios (CA1 to CA13). The bubble color corresponds to the predefined risk tiers: Green (Low Risk, $5 \leq R_i < 10$), Yellow (Medium Risk, $10 \leq R_i < 15$), Orange (High Risk, $15 \leq R_i < 20$), Dark Red (Very High Risk, $R_i \geq 20$). When comparing the two figures, it is evident that control action scenarios with higher impact factors tend to correspond to higher risk values. For instance, control action scenarios like CA1 and CA13 show a high correlation between the elevated probability and impact factors and their high-risk values.

Table 4.5 Unsafe control actions

Control Action (CA) scenarios	Unsafe Control Action (UCA)			Related hazards	Case study		
	Not providing causes hazard	Providing causes hazard	Providing too early, too late, or out of sequence		1	2	3
CA1: Calibration regulations	UCA1: The wearables are not calibrated prior to use	UCA2: Incorrect calibration settings	N/A	H4, H5, H7, H8	*	*	*
CA2: Data of materials positioning	UCA3: Not sending data	UCA4: Sending incorrect data	UCA5: Sending data too late/too soon	H4, H8, H10	*	*	*
CA3: Haptic feedback / light feedback	UCA6: Not providing feedback	UCA7: Providing incorrect feedback	UCA8: Providing feedback too early or too late	H1, H4, H8, H10	*	*	*
CA4: Moving products (with conveyor/dolly)	UCA9: Not moving products when needed	UCA10: Moving products incorrectly	UCA11: Moving products out of sequence	H2, H4, H5	*	*	*
CA5: Production (disassembly) map and instructions	UCA12: Not providing production maps and instructions by the supervisor	UCA13: Providing unclear or incorrect instructions or maps	N/A	H3, H6	*	*	*
CA6: Worker training	UCA14: Not providing training for workers	UCA15: Providing inefficient training for workers	UCA16: Providing training late for workers	H1, H2, H7, H9, H10	*	*	*
CA7: Check the connections	UCA17: Wearables do not connect to each other	UCA18: Wearables are connected but not performing well	N/A	H4, H5, H7, H9, H10	*	*	*
CA8: (Wearable's) Programming	UCA19: Not providing necessary programming	UCA20: Providing incorrect programming	N/A	H4, H5, H7	*	*	*
CA9: Smart glasses provide assembly/ disassembly instructions	UCA21: Smart glasses fail to display correct disassembly instructions	UCA22: Smart glasses display incorrect parts for removal or assemble	UCA23: Instructions are delayed or not updated in real-time	H4, H8, H9, H10	*	*	*
CA10: Smart gloves guide to applied pressure	UCA24: Smart gloves do not provide guide pressure feedback	UCA25: Smart gloves provide inaccurate pressure feedback	UCA26: Smart gloves do not provide inaccurate pressure feedback in real-time	H4, H5, H8, H9	*	*	*
CA11: Place and sort parts in storage bins	UCA27: The worker does not place or sort the parts in storage bins	UCA28: The worker incorrectly sorts disassembled components	N/A	H10			*
CA12: Sequence (plan) of disassembly/ assembly	UCA29: Not providing the plan of the product	UCA30: Providing the wrong plan of the product	UCA31: Not providing the plan of the product on time	H3, H6	*	*	*
CA13: Highlight hazardous parts	UCA32: Not highlighting the hazardous parts for removal for the worker	UCA33: Providing the wrong hazardous parts for removal	UCA34: Not providing the hazardous parts for removal in real-time	H1, H8, H9, H10			*

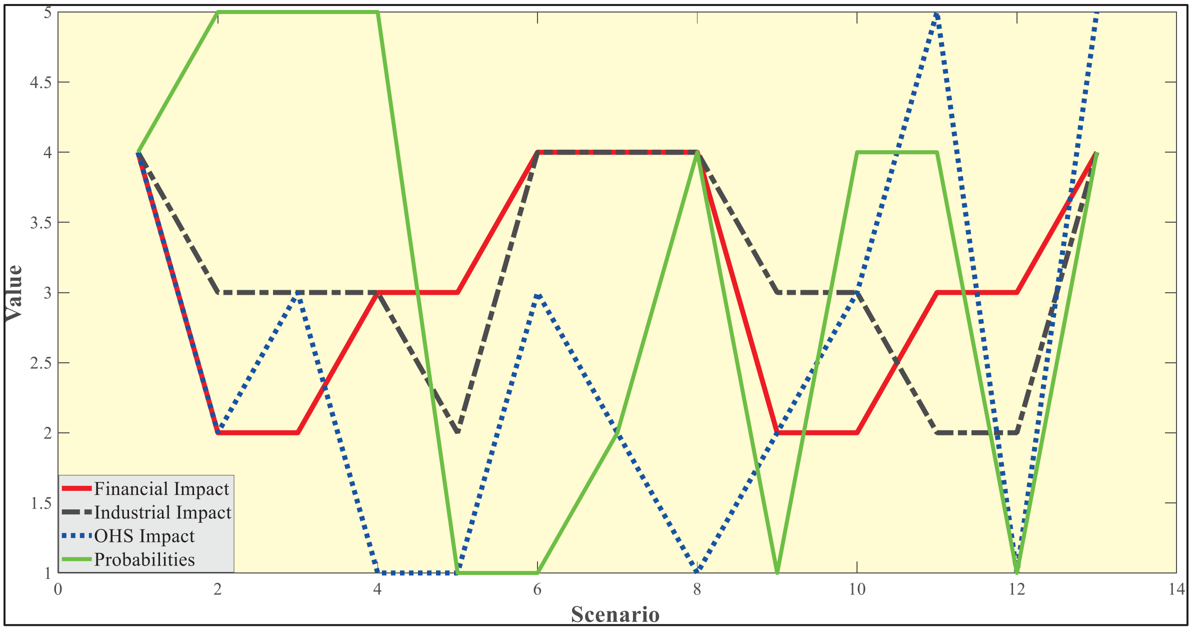

Figure 4.9 Values of impacts and probabilities for control action scenarios

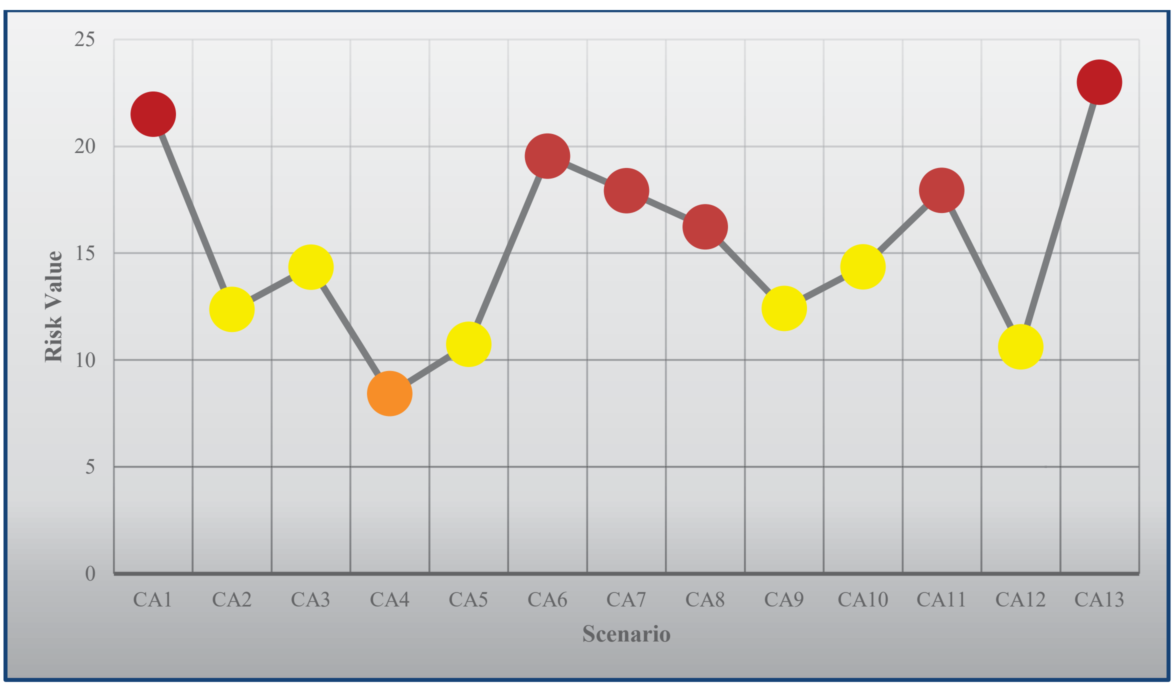

Figure 4.10 Control action scenario risk

4.4.5 Identify loss scenarios

Considering the risk associated with each scenario, we focus on factors categorized as high and very high risk on a five-point scale (dark red and orange bubbles). Based on the results from the previous step (risk calculations), where risks were ordered and classified by the algorithm, the high-risk scenarios selected (by the algorithm) for in-depth investigation are shown in Table 4.6.

Table 4.6 High-risk scenarios

#Control Action	**Scenario**	**Risk**	**Tier**	**Case study**		
				1	**2**	**3**
CA13	Highlight hazardous parts	23.00	Very High			*
CA1	Calibration regulations	21.50		*	*	*
CA6	Worker training	19.54	High	*	*	*
CA11	Place and sort parts in storage bins	17.93				*
CA7	Check the connections	17.91		*	*	*
CA8	(Wearable's) programming	16.23		*	*	*

Through the identification of potential loss scenarios, particularly by comprehending the risk factors associated with each control action, decision-makers can formulate more effective preventive and mitigation measures. This proactive approach contributes to mitigating the risk associated with each scenario, thereby reducing overall STPA-PSO model risk.

4.4.6 Identify mitigation strategies

Following the identification of high-risk scenarios, this step focuses on suggesting mitigation strategies using the semi-automated approach. Table 4.7 provides the potential improvement recommendations derived from both the literature and industrial experiences relevant to this study. Whenever a control action is identified as high-risk, any of these recommendations can be applied to decrease the probability of that event. Reducing the probability of each event minimizes the overall risk of the model. As shown in Figure 4.1, this step involves collaboration between humans and the meta-heuristic algorithm. Humans prepare the initial list, and the intelligent algorithm then associates appropriate mitigation strategies based on the previously identified loss scenarios. After applying the identified strategies, the model should be recalculated to analyze the risk of the model.

For example, for CA1 (Calibration regulations), identified as very high risk (Ri=21.50) due to UCA1 (The wearables are not calibrated prior to use) and UCA2 (Incorrect calibration settings): The algorithm might propose: "Set an automatic alert system for calibration reminders," "Install sensors that detect when equipment is out of calibration," and "Implement automatic shutdown if calibration thresholds are exceeded." Then, it should assess these options and apply the option. This decision leads back to risk recalculation to quantify the model and assess the improvement.

4.5 Discussion

The collaboration between humans and machines, coupled with an emphasis on human-centered smart manufacturing, represents critical components of Industry 5.0. This evolving paradigm underscores the vital roles that humans play within these systems. Integrating humans into the operational loop has become a widely adopted strategy aimed at enhancing collaboration (K. Huang et al., 2024). A particularly noteworthy advance in this area is the use of wearables. These devices, equipped with advanced sensors, hold the potential to significantly mitigate workplace injuries and hazards, thereby contributing to a safer and healthier work environment (Riso, 2021). Furthermore, wearables can improve management strategies, ultimately boosting workplace efficiency (Krzywdzinski et al., 2022).

However, the effective integration of wearables into manufacturing systems and their optimization for both efficacy and effectiveness remain critical challenges (Hao & Helo, 2017). The findings of this study indicate that integrating two wearables concurrently in a complex hybrid system, if not thoughtfully designed, can indeed lead to an increased number of potential unsafe control actions and, consequently, a higher overall system risk compared to single-wearable scenarios (Karevan & Nadeau, 2024a). This underscores the necessity of defining robust control measures specifically to address the interactions between multiple wearable devices and the human operator.

The successful application of the proposed improved STPA-PSO methodology highlights its value in equipping decision-makers with critical, quantitative information about the risk factors inherent in such advanced wearable integration. While some of the identified high-risk control action types—such as implementing calibration regulations, ensuring adequate worker training, and highlighting hazardous areas during disassembly—are indeed well-established principles in operational safety, the challenge and novelty of this research lie not in merely identifying these broad categories, but in their systematic identification, quantification, and prioritization within the specific and complex context of integrating smart glasses and smart gloves simultaneously into hybrid assembly/disassembly systems. The concurrent use of these devices introduces novel interaction points, potential for conflicting information, new human error, and systemic complexities that are not fully addressed by generic safety guidelines or single-wearable risk analyses.

The STPA component of our methodology facilitated a rigorous, top-down decomposition of the system, systematically identifying all relevant control actions and their potential failure modes (UCAs) related to the dual-wearable setup. This ensures a comprehensive sweep beyond just obvious hazards, capturing subtle interaction risks. Crucially, the integration of PSO enabled the quantitative assessment and prioritization of these UCAs based on a multi-criteria risk score. For instance, while 'worker training' is a known control, our STPA-PSO framework identified the specific scenarios where inadequate training for dual-wearable use posed the highest quantifiable risk compared to other UCAs. This data-driven prioritization is essential for resource-constrained environments, allowing decision-makers to focus on the most impactful interventions. This study specifically addresses the gap concerning the simultaneous use of multiple wearables, demonstrating how interactions between devices and with the human operator contribute to overall system risk.

Table 4.7 Improvement recommendations

Control action	**Improvement recommendations**
Calibration regulations	• Set an automatic alert system for calibration reminders • Install sensors that detect when equipment is out of calibration • Implement automatic shutdown if calibration thresholds are exceeded
Data of materials positioning	• Periodical maintenance • Adding an alarm sensor to stop the worker when the performance is not good • Adding a sensor to check the wearable's condition
Haptic feedback / light feedback	• Customize haptic feedback or light feedback based on specific tasks to enhance safety • Add warning indicators when an incorrect procedure is detected • Verify the reliability of feedback mechanisms by running routine checks
Moving products (with conveyor/ dolly)	• Adding a sensor to control the speed of conveyor/dolly based one the assembly/disassembly speed • Set up an alert system to warn if products are incorrectly placed on the conveyor
Production (disassembly) map and instructions	• Use smart devices for direct updates and changes to instructions • Use digital platforms to display maps and instructions with real-time updates
Worker training	• Evaluate workers' skills through assessments and training based on results • Ensure workers regularly update their skills with periodic training sessions
Check the connections	• Implement alarms that notify workers if a connection is lost during critical operations • Use software to check for any inconsistencies in data transmission from wearables • Add an automatic check at the start of each shift to ensure connections are active
(Wearable's) Programming	• Simplify programming interfaces to reduce potential errors • Use software to diagnose any issues with wearable devices and suggest immediate fixes
Smart glasses provide assembly/ disassembly instructions	• Provide visual step-by-step guides for complex assembly/disassembly procedures • Integrate voice commands to allow workers to request specific instructions • Implement a system that automatically updates instructions based on assembly progress

Control action	Improvement recommendations
Smart gloves guide to applied pressure	• Use pressure sensors to prevent overexertion or improper application of force • Incorporate data analytics to track pressure trends and offer real-time feedback • Integrate warning signals that alert workers if they are exceeding or under-applying the required pressure
Place and sort parts in storage bins	• Organize parts in bins with distinct color codes for easy identification • Add visual or sound alerts when incorrect parts are sorted
Sequence (plan) of disassembly/ assembly	• Use digital systems that update the plan in real-time based on changes in production • Add reminders for key steps in the plan to prevent sequence errors
Highlight hazardous parts	• Use color-coded labels or LED lighting to mark hazardous parts • Implement AR systems that highlight hazards in workers' smart glasses displays • Equip workstations with alarms that sound when hazardous parts are detected in an unsafe context

Furthermore, the extension of the STPA-PSO framework with a semi-automated, circular mitigation step offers a practical tool. While the types of mitigation strategies (Table 4.7) might be familiar, the methodology assists in linking specific, prioritized UCAs to relevant mitigation options and, importantly, allows for a recalculation of risk, demonstrating an iterative, improvement-focused approach to risk management. This moves beyond identification to active, guided risk reduction. The comparisons between the case studies also yielded valuable insights, indicating, for example, that disassembly processes inherently require more complex control actions than assembly, and that environmental factors can significantly influence the risk profile of such operations, suggesting areas for future focused research. The value for industry, therefore, lies not just in confirming that 'training is important,' but in understanding which specific training-related unsafe control actions in a dual-wearable system pose the highest quantifiable risk and therefore warrant immediate attention.

While this study focused on assembly and disassembly operations in manufacturing, the proposed STPA-PSO methodology can be used in other sectors. Its core logic of modeling control structures could be adapted to manage risks in diverse fields, such as healthcare, for remote surgical assistance. In logistics and warehousing, it could assess risks associated with smart gloves for picking and sorting. In civil maintenance, where human-robot collaboration presents known safety challenges (Bavelos, Anastasiou, Dimitropoulos, Oikonomou, & Makris, 2024). The core components (modeling the control structure, identifying unsafe control actions, and quantifying risk) remain robust across these varied applications.

It is also important to acknowledge the limitations of this study. The risk quantification relied on simulated probabilities due to the novelty of dual-wearable systems and the consequent lack of extensive real-world incident data. Similarly, impact weights were assigned equally for methodological demonstration. Therefore, to enhance the model's validity and test its reliability against this assumption, a sensitivity analysis was conducted, examining six different cases with varying weight factors (Table 4.8, Figure 4.11).

Despite this analysis, a full industrial application would still require formal expert elicitation to tailor risk prioritization to organizational values, a process that can be resource-intensive and requires clear organizational involvement. It must be noted that conducting a thorough STPA also requires deep system knowledge and training in the methodology itself.

The study also focused on systemic operational and safety risks, without delving into detailed ergonomic usability assessments of the wearables, which remains an important area for consideration. Finally, the generalizability of findings from three specific case studies is inherently limited, and results might vary with different industrial contexts, tasks, or wearable types.

Despite these limitations, this research makes several key contributions:

- Determine the integration of smart wearables in a complex hybrid assembly/disassembly process and their interactions.
- Systematically identify potential unsafe control actions arising from complex interactions.
- Quantitatively prioritize these risks using STPA-PSO.
- Provide a semi-automated, structured approach to suggesting targeted mitigation strategies, closing the risk management loop.

The results, therefore, validate the methodology's applicability in pinpointing and prioritizing critical control requirements within this specific, complex dual-wearable integration context, providing a valuable tool for engineers and safety managers aiming for safer and more efficient human-centered manufacturing.

Table 4.8 Different cases for each impact

# Weight Case	Industrial impact	Financial impact	OHS impact
Case 1	0.22	0.12	0.66
Case 2	0.50	0.25	0.25
Case 3	0.25	0.25	0.50
Case 4	0.25	0.50	0.25
Case 5	0.66	0.22	0.12
Case 6	0.12	0.66	0.22

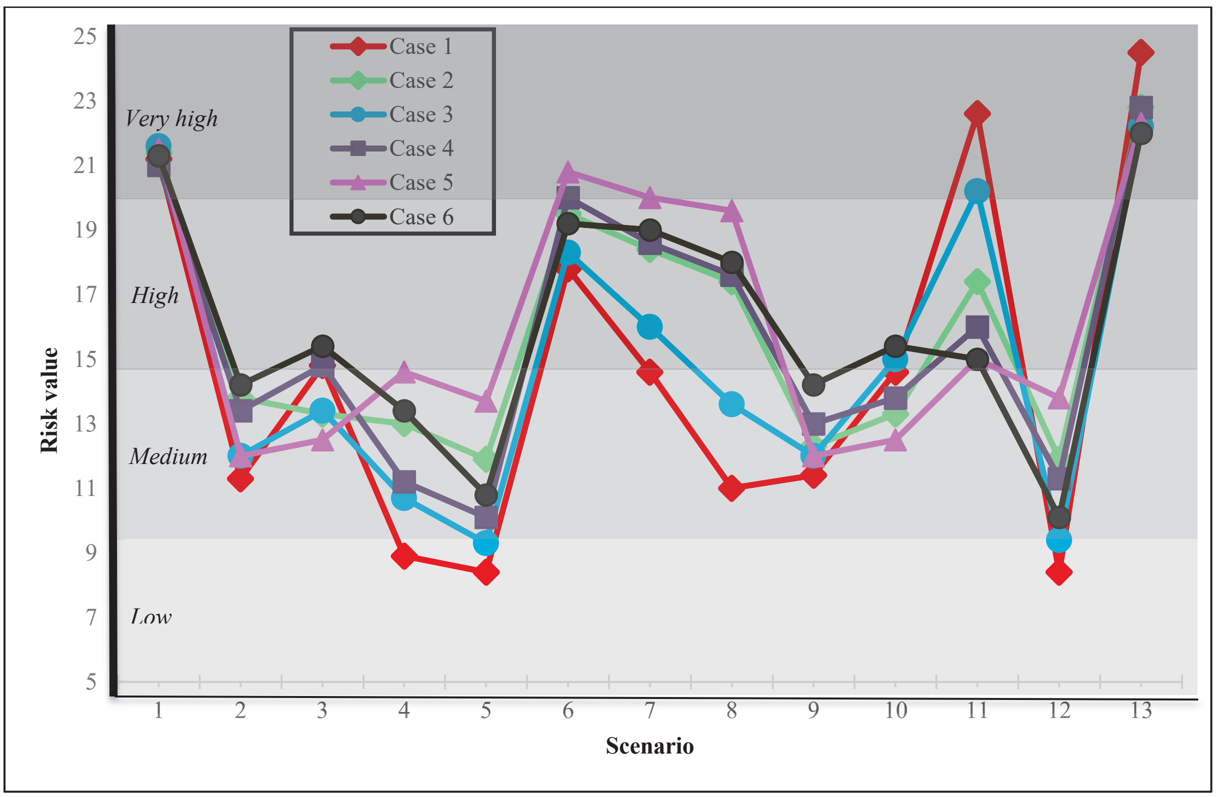

Figure 4.11 Sensitivity analysis of the risk of each control action scenario testing with different weight factors

4.6 Conclusions

In conclusion, this study underscores the increasing importance of human-machine collaboration and the integration of wearables within the framework of Industry 5.0, particularly in assembly and disassembly operations. By leveraging the improved STPA-PSO methodology, we have assessed the risks associated with the integration of smart glasses and smart gloves across three complex case studies. This research highlights the complexities in human-machine interactions and the challenges posed by the simultaneous use of multiple wearables.

Although the findings reveal increased risks associated with the use of two wearables, they also introduce a valuable mitigation decision-making tool. The core contribution of this work lies not just in identifying general risk categories like calibration or training, which are foundational to safety, but in the methodological rigor applied to their identification and quantitative prioritization within the novel and intricate context of dual-wearable human-system interaction.

This circular approach allows for the active identification, assessment, analysis, and mitigation of risks, providing a comprehensive strategy for decision-makers. It equips decision-makers with essential knowledge to navigate the complexities of integrating wearables into complex and hybrid industrial systems safely and effectively. Ultimately, this work not only advances the understanding of risk management in this emerging field but also lays the groundwork for future exploration and innovation in human-centered manufacturing practices.

Future work should focus on several key areas to enhance the robustness and applicability of the proposed methodology:

Firstly, validating the approach with real-world operational data is crucial to refining probability estimations and confirming risk rankings. Secondly, applying formal expert elicitation methods for determining impact weights would provide more contextually relevant risk prioritization. Thirdly, expanding the scope of case studies to different industries, task complexities, human-robot collaboration scenarios, and additional types or combinations of wearables would test the methodology's generalizability. And finally, integrating detailed ergonomic usability testing related to wearable use could provide a more holistic view of worker well-being.

CHAPTER 5

FRAM-PSO: A SEMI-QUANTITATIVE FRAMEWORK INTEGRATING MULTI-DIMENSIONAL SUSTAINABILITY CRITERIA

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Abstract

The increasing complexity of modern industrial systems, particularly those integrating smart wearables, makes it harder for traditional risk analysis methods to keep up. Systemic approaches such as the Functional Resonance Analysis Method (FRAM) help to understand how systems behave; however, there is an opportunity to develop more reliable quantification methods and integrate sustainability criteria, which current methods often do not emphasize. To address these gaps, this paper introduces a novel semi-quantitative framework that integrates FRAM with the Particle Swarm Optimization (PSO). This hybrid approach provides a structured methodology to systematically identify system functions, quantify performance variability, and model risk propagation. A key contribution is the explicit integration of multi-dimensional sustainability criteria (environmental, economic, and social) into the risk management process. This allows for the selection of optimized mitigation strategies. Three case studies involving smart wearables in assembly and disassembly systems were used to demonstrate the effectiveness of the proposed methodology. The results showcase the model's ability to identify high-risk pathways and prioritize mitigation efforts. This confirms its potential as a decision-support tool. This study contributes a novel methodological structure for embedding sustainability and optimization into systemic risk management.

Keywords: FRAM, PSO, Risk Management, Smart Wearables, Sustainability

5.1 Introduction

The increasing complexity of Industry 4.0 systems challenges (Aniceski, Miranda, Junior, & Benitez, 2024; Zheng & Liu, 2025) the efficacy of traditional risk assessment methods (Berx, Decré, Morag, Chemweno, & Pintelon, 2022), driving the adoption of systemic approaches that analyze how entire systems function rather than focusing solely on component failures (Karevan & Nadeau, 2024c; Read et al., 2021). Among prominent systemic methods like STAMP (System Theoretic Accident Model and Process) and AcciMap (Accident Causation, Consequence, and Investigation Mapping Process), FRAM has gained significant popularity for its ability to model non-linear interactions and performance variability in complex sociotechnical systems (Bellini et al., 2019; Hollnagel, 2012; Karevan & Nadeau, 2024d; Patriarca et al., 2020). In systemic models, STAMP, FRAM, and AcciMap are some of the most commonly referenced (Moslem et al., 2025; Yousefi et al., 2019).

FRAM is widely applied in aviation, healthcare, and industrial processes and accounts for over half of the published studies on the method (Patriarca et al., 2020). Beyond these fields, FRAM has also been popular and used in maritime operations (Salihoglu & Beşikçi, 2021), offshore drilling (França et al., 2021), coal mine accidents (Wanguan Qiao et al., 2019), and software engineering (E. A. de Carvalho et al., 2021). While FRAM is typically used in high-risk industries, it has also been found to be relevant in manufacturing (Melanson & Nadeau, 2019). It provides valuable qualitative insights into system resilience and potential hazards.

However, FRAM's inherently qualitative nature presents limitations when precise risk quantification is needed. Recognizing this, researchers have explored various quantitative extensions (Patriarca et al., 2020). Monte Carlo Simulation (MCS) is the most common, particularly in oil and gas (Yu et al., 2025), healthcare (Kaya & Hocaoglu, 2020; Zhou et al., 2023), transportation (Kaya et al., 2021), aviation (Patriarca, Di Gravio, & Costantino, 2017), manufacturing (Costantino et al., 2018), offshore wind farms (Köpke et al., 2020), marine industry (Peng et al., 2022), due to its ability to model uncertainty. As demonstrated by Patriarca, Di Gravio, and Costantino (2017), the primary strength of the FRAM-MCS approach is diagnostic risk analysis. It uses simulation to generate a probability distribution of risk (the VPN) to identify which parts of a system are most likely to become critical.

Beyond simulation, other prominent quantitative extensions have focused on probabilistic modeling and structured decision-making. Bayesian Networks (BN) and Dynamic Bayesian Networks (DBN) are also widely applied in the construction (Q. Wang et al., 2023), marine (Guo et al., 2022), gas pipeline industry (Xinqi Zhang et al., 2022), oil and gas industry (Bahoo Toroody et al., 2017), and chemical industries (Zinetullina et al., 2021) for predictive risk assessment. Their strength lies in dynamic resilience assessment and tracking system performance over time. The Analytic Hierarchy Process (AHP) is frequently used in construction (Haddad & Rosa, 2015; Lucio Villarinho Rosa et al., 2020; Lucio V Rosa et al., 2017), the oil and gas industry (França et al., 2020), and socio-technical systems (P. de Carvalho et al., 2016) for structured decision-making. Additionally, newer approaches like fuzzy logic rough sets (Slim & Nadeau, 2019), reinforcement learning (Salehi et al., 2022), and genetic algorithms (Patriarca et al., 2025) are emerging, signaling a shift toward AI-driven risk analysis in complex systems from diverse industries.

While these methods provide powerful tools for risk analysis, they are primarily diagnostic. Techniques like MCS and DBN allow the identification of the parts of a system that are most at risk, but they do not inherently guide the selection of optimal interventions. This challenge is particularly relevant in modern industrial environments where processes like assembly and disassembly involve intricate interactions between humans, machines, advanced robotic systems (Torres, Nadeau, & Landau, 2022), and smart wearable technologies (Karevan & Nadeau, 2024a). While wearables, such as smart gloves and glasses, have benefits for maximizing efficiency and safety, a systematic understanding and quantification of the risks associated with their deployment is lacking in the literature (Karevan & Nadeau, 2023). Prior work has initiated qualitative analysis using FRAM/STPA (Mofidi Naeini & Nadeau, 2023) and quantitative assessment via STPA-PSO for specific wearables (Karevan & Nadeau, 2024a, 2025c), highlighting the need for more integrated and comprehensive systemic approaches.

This paper addresses this gap by proposing a hybrid methodology that moves beyond risk analysis to prescriptive risk optimization. Our contribution is a novel framework that integrates three distinct elements:

- Systemic Modeling (FRAM): Capturing the non-linear interactions and functional resonance of complex systems.
- Automated Optimization (PSO): Moving beyond simulation to actively search for and identify the most effective mitigation strategies from a predefined set of options.
- Integrated Sustainability Criteria: Explicitly embedding environmental, economic, and social factors as core objectives within the optimization process, a dimension largely absent from prior quantitative FRAM literature.

The FRAM-PSO method is designed to systematically identify, quantify, and guide the mitigation of risks within complex industrial processes that incorporate smart wearables. To clarify its unique contribution, a comparative analysis of this method against other quantitative FRAM methodologies is summarized in Table 5.1. This work, therefore, contributes a novel framework specifically designed for sustainability-driven, multi-objective risk optimization, filling a gap between purely diagnostic risk analysis models and single-objective optimization approaches. By applying this integrated framework, we anticipate the establishment of a feedback loop that continuously enhances sustainability and reduces system risk over time. We believe this work establishes a foundation for future research aimed at promoting more sustainable and resilient industrial practices.

The remainder of this paper is organized as follows: Section 2 details the FRAM-PSO methodology. Section 3 presents the case studies. Section 4 outlines the results. Section 5 discusses the findings and limitations. Section 6 provides conclusions and future studies.

5.2 Methodology

This study uses FRAM to identify and analyze the system’s risks, and PSO is added to effectively quantify, mitigate, and improve the identified risks.

Table 5.1 Comparative analysis of quantitative FRAM methodologies

Feature	FRAM-MCS (Patriarca, Di Gravio, Costantino, & Tronci, 2017)	FRAM-GA (Patriarca et al., 2025)	FRAM-DBN (Xinqi Zhang et al., 2022)	FRAM-PSO (This study)
Primary goal	Risk analysis (diagnostic)	Cost optimization (single-objective)	Resilience modeling (dynamic)	Risk optimization & decision support (multi-objective)
Core engine	Monte Carlo Simulation	Genetic Algorithm	Dynamic Bayesian Network	Particle Swarm Optimization
Primary output	Probability distribution of risk (VPN)	Cost-effective maintenance plan	System performance profile over time	An optimal sequence of mitigation strategies balancing risk and sustainability
Handling of mitigations	Manual, post-analysis task	Optimized based on cost	Modeled as events in a timeline	Automatically selected and sequenced based on both risk reduction and sustainability scores
Sustainability integration	Not included	Not included	Not included	Explicitly integrated as a core, multi-pillar component of the optimization objective.
Key question answered	Which parts of my system are most at risk?	What is the cheapest way to schedule maintenance?	How will system's performance evolve during an incident?	What is the best sequence of actions to reduce overall risk in a sustainable way?

The FRAM analysis process typically includes four key steps: defining the functions within the system, analyzing the variations in how each function performs, exploring the relationships and interactions among functions, and developing methods to observe and regulate these variations (Sujan, Slater, & Crumpton, 2025). However, before proceeding, it is essential to define the primary objective of the study, whether it is an accident investigation or a system risk assessment, commonly referred to as Step 0 (Patriarca, Di Gravio, & Costantino, 2017). In this case, the analysis focuses on assessing the system's risk. The next steps are outlined below and illustrated in Figure 5.1.

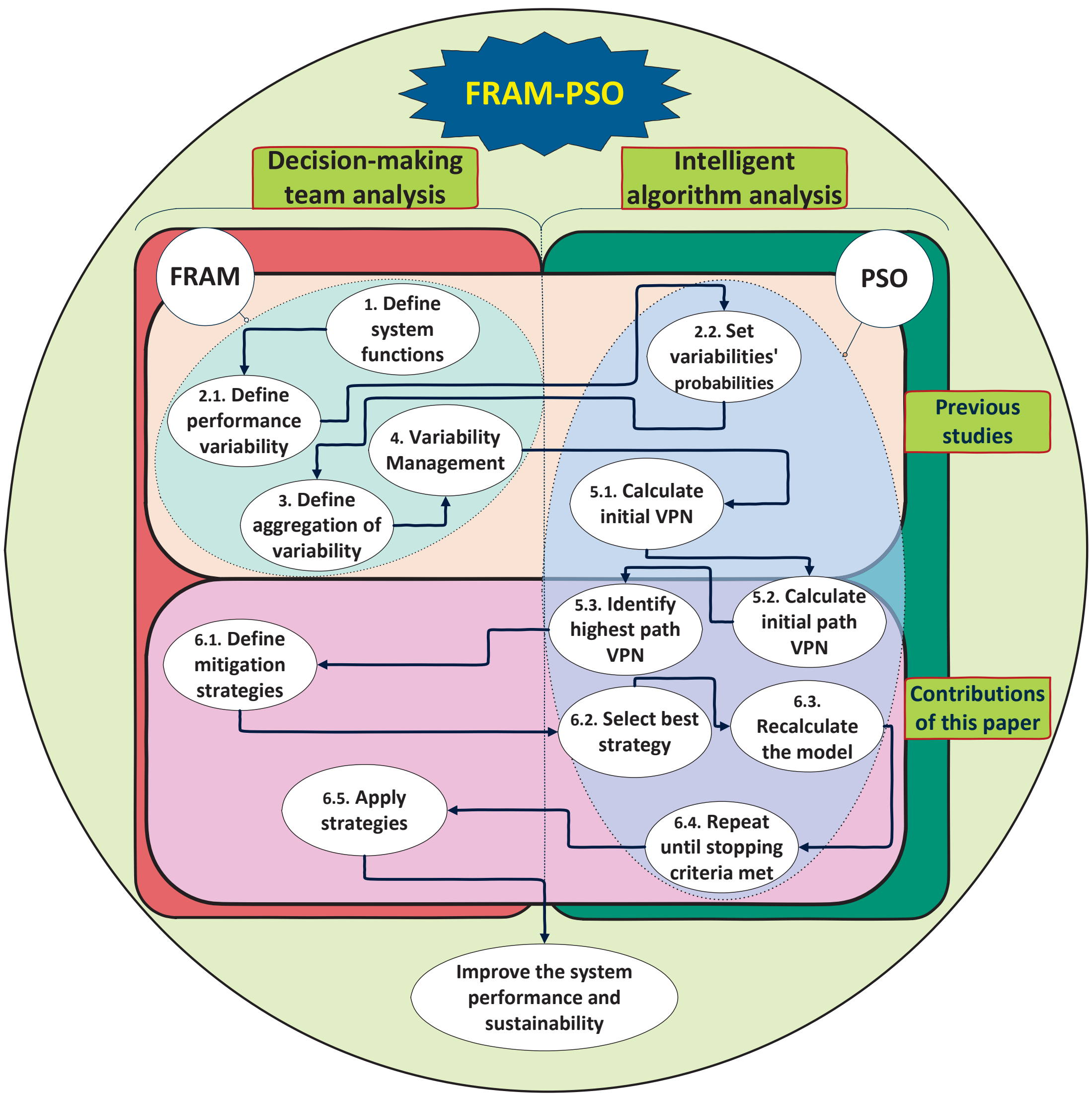

Figure 5.1 Methodology process

The figure presents the FRAM-PSO framework, illustrating the sequence of steps involved. It distinguishes between steps requiring human input from the decision-making team and steps processed by the intelligent algorithm (PSO). The diagram also highlights which elements build upon previous studies and pinpoints the specific contributions introduced in this paper. The entire framework is encompassed by a green border, visually emphasizing the ultimate objective: to improve system performance and sustainability.

5.2.1 Identification and description of the system's functions

Each function can be described through six key attributes: Input (function trigger), Output (function results), Precondition (actions to be considered or prepared), Resource (consumable resources), Control (any instruction that controls the function), and Time (time requirements) (Kaya & Hocaoglu, 2020; Weiliang Qiao et al., 2022). Also, these functions can be categorized into foreground functions and background functions. Foreground functions are central to the analysis and require a definition of all six aspects whenever feasible. In contrast, background functions are outside the scope of the analysis and only require a definition of either one input or one output (Patriarca, Di Gravio, & Costantino, 2017). Identifying background functions helps clarify how different parts of the system interact and affect overall performance and reliability. This distinction allows analysts to focus on key functions while still considering the broader system. The specifications of FRAM functions can be visually represented using a Functional Model Visualizer (FMV) (Mofidi Naeini & Nadeau, 2022a). This step is also the first (1) step demonstrated in Figure 5.1.

5.2.2 Identification of performance variability

This step involves analyzing function variability specific to each risk scenario by creating instances of the FRAM model. This includes identifying potential variability under different conditions and examining actual variability in each instance (Y. C. Kim & Yoon, 2021). Variability in a function can arise due to its connection with upstream functions, where changes or fluctuations in upstream outputs can directly impact the performance and behaviour of downstream functions (Lucio Villarinho Rosa, Haddad, & de Carvalho, 2015). Function variability arises from three main sources: internal (changes within the function), external (influences from the work environment), and coupling (effects from upstream functions). Understanding these factors helps explain why function outputs differ (Y. C. Kim & Yoon, 2021). Variability can be categorized into several types based on characteristics such as timing, precision, speed, distance, sequence, object, force, duration, and direction (Zinetullina et al., 2021). However, most researchers simplify the approach by focusing primarily on timing and precision (A. Kumar et al., 2024), such as those by (Kaya & Hocaoglu, 2020; Kaya et al., 2021; Mofidi Naeini & Nadeau, 2023; Patriarca, Di Gravio, & Costantino, 2017; Slim & Nadeau, 2019; Yu et al., 2025; Zinetullina et al., 2021).

In this work, we focus on assembly and disassembly operations, where time, precision, force (exerted by the worker), and sequence are key factors. These were selected as they directly map to the primary failure modes and performance enhancements associated with the use of smart wearables in manual tasks. For instance, smart glasses provide visual cues that directly influence the sequence of operations, while smart gloves provide haptic feedback affecting the force and precision of handling components. Time is a critical overarching factor in production line efficiency. Given their interdependence and impact on overall performance, we consider them for further analysis. Table 5.2 shows the variability values for each characteristic considered in this study.

OV_j is the variability of the upstream output j, which is calculated by equation 5.1.

$$OV_j = V_j^T * V_j^P * V_j^F * V_j^S \tag{5.1}$$

Where V_j^T, V_j^P, and V_j^F represent the variability in timing, precision, and force, respectively, while V_j^S accounts for sequence variability. This equation provides a systematic approach to quantifying how these variations collectively influence system outputs. To improve the reliability of the results, an occurrence probability vector is introduced for each output, considering its timing, precision, force, and sequence.

Table 5.2 Proposed variability values

Characteristic	Variability	Value
Time (V_t)	Too early	1
	On-time	2
	Too late	3
	Not at all	4
Precision (V_p)	Precise	1
	Acceptable	2
	Imprecise	3
	Wrong	4
Force (V_f)	Too low	1
	On Target	2
	Too high	3
	Not at all	4
Sequence (V_s)	Correct order	1
	Wrong order	2

Since simulated data are used in this study, MCS will be used to estimate the probability distribution of the outputs, which can be used in the design phase analysis; however, in the running cases, the past behavior of these variabilities should be considered. Table 5.3 provides an example of a probability distribution for a randomly selected function.

Table 5.3 Example of the probability distribution for the variability output of a function

Characteristic	**Too Early / Acceptable / Too Low**	**On-Time / Precise / On-Target/ Correct Order**	**Too Late / Imprecise / Too High**	**Not at All / Wrong**
Time (V_t)	0.08	0.80	0.09	0.03
Precision (V_p)	0.15	0.75	0.08	0.02
Force (V_f)	0.20	0.65	0.14	0.01
Sequence (V_s)	-	0.90	-	0.1

5.2.3 Aggregation of variability

The aggregation of variability is a crucial aspect of analyzing the functional relationships within a system. By using FRAM, the interplay among system functions is graphically modelled to reveal how the variability of upstream functions propagates downstream (Kaya & Hocaoglu, 2020). This variability arises from a combination of a function's inherent characteristics and the input it receives from upstream functions (Patriarca, Di Gravio, & Costantino, 2017). When the variability from upstream functions amplifies, it can create resonant effects within the system, potentially leading to critical paths or cascading failures (Zinetullina et al., 2021).

Examining these couplings highlights the dual nature of variability's impact. On one hand, negative variability can resonate across interconnected functions, magnifying system risks and identifying critical areas of concern, such as accident precursors or key contributors to hazards. On the other hand, positive variability can serve as a stabilizing force, mitigating downstream variability and enhancing system resilience (Zinetullina et al., 2021). A comprehensive understanding of these dynamics is essential for identifying critical couplings and assessing how variability propagates through the system, ultimately improving risk management and system performance (Yu et al., 2025).

The values for these factors, presented in Table 5.4, were chosen based on their proven reliability in previous studies (Kaya & Hocaoglu, 2020; Kaya et al., 2021; Mofidi Naeini & Nadeau, 2023; Patriarca, Di Gravio, & Costantino, 2017; Slim & Nadeau, 2019; Yu et al., 2025; Zinetullina et al., 2021). Using established values ensures consistency and enables meaningful comparisons with other studies. These parameters could be varied according to each system and industry. The parameters α_{ijn}^{T}, α_{ijn}^{P}, α_{ijn}^{F}, and α_{ijn}^{S} represent the effect of output *n* from upstream function *j* on downstream function *i*, in terms of time, precision, force, and sequence, respectively. These factors are incorporated to assess their impact on the overall system performance. To quantify the overall impact of timing, precision, force, and sequence on system performance, we define the cumulative interaction effect (CI_{ij}), as demonstrated in equation 5.2.

$$CI_{ijn} = \alpha_{ijn}^{T} * \alpha_{ijn}^{P} * \alpha_{ijn}^{F} * \alpha_{ijn}^{S} \tag{5.2}$$

Table 5.4 Damping and amplifying factor values

Effect type	Value
Damping effect	0.5
No effect	1
Amplifying effect	2

5.2.4 Management of variability

Managing variability focuses on amplifying positive outcomes and minimizing negative ones by addressing critical couplings identified through functional resonance analysis (Patriarca et al., 2025). Improvement measures aim to prevent accidents or restore the system to optimal functionality in case of disruptions (Zinetullina et al., 2021).

After analyzing the core performance characteristics, the next step is to integrate the influence of external operating conditions on the system's performance. This involves defining a set of Scenario Performance Conditions (SPCs) that capture various internal and external factors, such as environmental influences (e.g., temperature, lighting), equipment reliability, workload variations, etc., that may affect overall performance.

For each function within the system, the impact of each SPC is evaluated by assigning an impact rating, where a value of 1 indicates a high impact, a value less than 1 indicates a moderate impact, and 0 indicates no impact. This method creates a clear relationship between external conditions and the system's functions. These values should be assessed by the decision-making team based on the past system behavior. In a practical application, ensuring the reliability of these subjective inputs would be critical. In a practical application, these values would be established through structured workshops with domain experts, leveraging techniques like pairwise comparison or direct rating scales to ensure consistency and justification for the assigned weights (Afnor, 2024; O'Hagan et al., 2006). Furthermore, prior to integrating assigned impact ratings into the model, calculating inter-rater reliability scores among experts, such as Cohen's kappa or intraclass correlation, is essential to validate the consistency and robustness of their judgments to ensure alignment with structured elicitation protocols (O'Hagan et al., 2006).

Once the influence of the SPCs on the functions is established, distinct operating scenarios are defined by assigning specific ratings to each SPC. Each scenario is characterized by a particular combination of performance condition effects. Decision makers must identify the most critical scenarios which can influence the system. The overall effect of a scenario on a given function is determined by summing the weighted contributions of each SPC, as shown in Equation 5.3.

$$e_j^z = \sum_{k=1}^{m} SPC_z^k * b_j^k \tag{5.3}$$

Here, e_j^z is the conditional variability of function j under scenario z, SPC_z^k denotes the rating of the k^{th} condition in scenario z, and b_j^k represents the impact of the k^{th} condition on function j. If a function is not influenced by any external condition (i.e., all b_j^k equal zero), the variability is considered a baseline value of 1 (Patriarca, Di Gravio, & Costantino, 2017).

5.2.5 Quantifying the risks

The index for each coupling, Variability Propagation Number (VPN) can be derived from equation 5.4. This index combines the inherent variability of the upstream function j (OV_j), the cumulative interaction effect between upstream and downstream functions (CI_{ij}), and the conditional variability e_j^z, which represents how external factors in scenario z influence the system's performance. By incorporating these elements, this equation provides a detailed and dynamic measure of the coupling's variability, capturing internal performance fluctuations and the effects of external operating conditions.

$$VPN_{ij}^z = OV_j * CI_{ij} * e_j^z \tag{5.4}$$

In the next step, the data collected through FRAM will be used to apply the PSO algorithm, providing a structured and systematic way to quantify the model. PSO is inspired by the movement of swarms in nature, where candidate solutions are represented as particles navigating a multi-dimensional search space. Each particle has a position $X_i = (x_{i1}, x_{i2}, \dots, x_{id})$, a velocity $V_i = (v_{i1}, v_{i2}, \dots, v_{id})$, and a personal best position $P_i = (p_{i1}, p_{i2}, \dots, p_{id})$. The algorithm continuously updates each particle's velocity and position to move toward an optimal solution. The velocity update follows equation 5.5 (Karevan & Vasili, 2018; Marini & Walczak, 2015).

$$V_k(i+1) = V_k(i) + c_1 r_1 \left(P_{best,i}^k - X_k(i)\right) + c_2 r_2 \left(g_{best,i} - X_k(i)\right) \tag{5.5}$$

This update consists of three components: momentum, which helps maintain previous velocity for smoother movement; cognitive influence, which pulls the particle toward its own best-known position; and social influence, which directs the particle toward the global best solution found by the swarm. Once the velocity is adjusted, the particle's new position is calculated as equation 5.6 (Karevan et al., 2020; Lalwani et al., 2013).

$$X_k(i+1) = X_k(i) + V_k(i+1) \tag{5.6}$$

To initialize the algorithm, the variability values of each output ($V_j^T, V_j^P, V_j^F, V_j^S$) are first defined. Then, the relationships between outputs, including upstream and downstream dependencies, are mapped, creating function paths. A Monte Carlo Simulation is employed to estimate the occurrence probability of each output under four different variabilities. Based on these probabilities, the OV of each output is calculated (Eq.5.1).

Next, damping and amplifying factors are assigned, applying specific weighting factors to variability aspects such as timing, precision, force, and sequence based on predefined conditions (Eq.5.2). In real-world applications, these weighting factors can be determined through empirical data analysis, expert elicitation, or human factors and ergonomics (HF/E) assessments. Decision-makers identify the most influential factors by conducting task analyses, observational studies, and data-driven risk assessments. Since this approach relies on measurable inputs and systematic evaluation, it can be readily applied in real-world cases, allowing decision-makers to adjust the factors dynamically to reflect actual operational conditions.

Following this, various SPCs and external influence factors e_j^z are considered. Using these inputs, the VPN is calculated for each function, followed by the computation of the path VPN based on the summation of downstream functions for each function. Then, the initial high path VPN is determined, leading to the identification of the critical path. The objective function is to minimize the path VPN, which results in minimizing the VPN for each function.

5.2.6 PSO implementation and parameters

For the results presented in this paper, the PSO algorithm was implemented with the following parameters, chosen based on common practices in the literature to ensure stable convergence. The swarm size was set to 50 particles for 500 iterations. An inertia weight (w) was used, linearly decreasing from 0.9 to 0.4 over the course of the iterations, to balance global and local search. The cognitive and social coefficients (c1 and c2) were set to 0.9 and 1.5, respectively. The decision vector for each particle represented a potential set of mitigation strategies to apply.

5.2.7 Sustainable mitigation strategies

After identifying the highest path VPN, the next step is to systematically mitigate it by selecting sustainable strategies (alternatives). Depending on each case study and industry, decision-makers may identify various sustainable mitigation strategies. These strategies must consider three main pillars of sustainability. Economically, manufacturers can improve cost efficiency through automation and lean practices (Hasanain, 2024), reduce operational costs via process innovation (Martín-Gómez, Agote-Garrido, & Lama-Ruiz, 2024), and simplify assembly processes to minimize downtime while recovering valuable components for cost savings (Machado, Winroth, & Ribeiro da Silva, 2020). Environmentally, initiatives include boosting energy efficiency with energy-efficient machinery and smart systems (Jovanović & Filipović, 2016), utilizing renewable energy at facilities (Machado et al., 2020), optimizing waste reduction (Martín-Gómez et al., 2024), and lowering carbon emissions through process optimization (Foo & Tan, 2016). Socially, efforts focus on investing in employee training (Ciccarelli, Papetti, & Germani, 2023), enhancing employee satisfaction through better work environments (Hasanain, 2024), and ensuring safe working conditions (Gualtieri, Rauch, & Vidoni, 2021).

Decision-making teams need to determine the associated functions and SPCs for each strategy, assess the level of difficulty in implementing each strategy (feasibility), evaluate the impact of each strategy on the system, and assess its contribution to the three sustainability pillars (environmental, economic, and social). The algorithm then selects the best strategy in each iteration, applies it to the model, and recalculates the overall risk profile from the beginning. Over successive rounds, this iterative process not only reduces high-risk outputs but also progressively transforms the entire model into a sustainable one, balancing risk reduction with long-term environmental, economic, and social benefits. The process involves:

- Identifying the function with the maximum Path VPN.

- Selecting the most effective available sustainable mitigation strategy from Table 5.9 relevant to that function's associated SPCs (with a constraint preventing the immediate re-selection of the same strategy for the same path if alternatives exist).
- Applying the chosen strategy's impact weight within the model.
- Recalculating all function VPNs and path VPNs.
- Repeating the process for a predetermined number of steps (four in this study).

5.3 Case studies

Case studies serve as a crucial research approach, particularly when investigating complex subjects with limited prior knowledge (Rashid et al., 2019). Also, using multiple case studies allows for comparative analysis across different contexts, facilitating the identification of patterns, trends, and underlying factors that may remain undetected in a single case study. Examining operations such as assembly and disassembly across various settings enhances theoretical generalization. The case studies presented in this research were originally examined in another paper (Karevan & Nadeau, 2025c) and are being reused to validate the proposed methodology. To ensure an extensive perspective, these cases represent different operational environments: an assembly line, a job shop assembly process, and a disassembly line. Each case is briefly summarized below. However, for a deeper understanding of the cases and their details, the authors recommend referring to the paper mentioned.

The first case study looks at an assembly section in a refrigerator manufacturing plant. In this setup, refrigerators move along a conveyor line, and workers perform specific tasks at each station along the way. In this particular assembly section, the worker's role involves selecting and assembling various components from bins. To assist with the task, they wear smart gloves that help with handling the parts more precisely. Additionally, smart glasses are used to display assembly instructions, guiding the worker step-by-step through the process.

In the second case study, the focus is on a job shop assembly process where the assembler is equipped with smart glasses and smart gloves to assist with the work. The workstation is organized with a tool cabinet containing the necessary tools for the task and seven bins of required parts positioned in front of the assembler. A dolly is used to transport the assembly structure, allowing the worker to move the parts and components easily. Work instructions are accessed through a computer, guiding the assembly process.

In the third case study, the focus is on a refrigerator disassembly process, where the worker's main job is to remove parts like the refrigerant for recycling, along with the freezer door, process pipe, and dry filter. The workstation is equipped with a tool cabinet and storage bins to sort the disassembled components. The smart glasses provide step-by-step instructions, visually guiding the worker on what needs to be removed. The smart gloves help the worker apply the right amount of force and even detect hazardous components.

This combination of wearables simplifies the workflow, ensuring that workers can follow instructions accurately and efficiently while minimizing the chances of errors. The use of these technologies enhances both the speed and accuracy of the assembly and disassembly processes and also improves sorting efficiency and enables real-time communication with supervisors.

5.4 Results

This section details the application of the proposed FRAM-PSO methodology to assembly and disassembly processes case studies, focusing on function identification, risk assessment via VPN calculation, and the impact of targeted mitigation strategies. The initial step involved identifying and characterizing the core functions essential to the system. These functions, derived from analysis of the case study operations, are listed and described in Table 5.5. This table also indicates the specific case studies where each function is relevant. Each function was examined based on six key attributes. Additionally, the FVM software was used to visually map these functions in Figure 5.2 for the first case study, Figure 5.3 for the second case study, and Figure 5.4 for the third case study. Table 5.6 presents a mapping of these outputs and their related downstream functions, illustrating the system's interconnected nature.

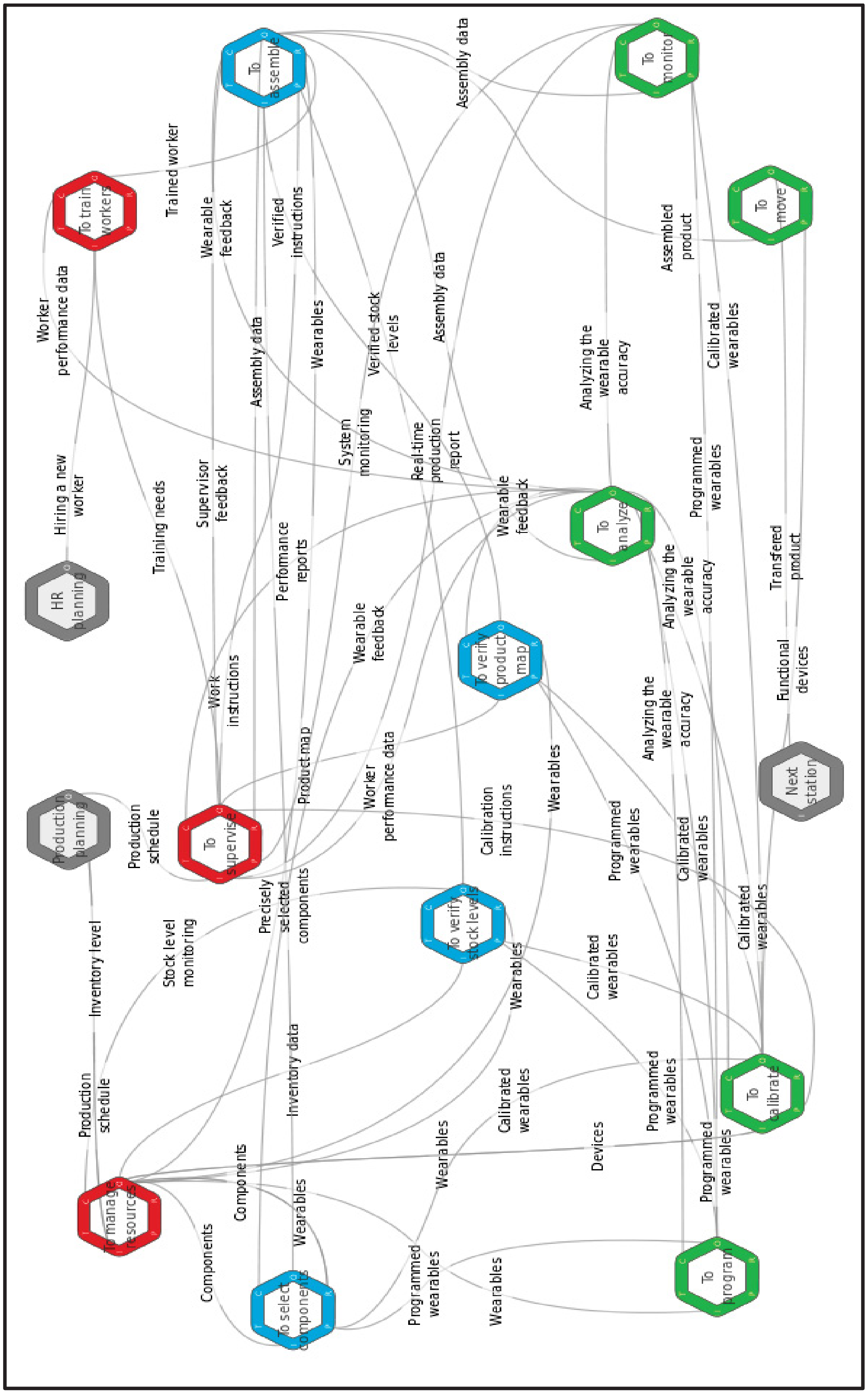

Figure 5.2 The FRAM model of the first case study

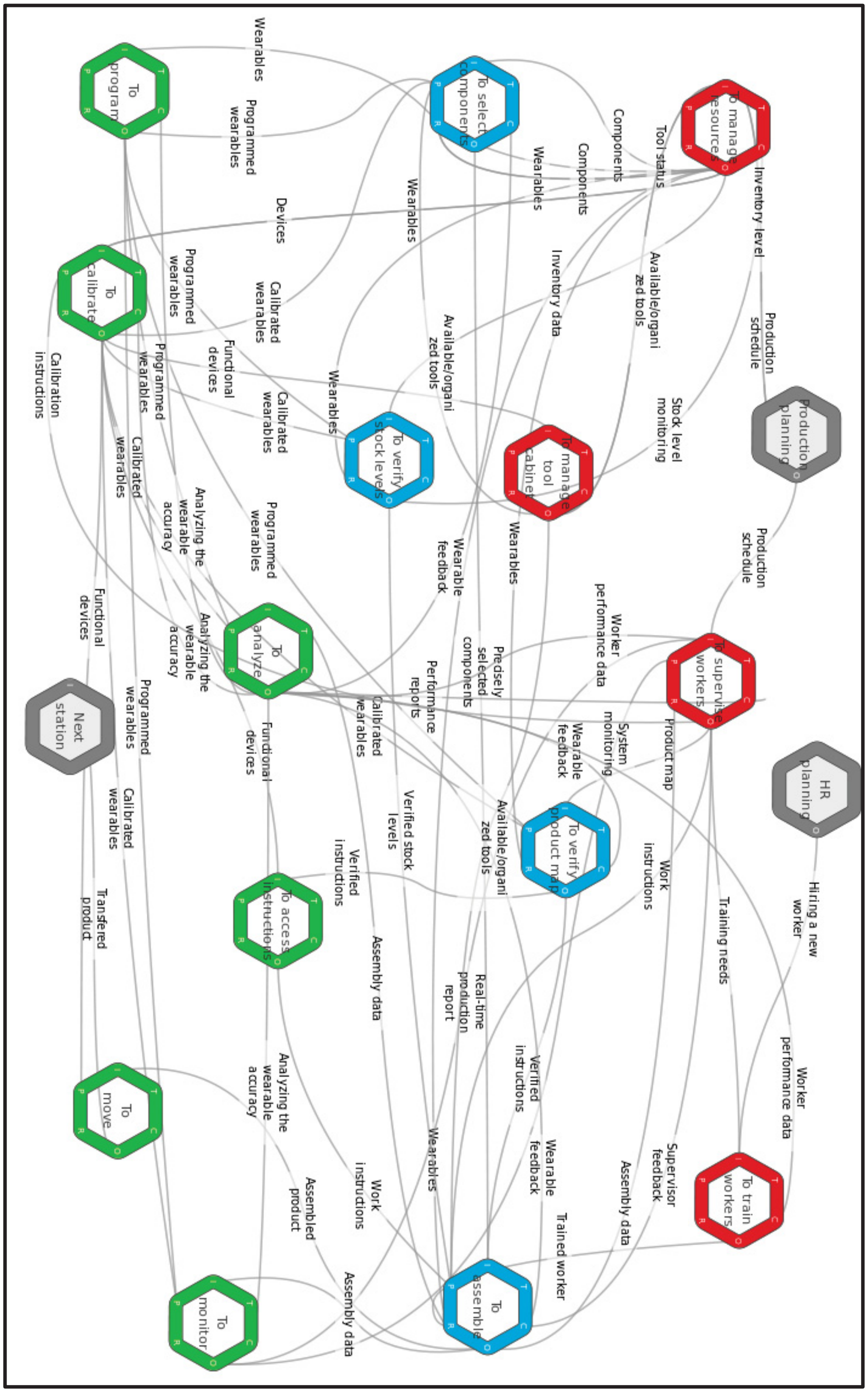

Figure 5.3 The FRAM model of the second case study

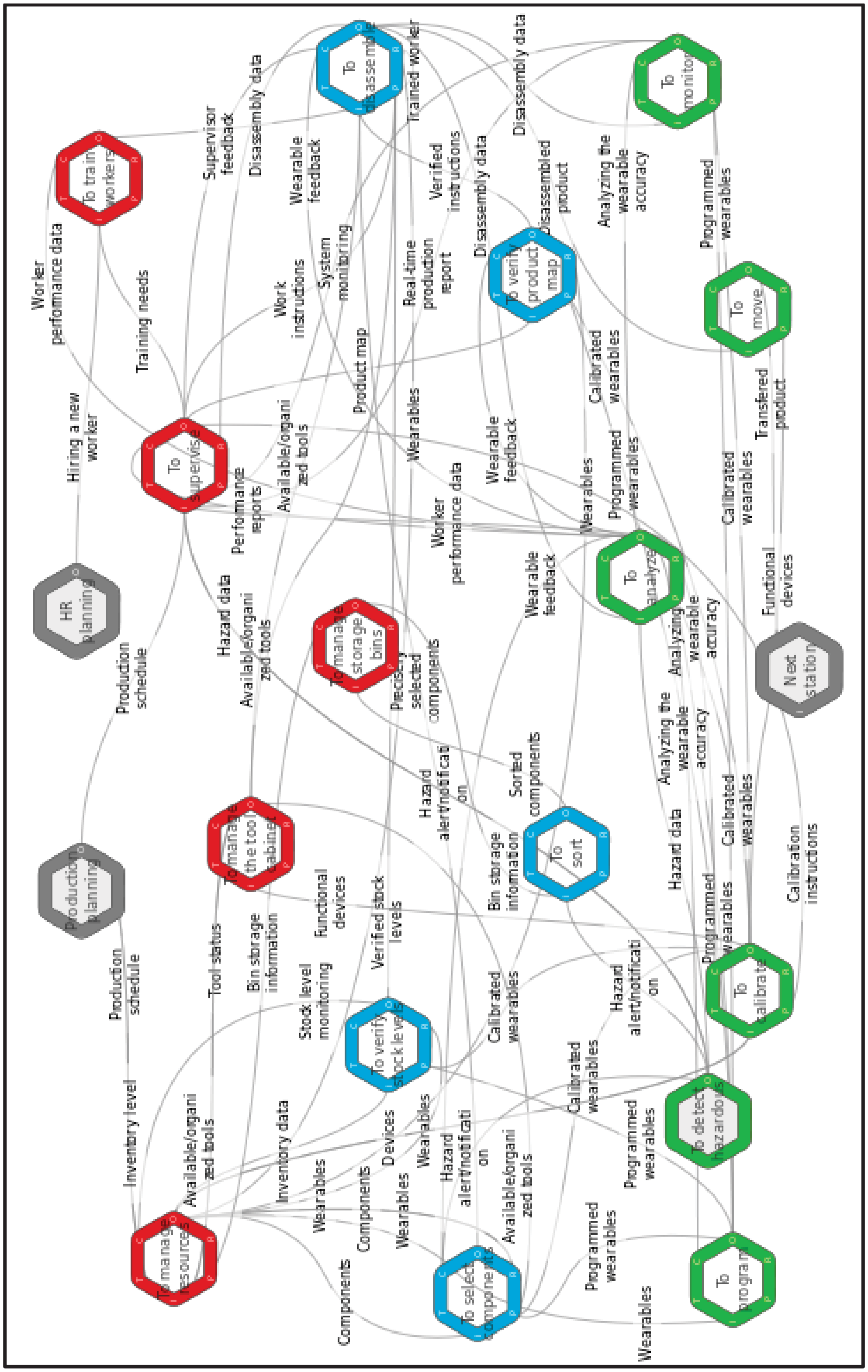

Figure 5.4 The FRAM model of the third case study

Table 5.5 Identified functions

Code	Function	Description	Related case study		
			1	2	3
F-1	To train workers	Workers must be trained to use the wearables effectively, ensuring that they understand how to interact with the smart devices during assembly.	*	*	*
F-2	To manage resources	Restock bins and ensure components/tools/wearables are available to prevent stoppages.	*	*	*
F-3	To calibrate and maintain	Calibration and maintenance of the wearables and devices to avoid any inaccuracy and stoppage.	*	*	*
F-4	To program wearables	Programming ensures that the smart gloves and smart glasses provide accurate feedback and guidance to the worker.	*	*	*
F-5	To verify stock levels	Workers use smart glasses to check stock levels to ensure that sufficient parts are available to avoid assembly stoppage.	*	*	*
F-6	To verify the product map	Before assembly, the worker verifies the correct components using the product map to ensure the right parts are being used.	*	*	*
F-7	To select and handle components	The worker uses smart gloves to select and handle components with precision and correct pressure.	*	*	*
F-8	To assemble the product	The worker assembles the product.	*	*	
F-9	To supervise workers	The supervisor remotely monitors the assembly process, ensuring adherence to quality and production standards.	*	*	*
F-10	To monitor and report production in real time	The production process is continuously monitored online. Data is collected in real time to track assembly performance and to ensure quality.	*	*	*
F-11	To move the product using a conveyor/dolly	The product transfers between the stations using a conveyor or a dolly.	*	*	*
F-12	Next station	The assembled product moves to the next station.	*	*	*
F-13	Human resource planning	Hiring new workers.	*	*	*
F-14	Production and resource planning	Providing the plan of the production and resources.	*	*	*
F-15	To receive and analyze data	Collect and analyze data from wearables.	*	*	*
F-16	To access work instructions (via computer)	The worker retrieves and views procedural guidance for the task using a workstation computer interface.		*	
F-17	To manage the tool cabinet	Ensure necessary tools are available, organized, and accounted for within the designated tool cabinet.		*	*
F-18	To disassemble the product	The worker takes apart the product, removing specific components according to the process requirements			*
F-19	To detect hazardous components	Use smart gloves and smart glasses to identify potentially dangerous materials or parts during handling or disassembly.			*
F-20	To sort disassembled components	Place removed parts into designated storage bins based on material type, destination, or other criteria.			*
F-21	To manage storage bins	Ensure storage bins are available, correctly labelled, and emptied or replaced as needed to facilitate sorting and storage.			*

Table 5.6 Functions and their outputs

Function Code	**Output**	**Downstream functions**
F-1	Trained worker	F-8
F-2	Inventory data	F-5
	Wearables	F-3, F-4, F-5, F-6, F-7, F-8, F-10, F-15
	Components	F-7
	Devices	F-3, F-11
F-3	Calibrated wearables	F-5, F-6, F-7, F-10, F-11, F-15
	Functional devices	F-11
F-4	Programmed wearables	F-5, F-6, F-7, F-10, F-15
F-5	Verified stock levels	F-8
	Stock level monitoring	F-2
F-6	Verified instructions	F-8
F-7	Precisely selected components	F-8
F-8	Assembled product	F-11
	Assembly data	F-9, F-10, F-15
F-9	Product map	F-6
	Work instructions	F-8
	Training needs	F-1
	Supervisor feedback	F-8
	Calibration instructions	F-3
F-10	Real-time production report	F-9
	System monitoring	F-9
F-11	Transferred product	F-12
F-13	Hiring a new worker	F-1
F-14	Production schedule	F-2, F-9
	Inventory level	F-2
F-15	Wearable feedback	F-6, F-7, F-8
	Analyzing the wearable accuracy	F-3, F-4, F-10
	Worker performance data	F-1, F-9
	Performance reports	F-9
F-16	Work instructions	F-8
F-17	Available/organized tools	F-2, F-7, F-8, F-18
	Tool status	F-2
F-18	Disassembled product	F-11, F-12, F-20
	Disassembly data	F-9, F-10, F-15
F-19	Hazard alert/notification	F-7, F-9, F-20
	Hazard data	F-9, F-15
F-20	Sorted components	F-21
F-21	Bin storage information	F-2, F-20

To evaluate system variability and potential vulnerabilities, we identified three key SPCs critical to the case studies:

- **Wearable Performance (WP):** Evaluates the effectiveness of smart wearables like gloves and glasses in terms of calibration, functionality, and accuracy.
- **Worker Condition (WC):** Encompasses the worker's physical, physiological, and cognitive state in response to task demands, drawing upon the Stress-Strain Model (Rohmert, 1973). This model distinguishes between stress (external demands such as task complexity, workload, and shift duration) and strain (the worker's response, influenced by factors like skill, fatigue, cognitive load, posture, and training). Maintaining a balance between these factors is crucial for efficiency, efficacy, safety, and well-being in assembly tasks (Djefour et al., 2024).
- **Resource Availability (RA):** Refers to the availability of essential components, tools, wearables, and devices required for the assembly process.

Table 5.7 SPC impact definition

The impact of SPCs	**Value**	**Wearable Performance (WP)**	**Worker Condition (WC)**	**Resource Availability (RA)**
No impact	0	Wearables do not affect the function	The worker's physical and cognitive state does not significantly affect the function	Resource availability does not significantly affect the function
Moderate impact	0.5	Wearables are useful but have limitations or occasional malfunctions	The worker's physical and cognitive state affects performance, but not critically	Limited resources may cause some delays or inefficiencies
High impact	1	Wearables are critical for functional success	The worker's physical and cognitive state is crucial for successful performance	Lack of resources causes significant delays or stoppages

The potential impact of suboptimal performance in each SPC on system functions was categorized using a standardized scale (Table 5.7), ranging from no impact (0) to high impact (1). These values are used based on the literature to have a more robust framework (Patriarca, Di Gravio, & Costantino, 2017). Applying this scale, we assessed the specific impact of each SPC on every identified function, based on the operational context of the case studies. The results of this assessment are presented in Table 5.8. For instance, 'To Assemble the Product' (F-8) and ‘F-18: To disassemble the product’ (F-18) are highly impacted by all three SPCs, while 'To Move the Product' (F-11) is unaffected under the defined conditions. Herein, the authors used arbitrary values based on their perspective; however, in real case studies, they should be determined by the decision-making team.

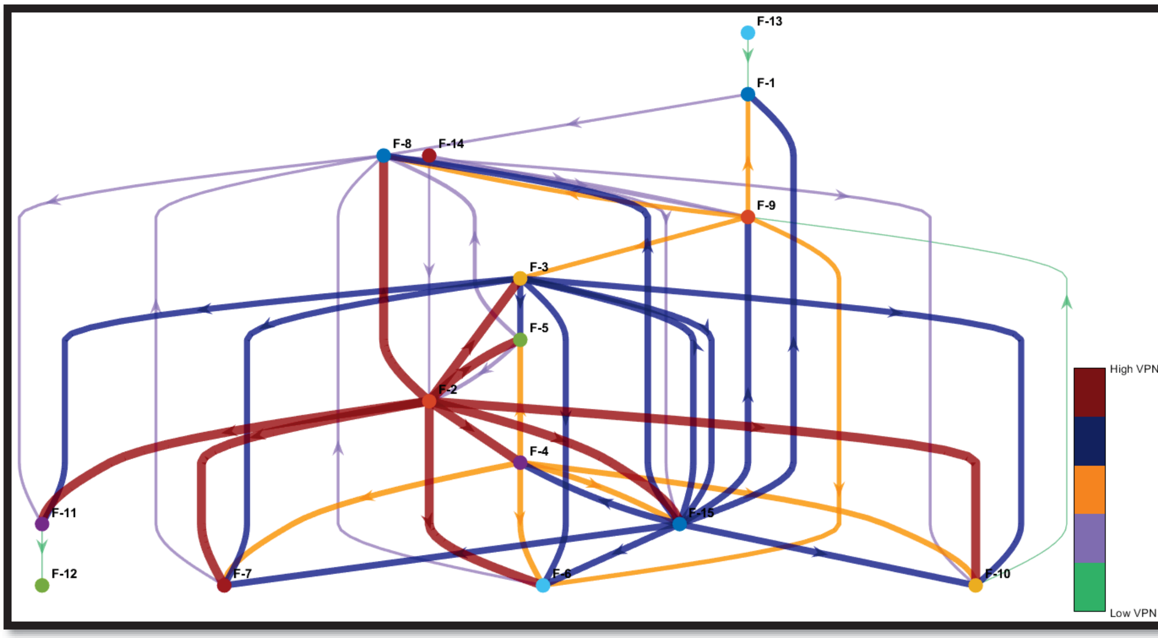

Figure 5.5 Path graph with VPN-weighted connections (first case study)

To simulate varying operational contexts and assess system resilience, four distinct scenarios were defined, modulating the impact level of the SPCs:

1- **Normal conditions:** Assumes moderate variability across all SPCs.
2- **Wearable malfunction:** Represents high variability in Wearable Performance (WP).
3- **High fatigue:** Simulates high variability in Worker Condition (WC).
4- **Resource shortage:** Introduces high variability in Resource Availability (RA).

By using the established function network, SPC impacts (Table 5.8), and scenario definitions, we employed the PSO algorithm integrated within the FRAM framework (FRAM-PSO) to calculate the VPN for each function. The VPN quantifies the potential variability or risk associated with each function under the defined scenarios.

Table 5.8 SPC impact on the process

Function	**WP**	**WC**	**RA**
F-1: To train workers	0	1	0
F-2: To manage resources	0.5	0.5	1
F-3: To calibrate and maintain	1	0	1
F-4: To program wearables	1	0	1
F-5: To verify stock levels	0.5	1	1
F-6: To verify the product map	1	1	0
F-7: To select and handle components	1	1	1
F-8: To assemble the product	1	1	1
F-9: To supervise workers	0.5	1	0
F-10: To monitor and report production in real-time	1	0.5	0
F-11: To move the product using a conveyor/dolly	0	0	0
F-12: Next station	0	0	0
F-13: Human resource planning	0	1	0
F-14: Production and resource planning	0	0.5	1
F-15: To receive and analyze data	1	0.5	0
F-16: To access work instructions (via computer)	0.5	1	0.5
F-17: To manage the tool cabinet	0.5	0	1
F-18: To disassemble the product	1	1	1
F-19: To detect hazardous components	1	1	0
F-20: To sort disassembled components	1	0.5	0.5
F-21: To manage storage bins	0.5	0	1

From the individual function VPNs (Eq.4), the Path VPN is calculated for each function, representing the cumulative variability propagated through its downstream dependencies. The initial state of the system, depicting the calculated Path VPNs before any mitigation, is visualized in Figure 5.5. In this graph, the intensity or thickness of the connections can represent the magnitude of the Path VPN, emphasizing critical pathways.

For this study, the algorithm's objective is to reduce the path VPNs, which results in the reduction of the function VPNs and improvement of the overall model. We defined a set of potential sustainable mitigation actions (Table 5.9), each linked to specific SPCs and associated functions.

For each strategy, we assigned illustrative values for implementation feasibility (from easy to difficult), impact weight (from low to high improvement), and contribution to sustainability pillars (environmental, economic, social – rated from low to high impact). To provide a clear perspective on how to use this methodology, the authors base these values on their assessment when assigning values to these variables. In a practical application, these values would be established through structured workshops with domain experts, leveraging techniques like pairwise comparison or direct rating scales to ensure consistency and justification for the assigned weights (Afnor, 2024; O'Hagan et al., 2006). Additionally, based on the level of importance for each industry, the sustainable aspects can be weighted to demonstrate their significance for each specific industry (Karevan & Vasili, 2018). However, this study assumes equal weight for each aspect.

The FRAM-PSO algorithm was used in an iterative mitigation process. In the interest of conciseness, the main body of this paper includes graphs and figures pertaining only to the first case study. The results derived from the other case studies can be found in the Appendix. The initial assessment performed showed that the sum of all path functions was 8736. The algorithm then starts by identifying the highest path VPN. The function with the highest initial path VPN was F-2 (to manage resources), which had a value of 1726.

Then, the four-step mitigation process unfolds as follows:

- **Step 1:** F-2 (to manage resources) was targeted as the highest path VPN. Then the algorithm selected and applied the most suitable mitigation strategy across all the options, “Digital inventory management”.
- **Step 2:** F-15 (to receive and analyze data) was identified as the next highest path VPN. The "Wearable maintenance program" strategy was selected and applied.
- **Step 3:** F-3 (to calibrate and maintain) emerged as the next target, and the "Worker-centric wearable design" strategy was implemented.
- **Step 4:** In the last step, F-8 (to assemble the product) was selected, and the "Wellness monitoring and breaks" strategy was applied.

Table 5.9 Sustainable mitigation strategies

Strategy	Description	Related functions	Related SPC	Feasibility level	Weight	Sustainability aspects		
						Envi.	Econ.	Social
Worker-centric wearable design	Use wearables with ergonomic features (e.g., lightweight, easily adjustable)	F-1, F-3, F-7, F-8. F-10, F-13, F-18	WC, RA	Difficult	High	Low impact	Medium impact	High impact
Low-power sensors	Use wearables with energy-efficient sensors powered by kinetic energy or solar cells	F-2, F-3, F-19, F-21	WP, RA	Difficult	Medium	High impact	Medium impact	Low impact
Wearable maintenance program	Regular calibration and repair using recycled parts	F-3, F-4, F-6, F-9, F-11, F-15, F-16, F-18, F-19	WP, RA	Medium	High	High impact	Medium impact	Low impact
Wellness monitoring and breaks	Equip wearables with real-time health tracking to trigger mandatory breaks and reduce physical strain	F-8, F-9, F-13, F-18	WC	Easy	High	Low impact	Medium impact	High impact
Tool sharing optimization	Use wearables to track and optimize tool-sharing across workers, reducing idle resources	F-2, F-9, F-14, F-17	WP, RA	Easy	Medium	High impact	Medium impact	Low impact
Reusable tool systems	Shift to modular, reusable tools with wearables for maintenance tracking	F-2, F-14, F-17	RA, WP	Medium	Medium	High impact	High impact	Low impact
Digital inventory management	Use wearables to monitor and optimize material stock digitally, reducing over-ordering	F-2, F-5, F-11, F-14, F-17, F-20, F-21	RA	Medium	High	Medium impact	High impact	Medium impact

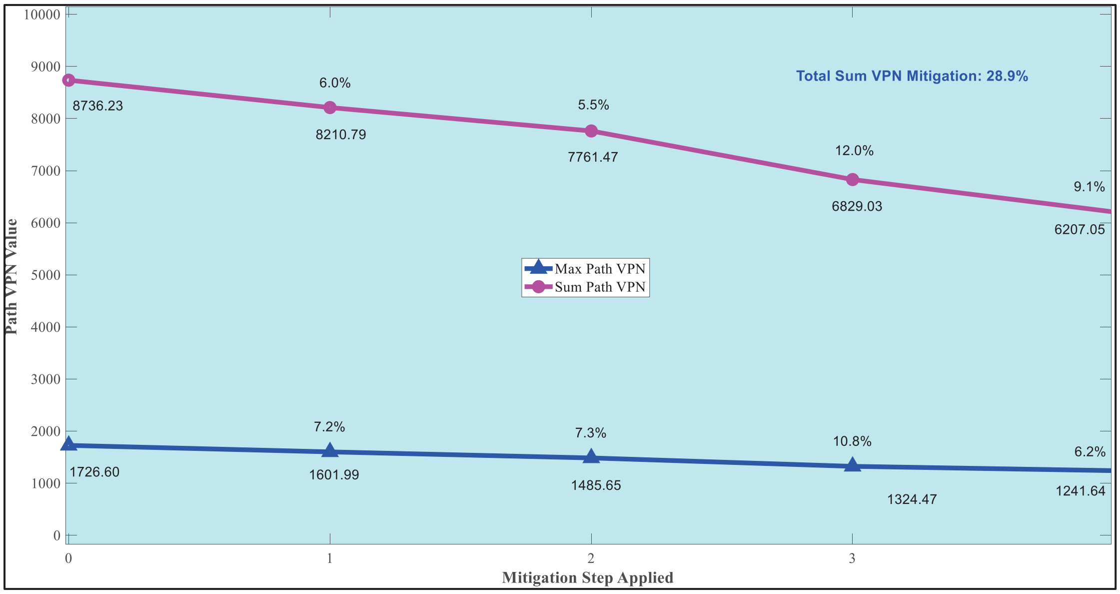

Figure 5.6 Mitigation progress: risk reduction over steps (first case study)

While the Path VPN provides a robust internal metric for quantifying systemic risk within the model, its direct managerial relevance can be enhanced by linking it to tangible Key Performance Indicators (KPIs). The mitigation strategies selected by the FRAM-PSO algorithm can be directly mapped to expected improvements in operational metrics that decision-makers track.

Table 5.10 provides an illustrative mapping for the four mitigation strategies applied in the first case study. This demonstrates how the concept of "risk reduction" can be translated into a practical performance monitoring plan. For example, the "Worker-centric wearable design" strategy, which reduced the Path VPNs, would be expected to yield measurable improvements in KPIs such as a lower human error rate and a reduction in reported musculoskeletal discomfort (Alenjareghi, Sekkay, Dadouchi, & Keivanpour, 2025). This translation is a critical step in bridging the gap between systemic modeling and practical, data-driven management.

After these four mitigation steps, for the first case study, the total sum of path VPNs decreased significantly to 6207, representing an overall risk reduction of approximately 28.9%. The maximum path VPN observed in the system was reduced to 1241. The progression of risk reduction (both maximum and sum path VPN) across the mitigation steps is illustrated in Figure 5.6. It clearly shows how much each strategy has influenced the path of VPN value.

This figure demonstrates that the third strategy (Worker-centric wearable design) has a greater impact on reducing the VPNs compared to others. The second and third case studies were also improved by 22.4% and 26.6%, respectively (see Appendix).

Table 5.10 Illustrative mapping of selected mitigation strategies to managerial KPIs

Mitigation Step	Primary Path VPN Reduction	Selected Mitigation Strategy	Illustrative Managerial KPIs to Monitor
Step 1	F-2 (to manage resources)	Digital Inventory Management	• Reduction in line stoppages due to part shortages • Improvement in inventory turnover rate • Decrease in ordering errors
Step 2	F-15 (to receive and analyze data)	Wearable Maintenance Program	• Reduction in wearable failure rate • Decrease in maintenance costs • Improvement in data accuracy from wearables
Step 3	F-3 (to calibrate and maintain)	Worker-Centric Wearable Design	• Reduction in human error rate • Decrease in reported musculoskeletal discomfort • Reduction in task completion time
Step 4	F-8 (to assemble the product)	Wellness Monitoring and Breaks	• Decrease in fatigue-related incidents • Improvement in employee satisfaction scores • Increase in adherence to mandatory break protocols

Figure 5.7 provides insight into the systemic impact of each applied strategy, mapping which functions were affected by each strategy. For example, implementing "Worker-centric wearable design" influenced the VPNs of six distinct functions (F-1, F-3, F-7, F-8, F-10, F-13). This occurs because an ergonomic and intuitive wearable (the mitigation strategy) directly improves the physical and cognitive aspects of tasks like handling components (F-7) and

assembling the product (F-8). It also reduces the training burden (F-1) and makes it easier for supervisors to monitor work (F-10).

A direct comparison of the initial and final Path VPNs for each function is presented in Figure 5.8. This figure highlights the percentage reduction achieved for each pathway. Notably, while mitigation efforts directly targeted only F-2, F-15, F-3, and F-8 in these steps, the interconnected nature of the system led to significant indirect improvements in other functions. For instance, the path VPN for F-1 (to train workers) decreased by 37.3%, demonstrating the cascading benefits of the applied strategies. This significant indirect improvement is because the implementation of more ergonomic and easier-to-use wearables (a mitigation for F-8) reduces the complexity and duration of the required training. Conversely, some functions like F-11 (To move the product), which had low initial VPN and weak connections to the targeted areas, only improved by 14.9%.

These results demonstrate the effectiveness of the FRAM-PSO approach in identifying critical risk paths and quantifying the system-wide impact of targeted, sustainable mitigation strategies. The significant reduction in overall path VPN, achieved through just four strategic interventions, underscores the value of this methodology for enhancing system resilience and sustainability.

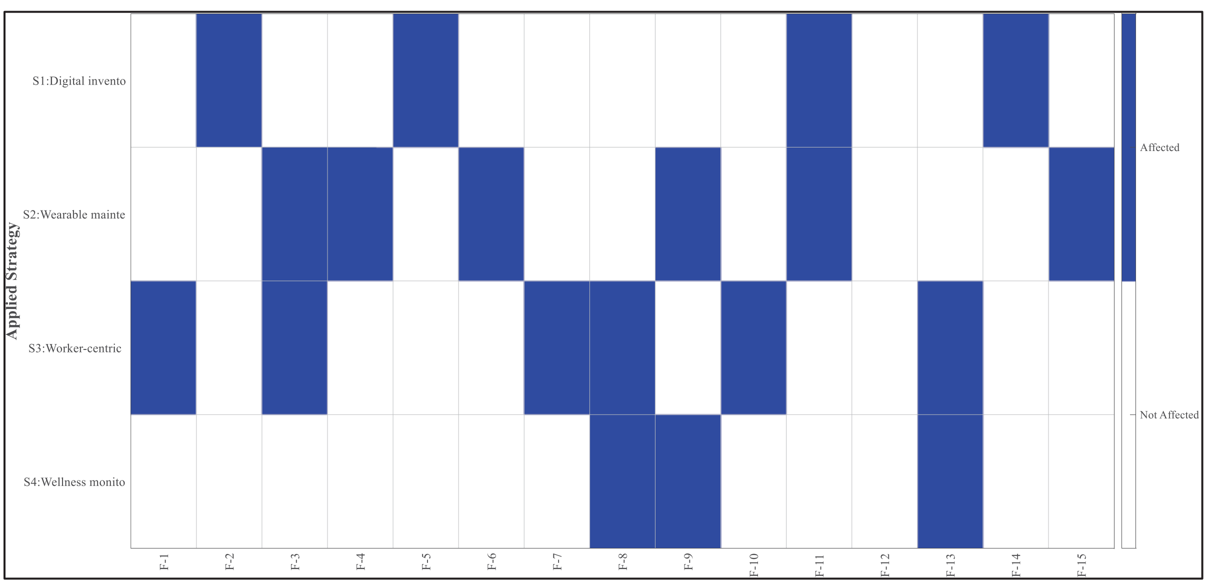

Figure 5.7 Functions affected by each applied strategy (first case study)

5.5 Discussion

Resilience is gaining growing importance in modern manufacturing environments (Chari et al., 2023). The resilience engineering community has successfully applied FRAM as both a retrospective and prospective method, explaining that system outcomes are shaped by how different functions vary and interact, often leading to unexpected results known as functional resonance (Lundblad et al., 2008; Yousefi et al., 2019; Zheng, Liu, Yang, Wang, & Adriaensen, 2024). However, FRAM is inherently qualitative, prompting numerous efforts to enhance its objectivity and quantification capabilities (Patriarca, Di Gravio, & Costantino, 2017). This study directly engages with this challenge within the context of modern industrial systems incorporating smart wearables.

The successful application of this novel FRAM-PSO framework resulted in a substantial 28.9% reduction in the overall system risk through four targeted sustainable mitigation steps (first case study). This highlights the methodology's effectiveness in not only modelling variability but also guiding practical interventions. Furthermore, the findings illustrate the systemic effects central to FRAM. While mitigation directly targeted functions F-2, F-15, F-3, and F-8, significant improvements propagated to interconnected functions, such as the 34.1% risk reduction observed in F-5 (to verify stock levels) (Figure 5.8). This demonstrates how targeted interventions can yield broader system resilience benefits.

Addressing the known challenge of FRAM quantification (Patriarca, Di Gravio, & Costantino, 2017), the integration of PSO offers a distinct contribution. Unlike other quantification methods (e.g., MCS, BN), PSO actively optimizes, allowing the framework not only to quantify variability (VPN) but also to search for and select optimal sustainable mitigation strategies to maximize risk reduction. To the best of our knowledge, this combination of FRAM and PSO for risk quantification and optimized mitigation represents a novel contribution to the field.

This study also tackles the specific gap concerning systematic risk assessment for smart wearables (Karevan & Nadeau, 2023). Moving beyond prior qualitative (Mofidi Naeini & Nadeau, 2023) or STPA-based analyses (Karevan & Nadeau, 2024a, 2025c), the FRAM-PSO approach provides a quantitative, systemic, and mitigation-oriented framework for these technologies. Another contribution is the explicit integration of sustainability (environmental, economic, and social factors) into the risk mitigation process. This integration addresses the critical need, highlighted by Karwowski et al. (2025) in their grand challenges, for human factors and ergonomics to contribute towards sustainability, including enhancing system resilience and developing ethical principles for sustainable futures (Karwowski et al., 2025; Valette, El-Haouzi, & Demesure, 2023). Also, achieving sustainable production is a key objective in today's manufacturing industry (Ma et al., 2024; S. Zhang et al., 2024). By adopting Industry 5.0 principles, this work introduces an integrated approach to understanding risk that fills a gap we identified in existing systemic risk frameworks through a literature review.

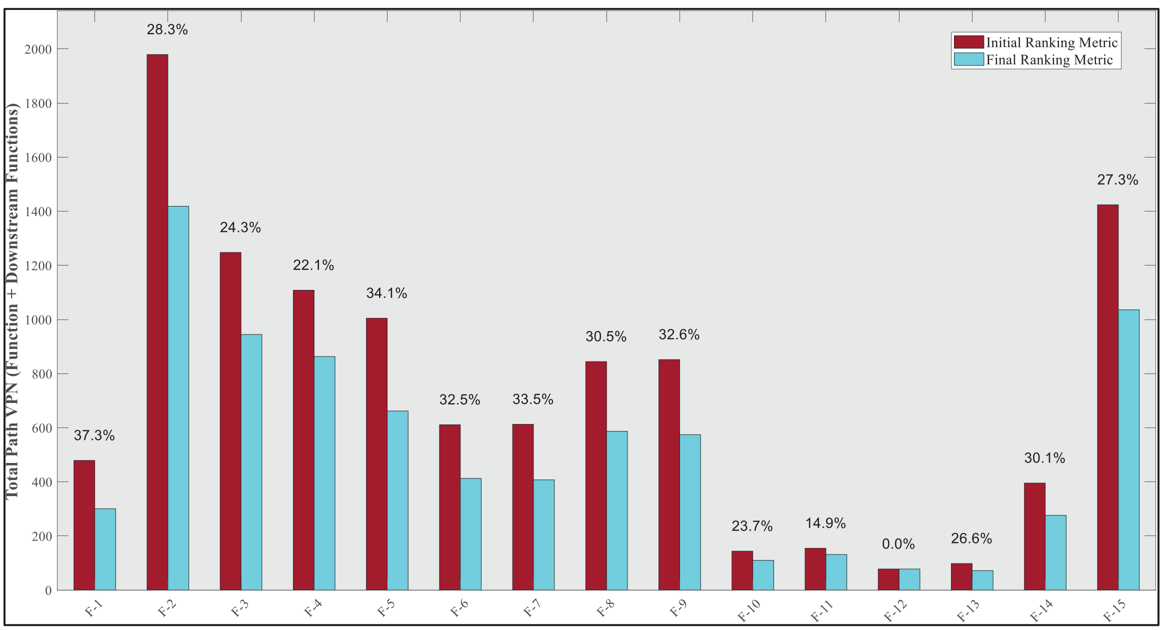

Figure 5.8 Path VPN comparison: initial vs. final mitigated (first case study)

An additional contribution is the framework's alignment with emerging regulatory and reporting standards for sustainability. Global frameworks, such as the International Sustainability Standards Board (ISSB) standards, the European Sustainability Reporting Standards (ESRS), and the Global Reporting Initiative (GRI) standards, increasingly require organizations to implement robust processes for identifying, assessing, and mitigating sustainability-related risks (Elidrisy, 2024; Krivogorsky, 2024). Our FRAM-PSO model provides a tangible, operational-level methodology to meet these requirements. By systematically linking system functions to environmental, social, and economic impacts, the model makes sustainability risks traceable and mitigation efforts transparent. This strengthens its utility for decision-makers who must navigate evolving regulatory landscapes while managing operational risk.

While the results are promising, limitations must be acknowledged.

- The findings are based on three specific case studies, necessitating further applications for broader generalizability. While the methodology is designed to be adaptable, its performance and the specific critical functions identified might differ in other industrial contexts or systems with different structures and technologies. The methodology can be generalized to other complex socio-technical domains such as aerospace, healthcare, and logistics by redefining the system functions, performance variabilities, and SPCs to match the specific operational context.
- The initial assessment of SPC impacts and the characterization of mitigation strategies (feasibility, weight, and sustainability impacts) relied on illustrative values. This approach was intentionally chosen to demonstrate the mechanics and viability of the FRAM-PSO framework as a methodological prototype. As is common in foundational studies that propose new models, the primary goal is to establish the framework's internal logic and potential before undertaking extensive, context-specific empirical validation. We fully acknowledge that for a real-world application, gathering these data and inputs from domain experts and empirical assessments is crucial for ensuring the practical reliability and robustness of the results.
- Furthermore, the assessment of sustainability contributions remains at a semi-quantitative level. To increase its practical utility, the framework would need to be enhanced to operationalize these dimensions with fully quantitative metrics, such as measured energy savings, specific cost reductions, or validated changes in worker satisfaction surveys.

5.6 Conclusions

This paper addresses the need for semi-quantitative, systemic risk assessment in complex industrial systems, particularly those utilizing smart wearables, while simultaneously integrating sustainability considerations. We developed and demonstrated a novel methodology integrating the FRAM with PSO. The FRAM-PSO model was applied in three case studies of the assembly and disassembly systems, which use smart gloves and smart glasses. We demonstrated that this is a powerful model to systematically identify, quantify, analyze, and mitigate the risks with sustainable strategies. The results demonstrate that applying this model can improve the system by reducing the risk of the model by more than 22% after four steps of mitigation for all three case studies.

The core contributions of this research are the synergistic integration of FRAM and PSO for quantitative risk analysis and optimized mitigation, and the pioneering incorporation of multi-dimensional sustainability criteria (environmental, economic, social) directly within this systemic risk management process. This work represents a valuable advancement towards building more resilient, efficient, and responsible industrial operations, in line with the goals of Industry 5.0. This method equips practitioners with a structured tool to identify vulnerabilities, quantify risks, and prioritize sustainable mitigation investments in complex, wearable-integrated systems. Theoretically, it advances quantitative FRAM approaches and pioneers the integration of sustainability within systemic operational risk management

Future research should prioritize broader application and validation across diverse industrial contexts, along with refining methods for robust input elicitation. Specific directions for future work include:

- Validating the model using real-time operational data from industrial partners to confirm its predictive accuracy and practical utility. This would also involve refining input elicitation methods through structured expert judgment or fuzzy logic techniques.
- Exploring the integration of alternative optimization algorithms to compare their effectiveness and computational efficiency in identifying optimal mitigation strategies.

- Developing a software-based decision-support tool to facilitate the practical application of the FRAM-PSO framework, enabling industry practitioners to conduct systemic risk assessments more easily and effectively.

5.7 Appendix

5.7.1 Case study 2 results

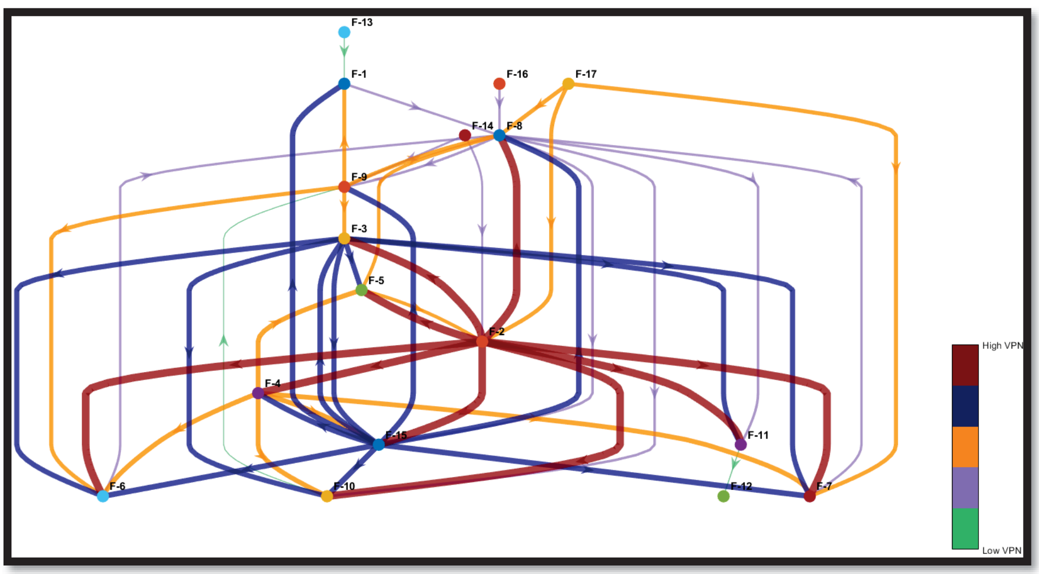

Figure 5.9 Path graph with VPN-weighted connections (second case study)

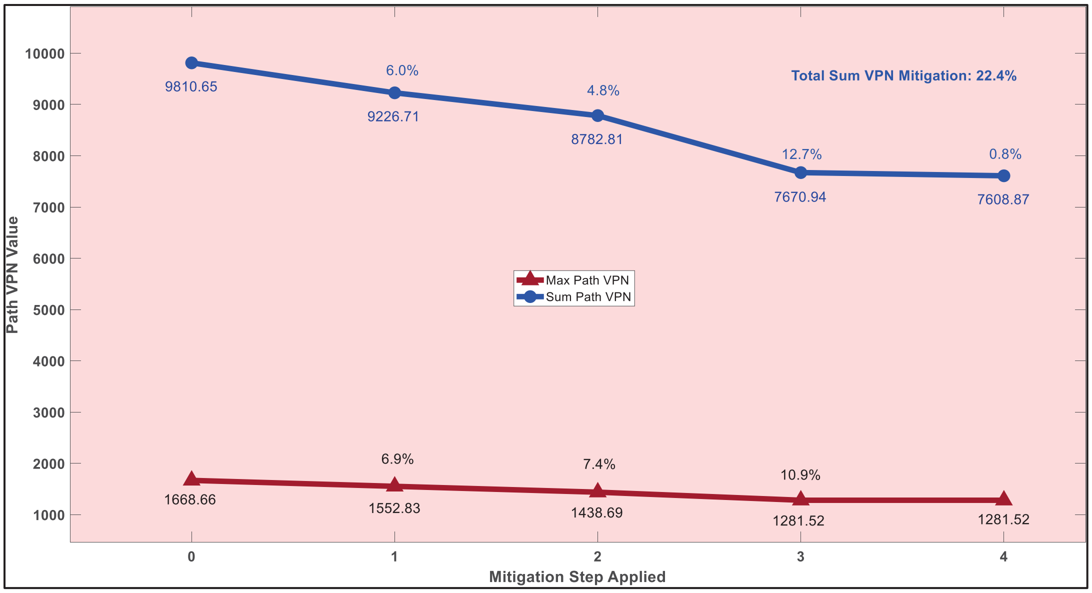

Figure 5.10 Mitigation progress: risk reduction over steps (second case study)

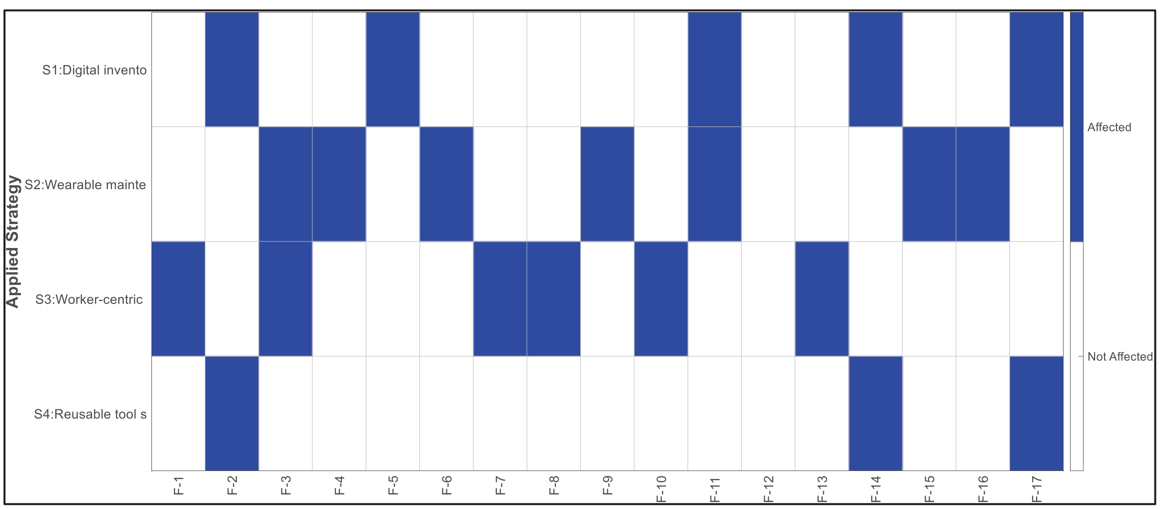

Figure 5.11 Functions affected by each applied strategy (second case study)

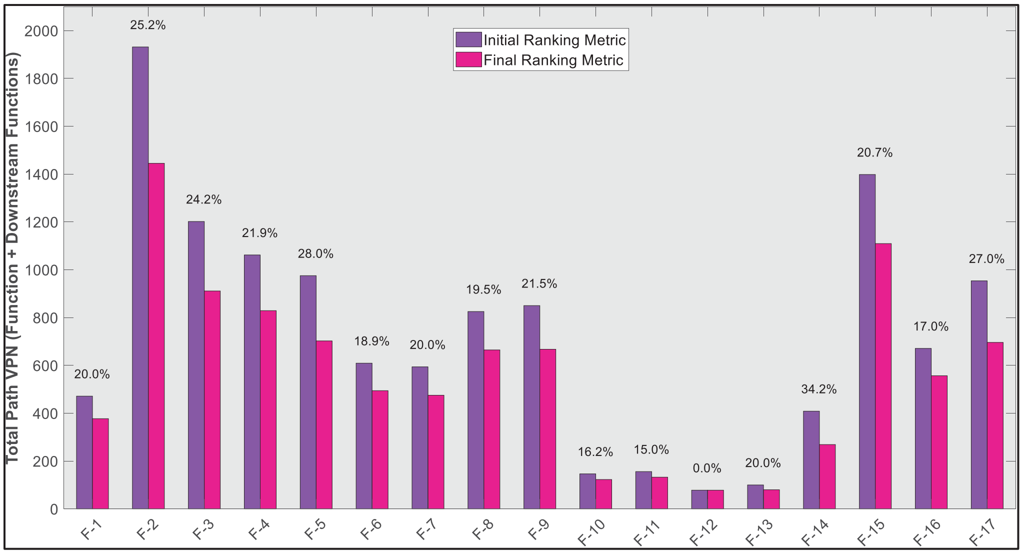

Figure 5.12 Path VPN comparison: initial vs. final mitigated (second case study)

5.7.2 Case study 3 results

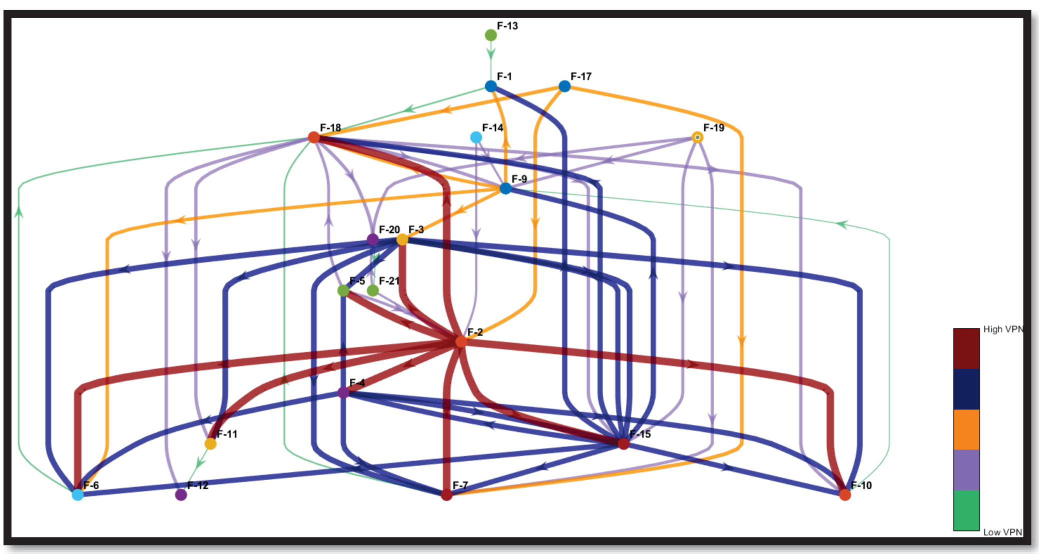

Figure 5.13 Path graph with VPN-weighted connections (third case study)

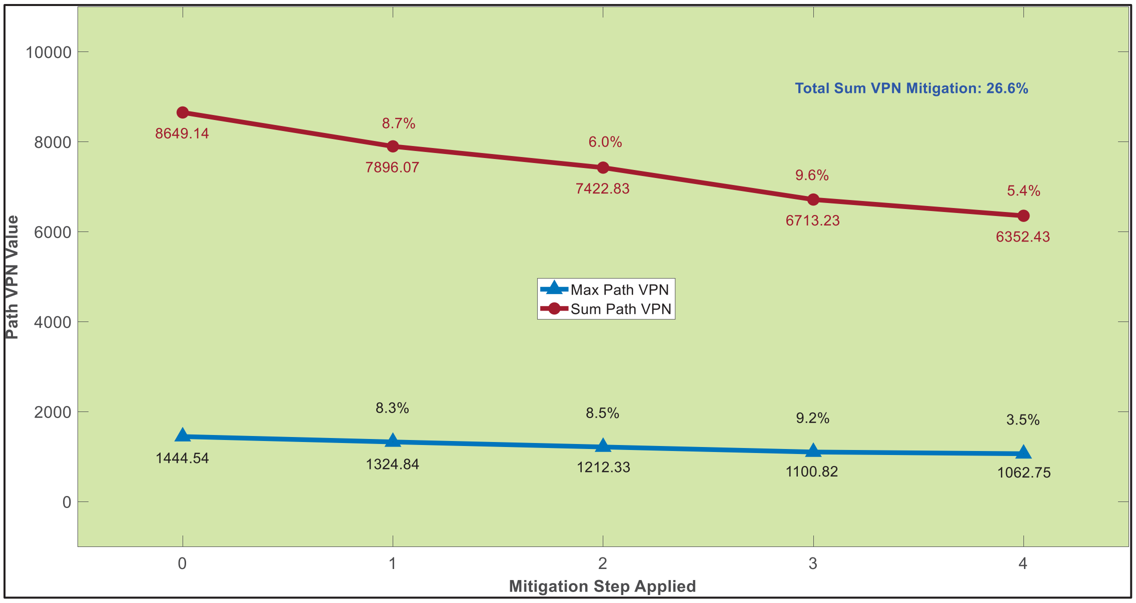

Figure 5.14 Mitigation progress: risk reduction over steps (third case study)

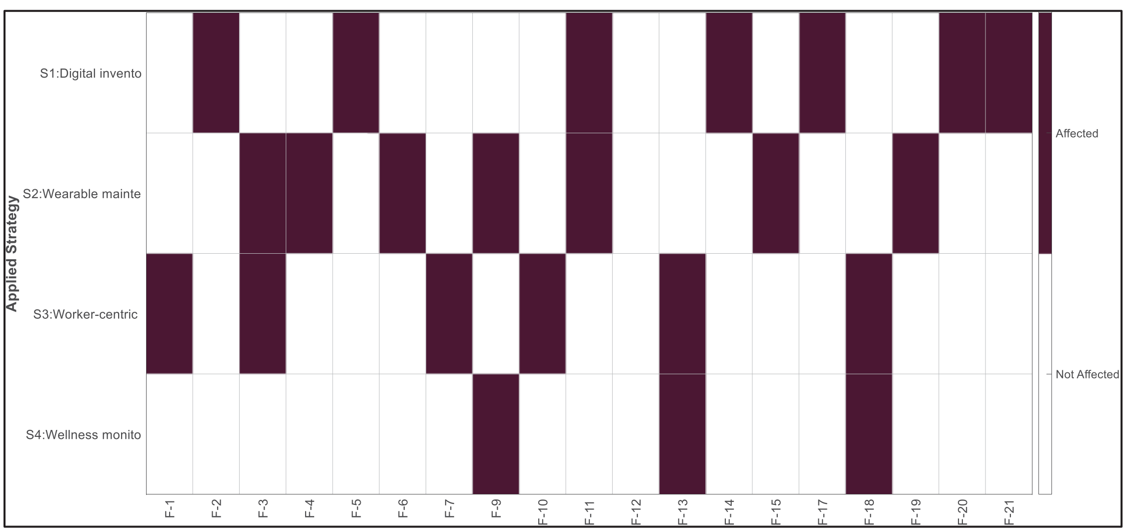

Figure 5.15 Functions affected by each applied strategy (second case study)

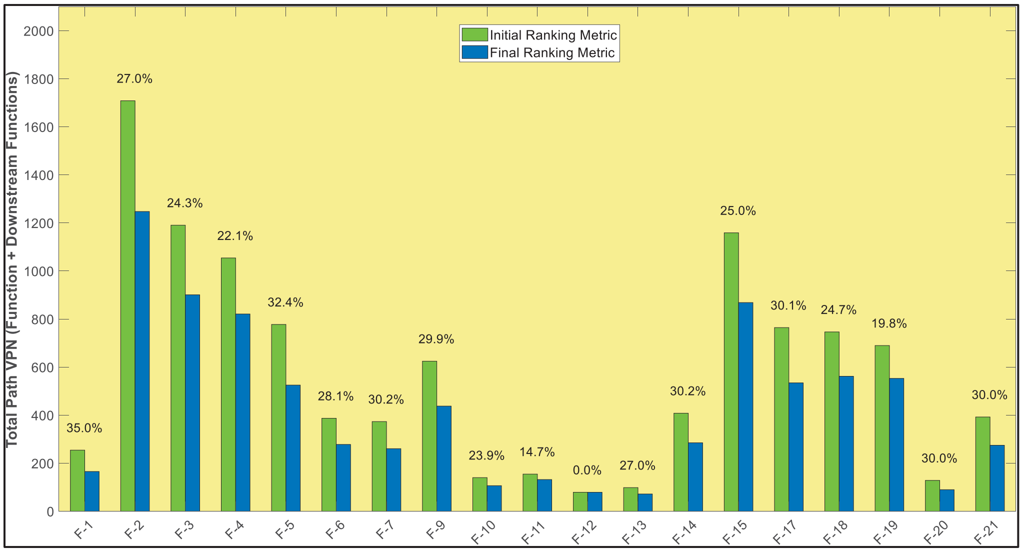

Figure 5.16 Path VPN comparison: initial vs. final mitigated (third case study)

CHAPTER 6

STPA-BN–PSO: A HYBRID PROBABILISTIC FRAMEWORK FOR MANAGING SYSTEMIC RISKS IN HUMAN-CENTRIC WEARABLES-ENABLED MANUFACTURING

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Abstract

The integration of smart wearables into manufacturing promises enhanced worker support but introduces poorly understood systemic risks. Traditional methods often fail to capture the uncertainty and interdependencies of these sociotechnical systems, particularly during the design and early integration phases, where data is scarce. To address this, this study develops a hybrid STPA-BN–PSO framework to resolve the parameterization gap. The BN structure is derived from Systems-Theoretic Process Analysis (STPA) to capture hierarchical control logic, while PSO is used to calibrate weighted conditional probability tables. The framework is applied to three case studies: assembly line, job-shop, and disassembly line. Quantitative results demonstrate that baseline unacceptable risk is context-dependent, reaching 31.5% in the job-shop compared to 28.0% in sequential assembly. Criticality analysis identifies that risk is driven by planning quality in sequential assembly (CA12, ΔRisk=0.181) and digital information quality in flexible job shops (H4, ΔRisk=0.286). Furthermore, multi-faceted sensitivity analyses reveal how risk-propagation pathways reorganize in response to operational layout. The performance of this framework is compared with recently developed STPA-PSO and FRAM-PSO methodologies, demonstrating its unique capability for path-based probabilistic quantification. The findings confirm that STPA-BN–PSO provides a

quantitatively rigorous, safety-centric tool for the proactive assessment of emergent risks in Industry 5.0 settings.

Keywords: BN, PSO, Systemic risk, STPA, Industry 5.0, Wearables-enabled manufacturing

6.1 Introduction

The manufacturing world is evolving, increasingly shaped by Industry 4.0 technologies and the push towards a more human-centric vision of Industry 5.0 (Wang, Liu, Wang, Li, & Wang, 2024; Xu, Lu, Vogel-Heuser, & Wang, 2021). A key part of this evolution involves integrating smart wearables, like smart glasses and gloves, directly into workflows. These devices hold significant promises: providing workers with real-time data, enhancing safety awareness, and potentially streamlining complex tasks such as hybrid assembly and disassembly (Karevan & Nadeau, 2024a; Romero et al., 2018). However, the introduction of these devices comes with different types of risks and challenges (Karevan & Nadeau, 2023; Tenholt et al., 2023). Potential human-system interaction errors, data security vulnerabilities, device reliability issues, and unforeseen consequences arising from the interplay between multiple wearables and existing systems are some of these sociotechnical risks that directly impact system reliability (X. Zhang et al., 2022). Thus, developing effective methods for assessing and managing these risks is becoming critical for the safe and successful adoption of wearable technology in manufacturing (Karevan & Nadeau, 2024b).

Traditional risk techniques struggle to capture the dynamic, interconnected, and uncertain nature of modern sociotechnical risks (Hulme et al., 2021). As a result, there is a growing demand for systemic and quantitative models that navigate this complexity and support risk-informed decisions (Karevan & Nadeau, 2026). BNs have emerged as a particularly well-suited approach for such scenarios, but doesn't provide a systemic view. BN is a powerful probabilistic framework that can model complex causal relationships and dependencies under uncertainty (Aghabegloo, Rezaie, Torabi, & Yazdani, 2023; Micu, Asgari, Khouadjia, Connolly, & Zavitsas, 2024; J. Sun, Fang, Wu, Sun, & Liu, 2019; Zhao & Xu, 2025). BNs allow for the integration of diverse information sources, including historical data, sensor readings, and expert knowledge. They are particularly strong to analyze multifaceted risk factors in areas ranging from infrastructure management and supply chains to healthcare predictions and fault diagnosis (Baglietto, Consilvio, Di Febbraro, Papa, & Sacco, 2018; Chien & Peng, 2025; Mukherjee, Patra, Samantaray, Barik, & Barik, 2022; Rathnakumar, Huang, Yan, & Liu, 2025). The ability to revise probabilities with new evidence enhances BNs for dynamic risk assessment in changing environments (Cao, Ren, Wang, & Sun, 2025; J. Sun et al., 2019).

While BNs provide a strong foundation for modeling risk probabilities, their effectiveness in sociotechnical systems is heavily dependent on the structural validity of the network (Chang, 2024; Sui et al., 2025). In this context, STPA provides a critical systemic view, allowing for the identification of causal relationships based on hierarchical control loops and feedback failures rather than purely statistical correlations (Karevan & Nadeau, 2026). By anchoring the BN architecture in the systemic outputs of STPA, the model captures a top-down perspective of safety boundaries. Once this foundational structure is established, optimizing the analysis benefits from complementary techniques like PSO. PSO, a population-based metaheuristic algorithm inspired by social behaviors, has proven highly effective in navigating complex, high-dimensional search spaces to find near-optimal solutions (Engelbrecht, 2007; Karevan, Tee, & Vasili, 2020). Its flexibility and practicality have led to its successful application across various domains, often in conjunction with other modeling techniques (including BNs) for tasks such as parameter optimization, calibration of CPTs, network structure learning, and efficient resource allocation (Aghabegloo et al., 2023; Du, Liang, Ouyang, & Wang, 2021; Sui et al., 2025; Wu & Jiang, 2025).

However, despite the capabilities of BN and PSO, a notable gap exists in the analysis of systemic risks introduced by modern digital tools, such as smart wearables, within complex operational contexts. Specifically, a critical challenge lies in the proactive assessment of systemic risks during the design and early integration phases, where empirical failure data for new wearable technologies is often non-existent. It remains unclear how to objectively calibrate probabilistic models under these conditions or how risk propagation pathways will reorganize across different Industry 5.0 layouts. To address this, this study proposes a hybrid STPA-BN–PSO method designed to systemically manage and predict the risks of integrating smart glasses and gloves in assembly/disassembly processes from the earliest design stages through to operation. This research aims to answer:

1. How can systemic human-wearable risks be structured into a hierarchical probabilistic model?
2. How can PSO reduce subjectivity in BN calibration under data uncertainty?
3. How do critical risk drivers differ across diverse manufacturing contexts?

The primary contribution of this work is a novel STPA-BN-PSO framework that anchors the BN structure to validate STPA outputs, calibrate all hazard/loss CPTs with PSO, and deliver multi-level analyses across three distinct wearables-integrated case studies. The performance of this STPA-BN-PSO approach will be explored and compared with alternative methodologies developed recently: STPA-PSO (Karevan & Nadeau, 2026) and FRAM-PSO (Karevan & Nadeau, 2025).

The rest of the paper is organized as follows. Section 6.2 reviews related work; Section 6.3 details the STPA-BN-PSO methodology; Section 6.4 presents results; Section 6.5 discusses implications and limitations; Section 6.6 concludes.

6.2 Literature review and research context

Modeling complex systems with inherent uncertainty is a persistent challenge in fields ranging from engineering to finance. To address this, researchers have increasingly turned to probabilistic graphical models. Among these, Bayesian Networks, which are founded on Bayes' theorem as shown in Equation 6.1, are considered one of the most effective theoretical models for illustrating relationships between system variables amidst uncertainty (Afenyo, Khan, Veitch, & Yang, 2017; G. Zhang & Thai, 2016):

$$(A|E) = \frac{P(E|A)P(A)}{P(E)} \tag{6.1}$$

As a combination of probability, graph, and decision theory, BNs offer a powerful graphical framework for probabilistic reasoning (Guo et al., 2022; X. Sun, Hu, Qin, & Zhang, 2024). Their distinct advantages include a high tolerance for incomplete data and the ability to represent complex interdependencies, including those with common causal factors (Castillo et al., 2016; Li, Ren, & Yang, 2023). However, in the context of Industry 5.0, the risks associated with smart wearables are predominantly sociotechnical, involving cognitive load, human-machine interface (HMI) distractions, and data privacy concerns (Tenholt et al., 2023; X. Zhang et al., 2022). While traditional BNs have been used for mechanical reliability (based on component-level breakdowns), their application to these emerging systemic wearable-driven risks requires a structure that can account for systemic control failures.

A significant challenge in BN modeling lies in constructing the network itself. While domain experts can define some dependencies, learning the BN structure from large datasets is often preferred. Modern research has proposed various approaches, including constraint-based methods (e.g., PC or IC algorithms), score-based methods, and more recently, Deep Bayesian Networks that utilize neural architectures to capture higher-order dependencies (Huang et al., 2024; Song, Zhang, & Xu, 2019). However, such data-driven methods are inherently inapplicable during the design and early integration phases of emergent technologies—such as Industry 5.0 smart wearables—where historical failure data is non-existent or extremely scarce. Relying on historical data for proactive safety is a fundamental limitation; therefore, this study addresses this "data-gap" by using STPA to define the causal structure based on hierarchical control logic rather than statistical history. By anchoring the BN in STPA, the model moves beyond purely statistical correlations to reflect the actual functional architecture of the manufacturing system. Crucially, this enables the framework to predict how risk propagation pathways reorganize when system layouts or control strategies are modified during the design phase. This provides a proactive, safety-guided assessment tool that identifies systemic vulnerabilities before the manufacturing process becomes operational, filling a gap that purely data-driven models cannot address.

Once the structure is defined, the secondary challenge is the calibration of CPTs. Finding the optimal parameters for a BN is an NP-hard problem. While Genetic Algorithms (GA) and Simulated Annealing (SA) have been used, they are often prone to becoming trapped in local optima and can lack the efficiency required for complex datasets (Song et al., 2019). Therefore, PSO has gained significant attention as a heuristic search method for parameter learning. Its appeal lies in its effectiveness at locating global optima and its relatively straightforward implementation, leading numerous researchers to combine PSO with BN to solve diverse problems (Aghabegloo et al., 2023; Cao et al., 2025; MacAllister, Kohl, & Winer, 2020; Song et al., 2019; B. Sun, Zhou, Wang, & Zhang, 2021).

While the combination of BN and PSO has been explored in other domains, such as healthcare and supply chain optimization (Aghabegloo et al., 2023; Sui et al., 2025), a notable gap exists in its application to systemic, path-based risk assessment. Most existing BN-PSO models use PSO for structure learning; in contrast, this study utilizes PSO to solve the "parameterization gap" specifically during the design and early integration phases, where low-level empirical data is naturally unavailable. By calibrating CPTs against high-level systemic risk profiles, the framework can quantify how a localized wearable failure propagates into a system-wide loss before the system is physically operational. By positioning the BN-PSO framework as a calibration engine for STPA-derived structures, this research provides a novel solution for predicting how risk pathways reorganize as different design configurations or manufacturing layouts are considered. This enables the management of emergent risks in Industry 5.0 through a proactive, logic-based approach rather than relying on retrospective historical data.

6.3 Methodology

This study introduces a hybrid STPA-BN-PSO framework designed to quantify and manage systemic risks in wearables-enabled manufacturing. The methodology is organized into four distinct stages:

- Qualitative hazard identification: Utilizing STPA to define the causal structure and control loops. While Fault tree analysis (FTA) is a common starting point for this task in the literature (Meng et al., 2024), it struggles to adequately model the complex interdependencies and feedback loops characteristic of modern sociotechnical systems (Karevan & Nadeau, 2024c).
- Probabilistic mapping: Translating STPA outputs into a three-tiered hierarchical Bayesian Network.
- Parameter calibration: Applying PSO to optimize CPTs against expert-derived reference profiles to mitigate the parameterization gap.

- Multi-level analysis: Executing baseline risk quantification, path-level criticality analysis, and multi-faceted sensitivity testing.

This integrated approach ensures that the resulting systemic risk model is not only mathematically robust but also grounded in systems theory. The overall process is illustrated in Figure 6.1.

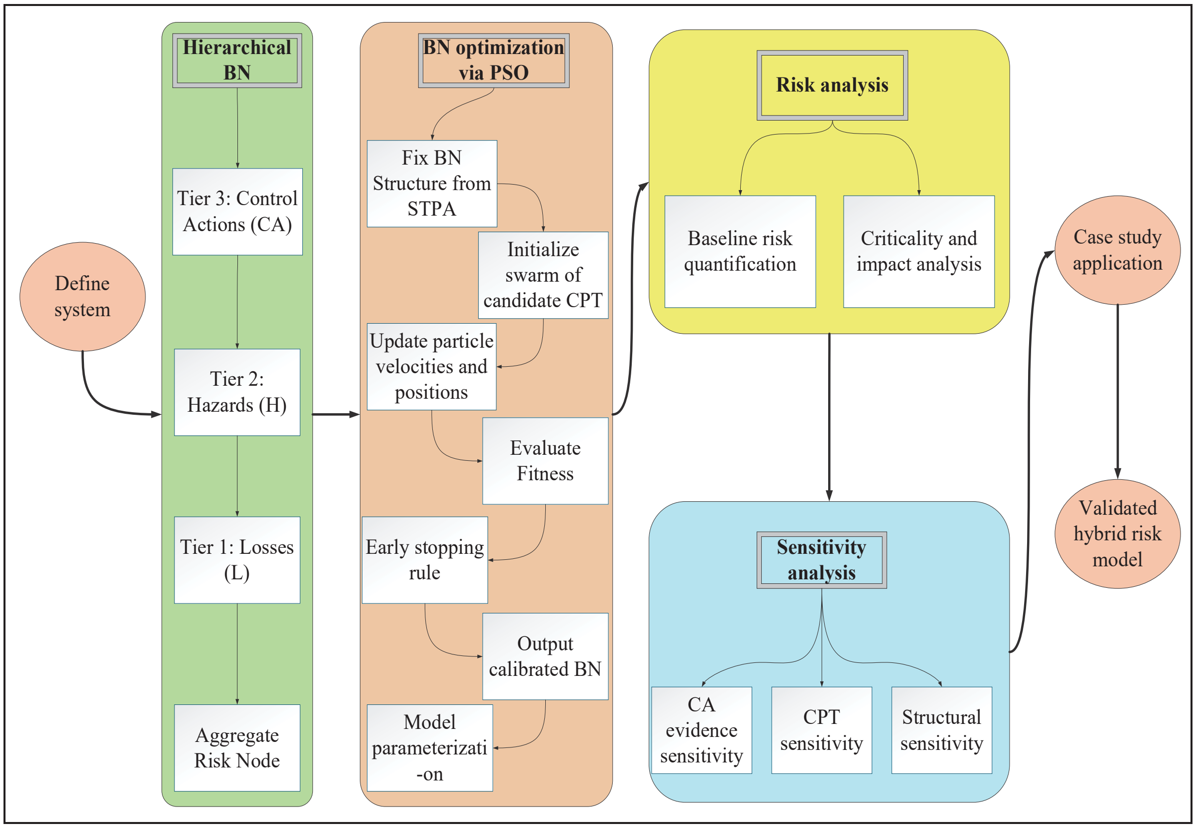

Figure 6.1 Methodology process

6.3.1 Hierarchical BN model formulation

The foundation of the methodology is a three-tiered BN that models the causal chain from root control failures to unacceptable system-level losses. This structure is built directly from the validated outputs of prior work (Karevan & Nadeau, 2026) to ensure that the model is grounded in a systemic understanding. STPA is a systemic safety analysis method introduced by Leveson (2004) that frames accidents not as single-point failures, but as inadequate control of complex socio-technical systems. Rather than focusing on component reliability, STPA identifies unsafe control actions, the hazards they may trigger, and the losses they can lead to (Lu et al., 2025; Riccardi, Compare, Mascherona, & Zio, 2025). The tiers are constructed from the bottom up and the directed arcs follow the STPA adjacency $CA \rightarrow H \rightarrow L \rightarrow Risk$. This architecture ensures that the BN captures the propagation pathways of risk, rather than just isolated failure probabilities. To maintain mathematical consistency, the network is enforced as a Directed Acyclic Graph (DAG). This hierarchical structure is designed to reflect the Industry 5.0 focus on sociotechnical resilience, specifically capturing how human-centric control actions (Tier 3) influence technical hazards (Tier 2) and subsequent system-level losses (Tier 1).

6.3.1.1 Tier 3 - Control Actions (CA)

The root nodes of the model represent specific, observable control action scenarios through which control over the manufacturing system may be lost. These nodes serve as the initiating events in the risk pathways. Because they are root nodes, they are defined by prior probability distributions. In this framework, these priors are derived from expert elicitation and STPA-defined control flaws.

6.3.1.2 Tier 2 - Hazards (H)

The intermediate nodes represent system-level hazards. Each hazard node is connected to its contributing CAs according to the STPA-defined control structure. These nodes represent states of the system that, under specific environmental conditions, will lead to a loss. The strength of the relationship between control failures and hazard activation is captured probabilistically in the node’s CPT, which is optimized during the calibration phase.

6.3.1.3 Tier 1 - Losses (L)

The top-level nodes represent system-level losses. As with the hazards, each loss node is connected to the specific hazards that may trigger it. These links are fixed by the STPA results to preserve the causal logic of the system. The corresponding CPTs quantify the likelihood that a hazard manifests as a tangible loss (e.g., worker injury, financial stoppage, or data breach).

6.3.1.4 Tier 0- Risk (R)

The terminal node provides an aggregate measure of system risk. To ensure the model remains fully probabilistic (addressing limitations of deterministic counts), the Risk node utilizes a weighted CPT. This probabilistic approach allows the model to account for differential severity among loss types, ensuring that safety-critical outcomes (e.g., worker injury) have a higher mathematical influence on the "High" and "Very High" risk states than lower-priority technical or equipment losses.

6.3.2 Bayesian Network optimization via PSO

After fixing the BN structure from STPA adjacency (CA→H→L→Risk), the unknown parameters Θ within the CPTs for all Hazard and Loss nodes are estimated using PSO. This framework utilizes a systematic simulation protocol designed for the design and early integration phases, where historical failure data is unavailable. The protocol initializes CA priors using a tiered mapping of control degradation and defines a synthetic target risk distribution $P(R)_{target}$ as the optimization objective.

The PSO algorithm maintains a swarm of 50 particles, where each particle represents a candidate set of CPT entries. To satisfy the probability simplex constraint, every CPT column is renormalized following velocity updates such that $\sum pi=1$. The calibration is driven by a multi-objective fitness function $F(\Theta)$, defined as the inverse of the weighted Mean Squared Error (MSE).

$$Loss = \alpha * MSE_{CA} + (1 - \alpha) * MSE_{Risk} \tag{6.2}$$

$$F(\Theta) = \frac{1}{Loss + \varepsilon} \tag{6.2}$$

Where:

- MSE_{CA} measures the deviation of the model's sampled root nodes from the STPA-derived priors.
- MSE_{Risk} measures the L2 norm between the model's 5-level risk distribution and the synthetic target profile.
- α is a weighting coefficient set to 0.6, prioritizing the causal anchoring of root control actions.
- ε is a small constant to prevent division by zero.

To ensure statistical significance and suppress noise in the fitness landscape, marginal probabilities are estimated via Monte Carlo sampling with 20,000 iterations per evaluation. The algorithm employs an early-stopping criterion, where optimization terminates if the global best fitness fails to improve for a predefined threshold of 50 consecutive iterations. By iteratively calibrating the CPTs to reconcile local control failures with global outcomes, the model captures how risk propagation pathways reorganize across diverse manufacturing layouts. This structured approach provides a proactive, logic-based assessment tool that identifies emergent vulnerabilities before the system is operational, filling the critical gap left by purely data-driven models that rely on retrospective history.

6.3.3 Model parameterization and quantification

After the BN is constructed and calibrated, a single terminal 'Risk' node provides an aggregate measure of system risk with five discrete states: Very Low, Low, Medium, High, and Very High (Karevan & Nadeau, 2024a). To ensure theoretical consistency and account for differential loss severity, the CPT of the Risk node is modeled probabilistically rather than as a simple deterministic count.

This probabilistic parameterization allows for the weighting of losses; specifically, safety-critical outcomes are assigned a higher conditional influence on the "High" and "Very High" risk states than lower-priority technical losses. For decision-making, these five states are categorized into Acceptable Risk (Very Low, Low, Medium) and Unacceptable Risk (High, Very High). This threshold can be adjusted based on the specific risk tolerance of an industrial application.

6.3.4 Risk analysis

Once the BN model is calibrated, a multi-faceted risk analysis is conducted to extract actionable insights. This framework moves from high-level systemic assessment to the identification of specific critical components and propagation pathways.

6.3.4.1 Baseline risk quantification

The baseline risk profile is established through Monte Carlo inference using 20,000 iterations, ensuring statistical significance and a stable probability distribution for the terminal 'Risk' node. This initial assessment is conducted without external evidence to characterize the inherent systemic risk during the design phase. By establishing this baseline, the framework provides a benchmark to evaluate how risk propagation pathways reorganize when control actions are modified. Within this model, "Unacceptable Risk" is quantified as the cumulative probability of the 'High' and 'Very High' states, serving as the primary metric for identifying systemic vulnerabilities before the system is operational.

6.3.4.2 Criticality and impact analysis

To identify the most significant contributors to risk, two forms of criticality are assessed. First, the Node-Level Systemic Impact (ΔRisk) is calculated by forcing a node (CA, Hazard, or Loss) to its True state and measuring the absolute increase in baseline risk. This identifies "risk amplifiers" within the system. Second, a Path-Based CA Impact analysis quantifies the total risk propagated through all downstream pathways originating from each specific control failure, providing a metric for prioritizing managerial interventions.

6.3.5 Sensitivity analysis

To test the model's robustness and simulate the impact of real-world operational changes, three distinct sensitivity analyses are performed:

- CA evidence sensitivity: This analysis simulates targeted management interventions. By perturbing CA priors by ±10%, we evaluate how a marginal improvement (or degradation) in a control action—such as worker training or device calibration—shifts the overall systemic risk.
- CPT sensitivity: This gauges the local brittleness of the model. By scaling the conditional probabilities of Hazard/Loss relationships by ±10%, we identify which causal links have the most profound influence on risk propagation.

Structural sensitivity: This evaluates the importance of the system's logic itself. Each edge in the STPA-derived structure is removed in turn (while preserving acyclicity) to quantify the leverage of specific parent-child dependencies on the final risk outcome.

6.3.6 Framework validation via case studies

To evaluate the diagnostic power and adaptability of the STPA-BN–PSO framework, a validation strategy is implemented using three distinct manufacturing contexts. These scenarios include: (1) sequential assembly, (2) flexible job-shop, and (3) disassembly for recycling, are specifically selected to represent the human-centric sociotechnical systems central to Industry 5.0. Unlike traditional models focused on machine failure, this validation demonstrates the framework's ability to model the complex interplay between human operators and smart wearables during the design and early integration phases.

By applying the same 4-stage methodology to these diverse layouts, the study identifies how risk propagation pathways reorganize when the role of the human worker shifts from a fixed sequence to a flexible, decentralized task. This comparative approach validates the framework's capability to prioritize human safety and operational resilience, directly reflecting the pillars of Industry 5.0. Detailed descriptions of the case parameters and structural interdependencies, building on the foundational qualitative analysis from prior work (Karevan

& Nadeau, 2026) are provided in Section 4 to maintain a clear distinction between the proposed methodology and its practical application.

6.4 Results

The results are reported across three case studies representing distinct operational contexts: sequential assembly (Case 1), job-shop assembly (Case 2), and disassembly for recycling (Case 3). A common, hierarchical network structure, derived from an STPA, provides the foundational model for all three analyses. Table 6.1 provides an overview of these contexts.

Table 6.1 Overview of three wearable integrated manufacturing contexts used for STPA-BN-PSO evaluation

Feature	**Case study 1**	**Case study 2**	**Case study 3**
Operational context	Assembly line	Job shop assembly	Disassembly line
Primary task	Sequential assembly of components from bins	Multi-step assembly of a custom structure	Sequential disassembly and sorting of components for recycling
Smart glasses usage	Display step-by-step assembly/disassembly instructions, and provide visual guidance		
Smart glove usage	Enhance precision in handling parts, apply correct force, and detect components		
Supporting equipment	Conveyor line, component bins	Tool cabinet, component bins, dolly, computer	Tool cabinet, storage bins, conveyor line

To ensure the replicability of the calibration process and address the query regarding variable identification, the standardized lists of Control Actions (CA), Hazards (H), and Losses (L) derived from the foundational STPA phase are presented in Table 6.2, Table 6.3 and Table 6.4. These tables represent the qualitative input variables that define the structural interdependencies for all three models.

Table 6.2 List of Control Actions (CA)

Code	Description	Code	Description
CA1	Calibration regulations	CA8	Wearable's programming
CA2	Data of materials and positioning	CA9	Smart glasses provide assembly/ disassembly instructions
CA3	Haptic feedback / light feedback	CA10	Smart gloves guide pressure feedback
CA4	Moving products with conveyor/dolly	CA11	Place and sort parts in storage bins
CA5	Provide maps and instructions from the supervisor	CA12	Plan of product/ sequence
CA6	Worker training	CA13	Highlight the hazardous parts
CA7	Wearable's connections		

Table 6.3 List of Hazards (H)

Code	Description	Code	Description
H1	Harmful activities that may lead to a worker's injury or death	H6	Communication problem between departments
H2	Insufficient training of workers to work with wearables	H7	Data security problem
H3	Not providing the required materials and structure on time	H8	Damage to the product during the process
H4	Not providing precise and real-time data	H9	Release of harmful refrigerants due to improper disassembly
H5	Connection problem between wearables	H10	Incorrect sorting of hazardous and non-hazardous components, leading to environmental or safety risks

Table 6.4 List of Losses (L)

Code	Description	Code	Description
L1	Loss or injury to the worker	L4	Financial losses due to the line stoppage
L2	Loss or unacceptable damage to the product	L5	Loss of sensitive information
L3	Loss or unacceptable damage to wearables	L6	Environmental loss

6.4.1 BN model calibration and baseline assessment

The first stage of the quantitative analysis involved calibrating the Bayesian Network for each case study. As defined in the methodology, the model's structure was fixed by the STPA results, while the unknown CPTs were estimated using the PSO algorithm. To ensure transparency and statistical stability, the PSO parameters used for the calibration are summarized in Table 6.5.

Table 6.5 PSO calibration parameters

Parameter	**Value**	**Description**
Swarm size *(N)*	50	Number of particles
Max iterations	200	Maximum optimization steps
Inertia weight *(w)*	0.9	Controls the impact of previous velocity
Cognitive constants *(c1)*	0.9	Weight of particle's personal best
Social constants *(c2)*	1.5	Weight of swarm's global best
Early stopping	50	Iterations with no improvement before termination
MC samples	20,000	Samples per inference for baseline stability

6.4.1.1 PSO convergence and stability analysis

The PSO was configured with a population of 50 particles and an early-stopping criterion applied whenever the global best fitness failed to improve for 50 consecutive iterations. To evaluate the stability of the heuristic optimization, the calibration was validated through multiple independent runs. Figure 6.2 illustrates the convergence of the optimization process across the three case studies. In practice, the algorithm successfully converged in all three operational contexts, but with notably different convergence dynamics that reveal the probabilistic character of each system.

In Case 1, the optimizer began from a modest initial fitness of 336.6, quickly climbed to 3406.4 by iteration 2, and then plateaued for more than 20 iterations before reaching 3946.9 at iteration 41. Several incremental improvements followed, but a decisive phase of rapid gains began at iteration 81, where the fitness jumped to 9267.2, then to 12,850.1 at iteration 83, and finally stabilized at 22,876.8 by iteration 103.

In Case 2, the optimization trajectory displayed a similar stair-step character but with even more pronounced plateaus. Starting from 313.0, the global best fitness leapt to 2,304.2 by iteration 3, then it reached 21,841.3 at iteration 22, and finally stabilized at 28,130.0 by iteration 70. Case 3 revealed a different pattern, with gradual improvement punctuated by a late-stage surge. Beginning from 341.2, the fitness rose through stable intervals—15,713.6 at iteration 45 and 23,541.4 at iteration 85—before a surge at iteration 178 increased the fitness to 31,073.2.

The observed stair-step character with pronounced plateaus and sudden surges in fitness across all cases can be attributed to the nature of the PSO algorithm interacting with a complex, multi-modal fitness landscape inherent in BN parameter learning. Specifically, particles may converge rapidly on local optima (explaining the plateaus) and only escape these through a global best update (explaining the sudden surges) that re-invigorates the swarm's exploration capabilities. The high consistency of these final fitness levels across multiple runs confirms the statistical stability of the framework.

The robustness of these convergence results is confirmed by the early-stopping criterion, where the optimization was only terminated after the global best fitness failed to improve for 50 consecutive iterations. This ensures that the final set of CPTs represents a state of mathematical equilibrium. Furthermore, the fact that the algorithm reached high fitness levels across three structurally different models demonstrates its reliability in reconciling the STPA control logic with the target systemic risk profiles. This internal consistency is vital during the design phase, as it confirms that the identified reorganization of risk pathways is not a mathematical artifact but a direct result of the framework successfully parameterizing the unique sociotechnical interdependencies of each operational layout

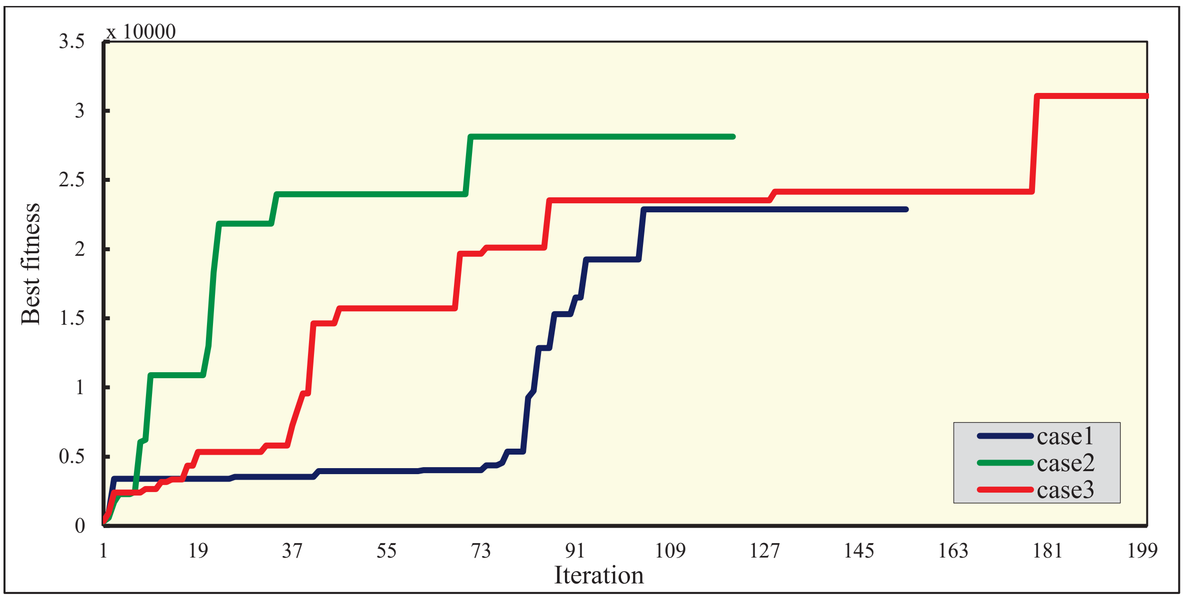

Figure 6.2 PSO convergence

6.4.1.2 Baseline risk quantification

Once calibrated, the CPTs were used to simulate baseline systemic risk distributions via Monte Carlo sampling (20,000 iterations). By utilizing a probabilistic terminal Risk node, the model reflects a safety-centric severity hierarchy where critical outcomes, such as worker injury (L1) and environmental loss (L6), are assigned higher conditional weights than other technical losses. In a practical industrial application, these weights should be determined through a formal expert elicitation protocol or aligned with specific corporate risk-tolerance policies. However, for the purpose of this study, representative arbitrary weights were utilized to demonstrate the framework's robustness and its adaptive capability in prioritizing human-centric safety over purely technical or equipment-related failures.

Unacceptable risk is defined as the cumulative probability of 'High' and 'Very High' risk states. The baseline results, summarized in Table 6.6, show that the Job-Shop (Case 2) has the highest baseline level of unacceptable risk at 31.5%. This is followed closely by Disassembly Line (Case 3) at 30.7%, and the Assembly Line (Case 1) at 28.0%. A primary factor driving this increased risk is the significantly higher number of interconnections and dependencies within job-shop and disassembly processes; as these connections become more complex, the risk of systemic propagation grows substantially, which aligns with findings regarding the risk profiles of flexible manufacturing systems (Vidal, Coronado-Hernández, & Minnaard, 2023).

Table 6.6 Baseline risk profiles

Case study	Very Low	Low	Medium	High	Very High	Unacceptable Risk (High + Very High)
Case 1	11.4%	20.1%	40.5%	19.3%	8.7%	28.0%
Case 2	10.4%	20.3%	37.8%	21%	10.5%	31.5%
Case 3	8.8%	19.9%	40.6%	20.0%	10.7%	30.7%

6.4.2 Risk analysis

Following calibration, a multi-faceted risk analysis was performed on the three case study models to identify critical nodes and propagation pathways. Figure 6.3 illustrates the final criticality rankings (ΔRisk) of all nodes, showing how the marginal contribution of each control action (CA), hazard (H), and loss (L) changes the expected systemic risk when perturbed. The results reveal a strong context-dependence in risk drivers, reflecting the structural differences between sequential, flexible, and disassembly operations.

6.4.2.1 Node criticality

The implementation of the probabilistic weighted Risk node (as detailed in Section 3.3) allows the framework to prioritize safety-critical outcomes. In the sequential assembly case (Case 1), the most influential nodes are not limited to losses but include both control and hazard layers. Here, L1 (Worker injury, 0.196) and L6 (Environmental loss, 0.189) dominate the ranking. Their high scores are a direct result of the severity-weighting scheme, confirming that the model effectively prioritizes human safety. These are followed closely by H10 (Incorrect sorting, 0.187) and CA12 (Plan of product/sequence, 0.181). This indicates that risks in sequential operations are tightly coupled to planning quality, where even minor sequencing errors can cascade into immediate consequences for worker safety.

Conversely, the job-shop case (Case 2) shifts the concentration of systemic risk toward the hazard layer, specifically those involving information flow and connectivity. The three most critical nodes are H4 (Lack of real-time data, 0.286), H5 (Wearable connection problems, 0.270), and H1 (Harmful activities, 0.269). This demonstrates that in flexible production contexts—central to Industry 5.0—unstable connectivity and poor data quality are the primary "risk amplifiers." In these decentralized layouts, the reliability of the Human-Machine Interface (HMI) is the most significant factor in maintaining system resilience.

The disassembly case (Case 3) reveals yet another shift: losses take precedence as the primary drivers of systemic vulnerability. L6 (Environmental loss, 0.196), L5 (Information loss, 0.186), and L1 (Worker injury, 0.186) top the ranking. The appearance of CA12 (Planning, 0.111) and H6 (Communication problems, 0.116) among the highest-ranked non-loss factors indicates that the inherent uncertainty of disassembly requires superior coordination to prevent the escalation of risk toward irreversible environmental or safety outcomes.

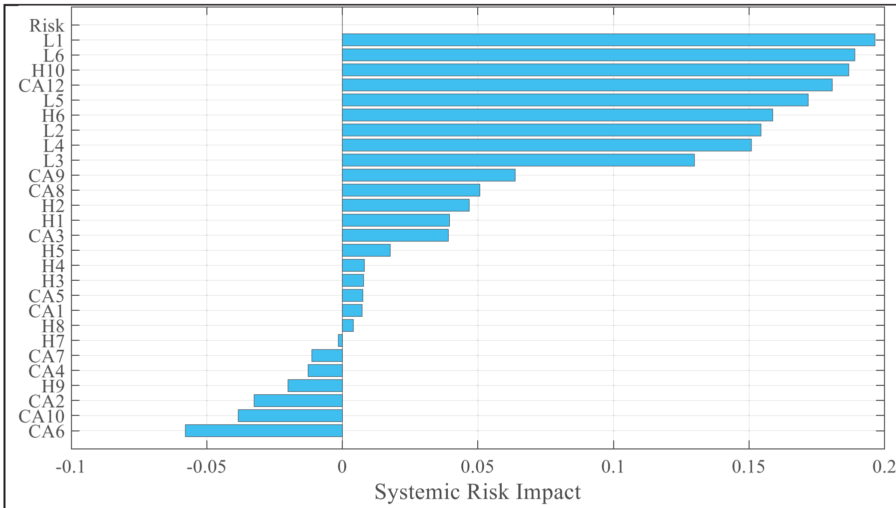

Figure 6.3 (a)- Case 1

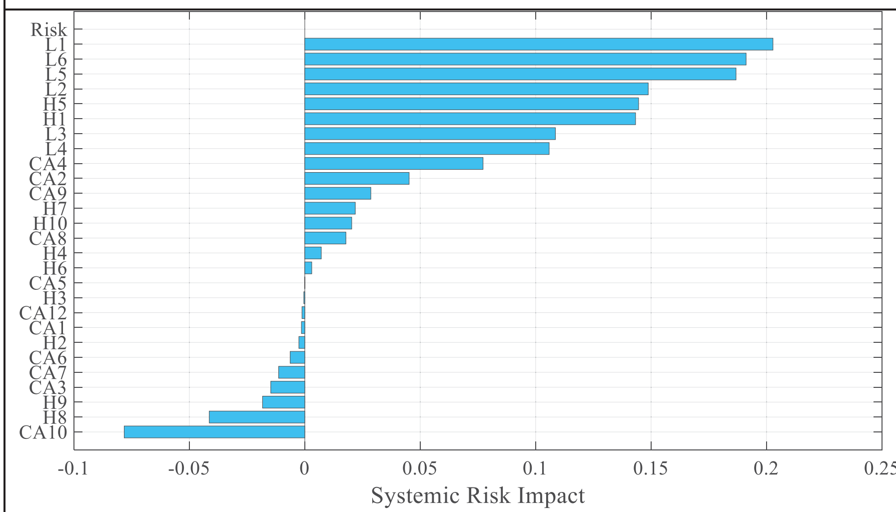

Figure 6.3 (b)- Case 2

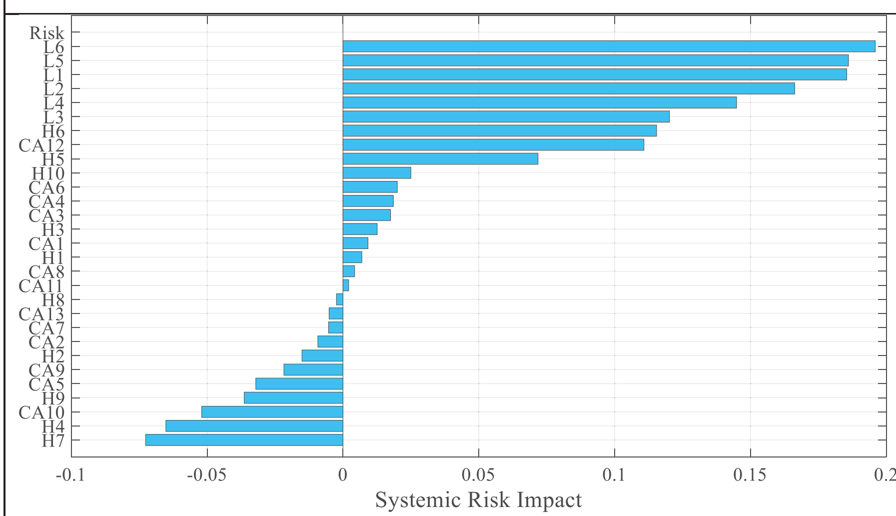

Figure 6.3 (c)- Case 3

Figure 6.3 Final criticality ranking of all nodes

6.4.2.2 High-risk pathway tracing

While Figure 6.3 reports node-level systemic impact, Figure 6.4 and Figure 6.5 move to a path-level view. Specifically, Figure 6.4 depicts the top control-to-loss routes (CA→H→L→Risk) as a risk-weighted network: edge thickness and color encode each route's contribution to expected severity. Figure 6.5 lists the same top routes as a horizontal bar chart, giving their exact expected-severity values.

In sequential assembly, the dominant pathways originate from CA12 (Plan of product/sequence) and CA5 (Supervisor instructions), which channel risk through H6 (Communication problems) toward L5 (Information loss) and L4 (Financial losses). Figure 6.5 confirms this pattern, with the highest bars corresponding to CA12- and CA5-driven routes, showing that even modest disruptions in planning and communication can cascade directly into significant financial and informational consequences.

In the job-shop system, the dominant pathways originate from CA7 (Wearables' connections) and CA4 (Moving products with conveyor/dolly), which channel risk through H5 (Connection problem between wearables) toward L2 (Loss or unacceptable damage to the product) and L4 (Financial losses). This confirms that vulnerabilities in digital guidance and connection reliability create disproportionate impacts in flexible, decentralized production contexts.

In disassembly, the network maps and bar charts demonstrate that CA4 (Moving products with conveyor/dolly), CA7 (Wearable's connections), and CA3 (Haptic/light feedback) feed into H5 (Connection problem between wearables), H10 (Incorrect sorting of hazardous and non-hazardous components, leading to environmental or safety risks), and H1 (Harmful activities that may lead to a worker's injury or death), ultimately culminating in L2 (Loss or unacceptable damage to the product), L3 (Loss or unacceptable damage to wearables), L6 (Environmental loss), and L1 (Worker injury). Taken together, these figures highlight the context-sensitive nature of systemic risk and demonstrate the ability of the BN–PSO framework to uncover not only which nodes are critical but also how risks propagate through pathways to generate systemic vulnerabilities.

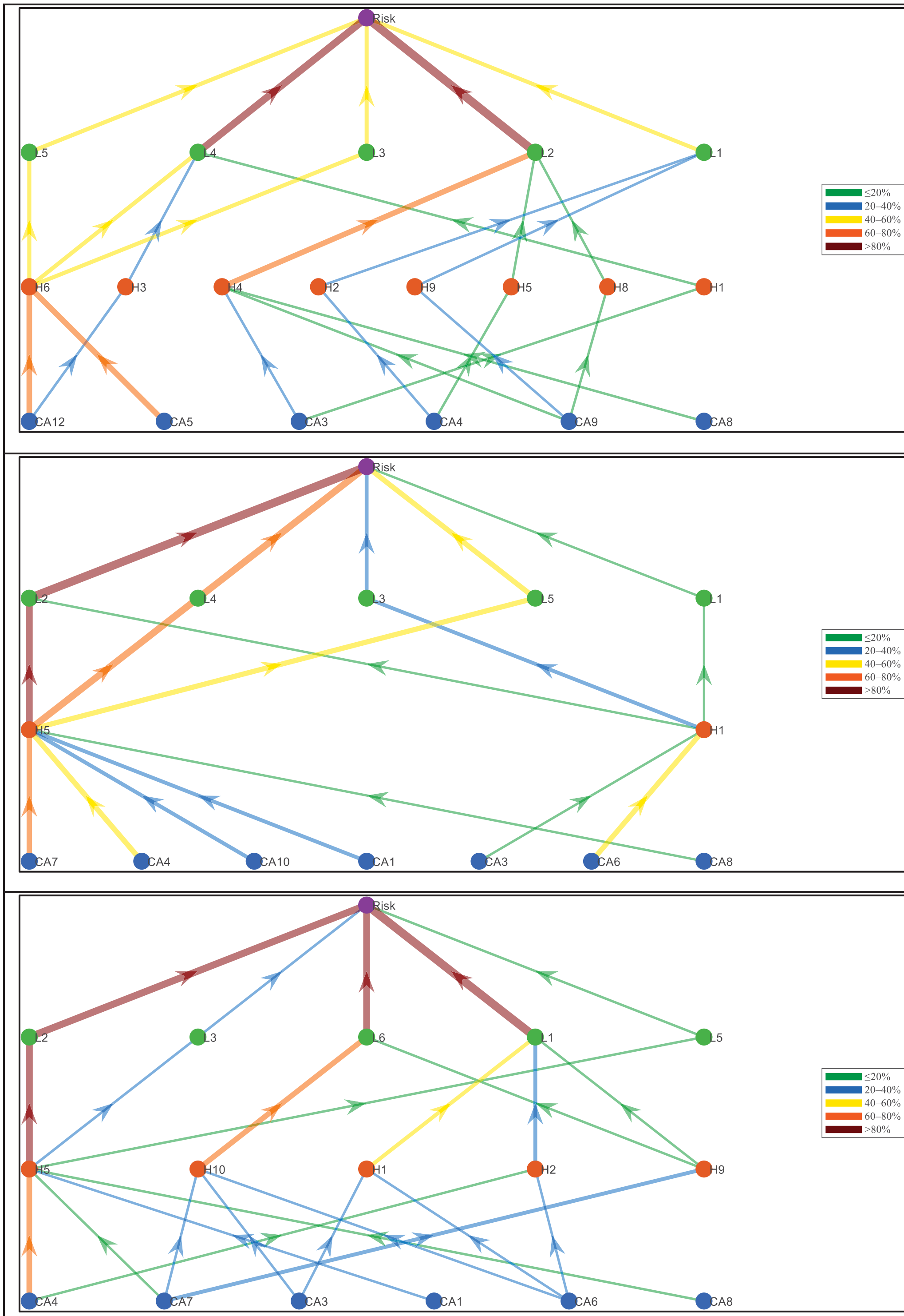

Figure 6.4 (a)- Case 1

Figure 6.4 (b)- Case 2

Figure 6.4 (c)- Case 3

Figure 6.4 Risk-weighted paths network

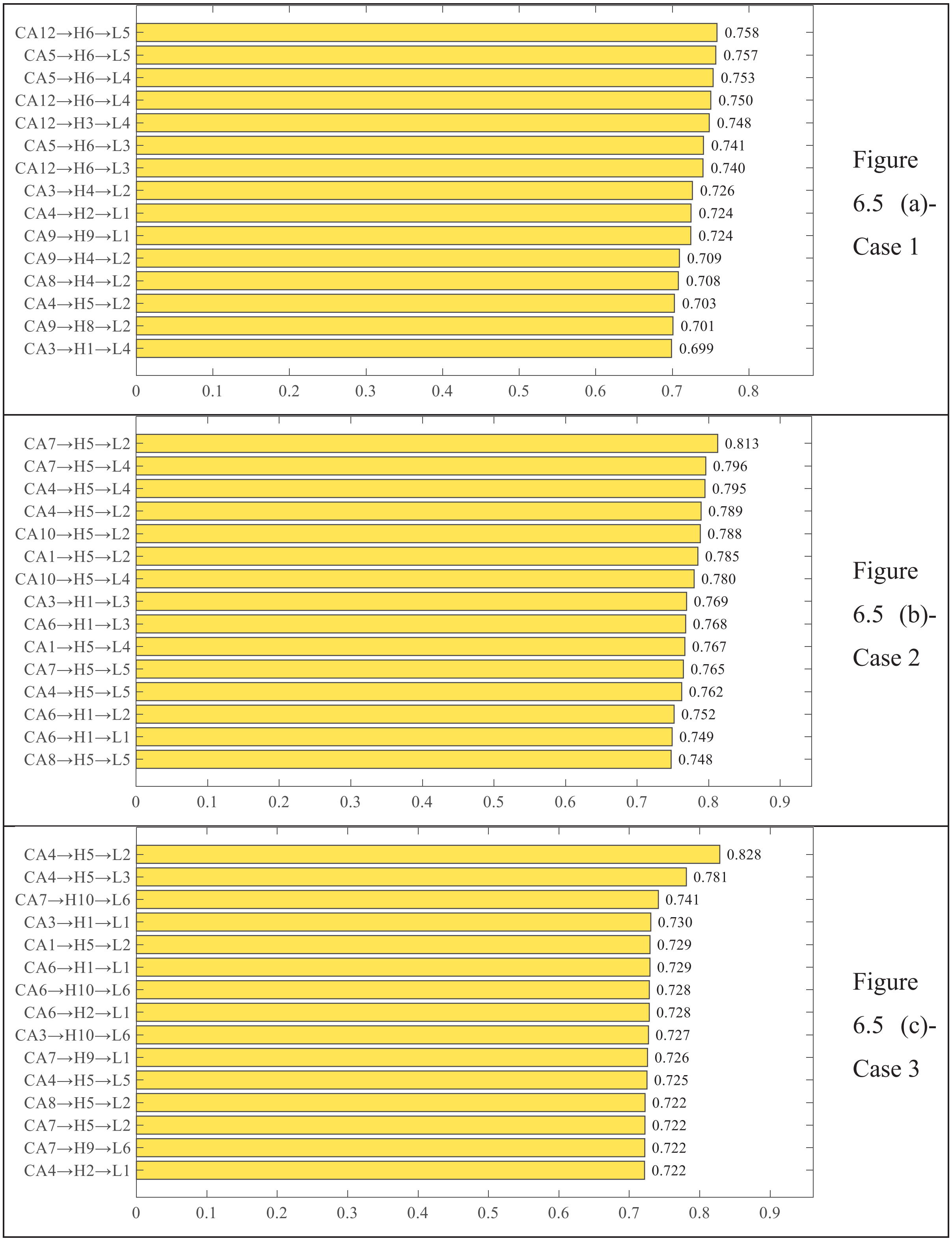

Figure 6.5 High-risk pathways sorted list

6.4.3 Sensitivity analysis

Building on the node and pathway-level findings, the final step examines how the network responds to perturbations in evidence, probability tables, and structural connections. This provides a comprehensive view of model robustness and systemic sensitivity, serving as a "what-if" simulation tool for managerial decision-support.

6.4.3.1 CA evidence sensitivity

The CA evidence sensitivity analysis is presented in Figure 6.6. These plots report how the expected severity of the Risk node changes when the marginal evidence for a given CA node is perturbed by +10% or –10%, holding the network structure and all CPTs fixed. In the panels, the blue bars correspond to a +10% increase in evidence for a given CA, and the pink bars represent a –10% decrease, with all other parts of the network held constant. Bars to the right indicate increases in expected severity (risk grows); bars to the left indicate decreases (risk falls).

Whether the most influential bar sits on the +10% or –10% side depends on the role a CA plays at the operating point of the model. When a CA behaves like a driver of risk at baseline, adding evidence to it (blue) pushes the system toward more hazardous states and produces a larger positive shift. When a CA behaves like a barrier, removing evidence (pink) weakens protection and produces the larger increase in risk. In some cases, both bars point in the same direction; this occurs when small moves either way redistribute probability toward (or away from) the same high-impact routes because of interactions with competing paths.

In Case 1, the sensitivity analysis reveals that the system's overall risk is particularly influenced by a small subset of control actions, most notably CA6 (Worker training). This node demonstrates a pronounced asymmetry between positive and negative perturbations: when its probability is reduced by 10%, systemic risk rises sharply, whereas an equivalent increase leads to a notable risk reduction. This behavior suggests that CA6 serves a critical stabilizing function, absorbing uncertainty and maintaining system balance under normal operating conditions. Its sensitivity indicates that even minor degradation in its performance or reliability could propagate significant risk across the network. By contrast, control actions such as CA1 (Calibration regulations) and CA8 (Wearable's programming) also display noticeable sensitivities but in a direction that amplifies rather than mitigates systemic risk. Increasing their likelihood appears to exacerbate overall vulnerability, suggesting that their influence is more disruptive than protective.

In Case 2, the sensitivity profile changes noticeably compared with the first scenario, showing that the propagation of risk depends strongly on the operational context. The most prominent variations appear around CA10, which produces the largest positive and negative deviations across all control actions. When the evidence supporting CA10 decreases by 10%, systemic risk increases sharply, while a 10% increase in its probability results in a marked reduction.

This clear asymmetry indicates that CA10 functions as a dominant protective mechanism in this configuration: its presence contributes to system stability, whereas its weakening immediately amplifies vulnerability. Moreover, CA1, CA6, and CA7 (Wearable's connections) share a similar pattern: each shows a slight increase in systemic risk when their probabilities rise and a corresponding decrease when they are reduced, suggesting a moderate stabilizing effect whose influence is directionally consistent but less intense than that of CA10. In contrast, CA2 (Data of materials and positioning) and CA8 display an opposite trend — both produce negative ΔScores under a –10% perturbation and minimal positive change under +10%, implying that these actions may exert a destabilizing or risk-amplifying influence when weakened.

In Case 3, CA13 (Highlight the hazardous parts) stands out as uniquely critical, exhibiting increased systemic risk under both positive and negative evidence perturbations, with the absence of evidence proving most detrimental. CA6 and CA12 (Plan of product/sequence) show a more complex behavior, where a reduction in evidence slightly decreases overall risk, suggesting that their activation may occasionally contribute to instability. By contrast, CA3 (Haptic feedback /light feedback), CA7, CA8, CA9 (Smart glasses provide assembly/disassembly instructions), and CA11 (Place and sort parts in storage bins) act as risk drivers, as greater evidence or confidence in their activation consistently corresponds to an escalation in systemic risk.

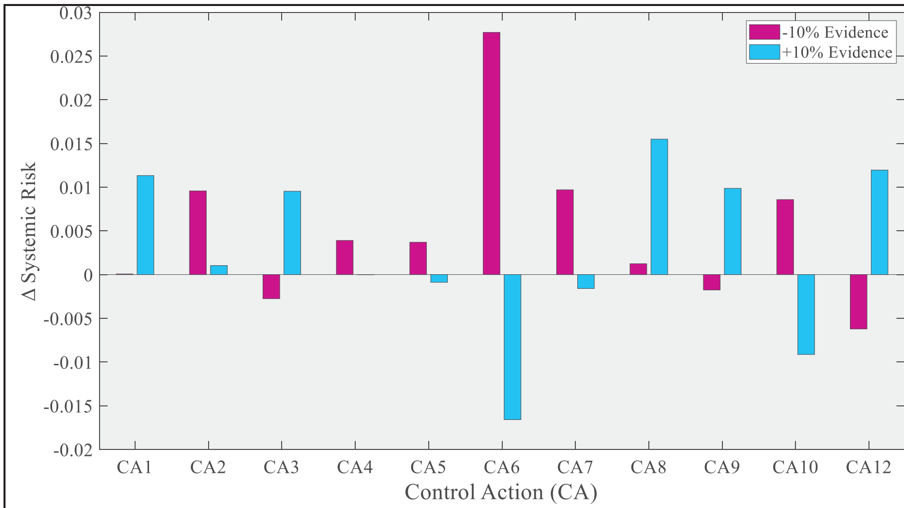

Figure 6.6 (a)-Case 1

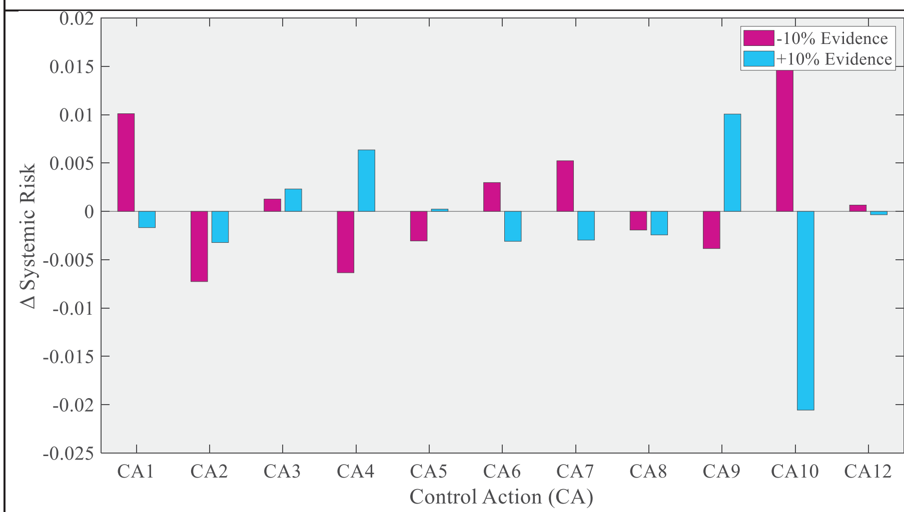

Figure 6.6 (b)-Case 2

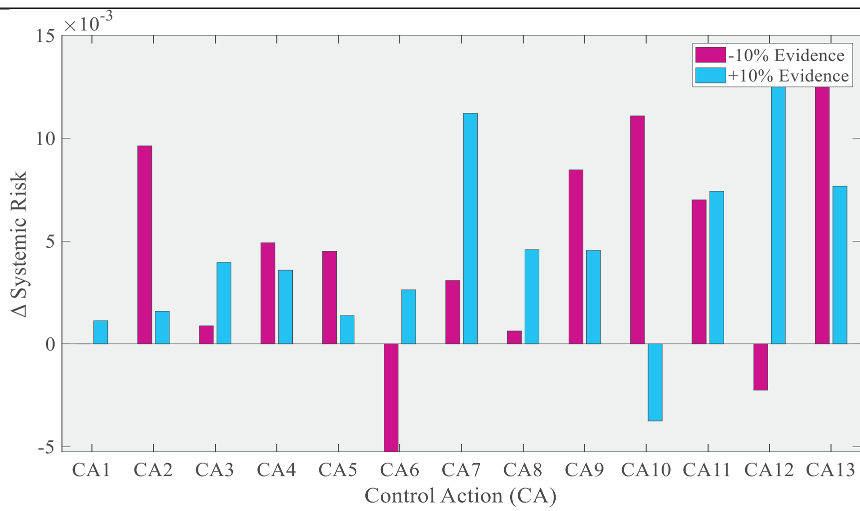

Figure 6.6 (c)-Case 3

Figure 6.6 Sensitivity of systemic risk to CA evidence perturbation

6.4.3.2 CPT sensitivity

The CPT sensitivity analysis is presented in Figure 6.7. This analysis evaluates how variations in the CPTs of the Hazard and Loss nodes influence the expected severity of the Risk node. Each node's CPT was perturbed by ±10% while maintaining the original network structure and all other CPTs constant. In the panels, the light-blue bars represent a –10% scaling of the CPT values, and the black bars correspond to a +10% scaling. Bars extending to the right indicate an increase in expected severity (the system becomes more risk-prone), whereas bars to the left denote a reduction in systemic risk.

Because this procedure alters the underlying conditional dependencies rather than direct evidence, it highlights which Hazard and Loss relationships exert the greatest structural influence on the propagation of risk through the network. Nodes whose bars show large or asymmetric deviations reveal where small changes in local probability relationships can shift the global risk profile, identifying the most sensitive points in the model's internal logic.

For Case 1, H1(Harmful activities that may lead to a worker's injury or death) and H9 (Release of harmful refrigerants due to improper disassembly) exhibit the strongest positive deviations in Δ Systemic Risk, particularly under a +10% CPT scaling (black bars). This indicates that even small increases in the likelihood relationships encoded in these nodes substantially raise the expected severity of the Risk node. Their sensitivity suggests that these hazards play a central role in transmitting or amplifying risk within the system structure. However, when their CPT values are reduced (–10%, light blue), H1 shows a slight increase in risk, and H9 demonstrates a modest increase. This observation reinforces their role as key contributors to upward risk propagation, suggesting that even a reduction in their internal probabilities does not mitigate risk, but rather maintains or slightly elevates it, confirming their critical nature as strong drivers. Among the Loss nodes, L4 (Financial losses due to the line stoppage) shows a similarly pronounced asymmetry: an increase in its CPT probabilities markedly elevates systemic risk, while a reduction produces only a minor mitigating effect. This asymmetric pattern implies that once a failure associated with L4 becomes more likely, its downstream impact grows disproportionately—an indication of nonlinear risk amplification. Other nodes, such as H7 (Data security problem), H8 (Damage to the product during the process), L5 (Loss of sensitive information), and L3 (Loss or unacceptable damage to wearables), show moderate sensitivity, reflecting secondary effects on the overall risk balance.

In Case 2, the CPT sensitivity analysis reveals a more balanced yet directionally complex behavior across the Hazard and Loss nodes, suggesting that risk propagation in this scenario is shaped by intricate interdependencies rather than dominance by a few nodes, as observed in Case 1.

Among the Hazard nodes, H6 (Communication problem between departments), H7 (Data security problem), and H9 stand out as the most influential. H7 exhibits a substantial negative Δ Systemic Risk when its CPT values are increased, and a smaller positive effect when decreased. This asymmetry indicates that increasing the likelihood of H7's causal relationships significantly reduces systemic risk, implying that H7 functions as a critical mitigating mechanism—its integrity helps contain uncertainty in downstream pathways and actively reduces overall risk. Conversely, weakening its probabilities leads to a slight amplification of risk. H6 shows a significant positive Δ Systemic Risk for both increased and decreased CPT values. This indicates that any perturbation to H6's conditional probabilities, whether an increase or a decrease, leads to a substantial increase in systemic risk, making it a highly sensitive and volatile risk amplifier in this scenario. By contrast, H9 demonstrates that a +10% increase in its CPTs elevates risk significantly, whereas a –10% decrease tends to reduce it. This analysis identifies its role as a risk-intensifying node, where stronger conditional links propagate instability through the network, but conversely, its mitigation can lead to a notable reduction in risk.

On the Loss side, L1 (Loss or injury to the worker) emerges as particularly sensitive. It exhibits the most extreme negative Δ Systemic Risk under –10% scaling, meaning that a small reduction in its conditional probabilities substantially lowers the expected severity. However, increasing its CPT reverses the effect, showing a significant increase in risk, confirming that L1 amplifies overall system vulnerability when its probabilities are strengthened.

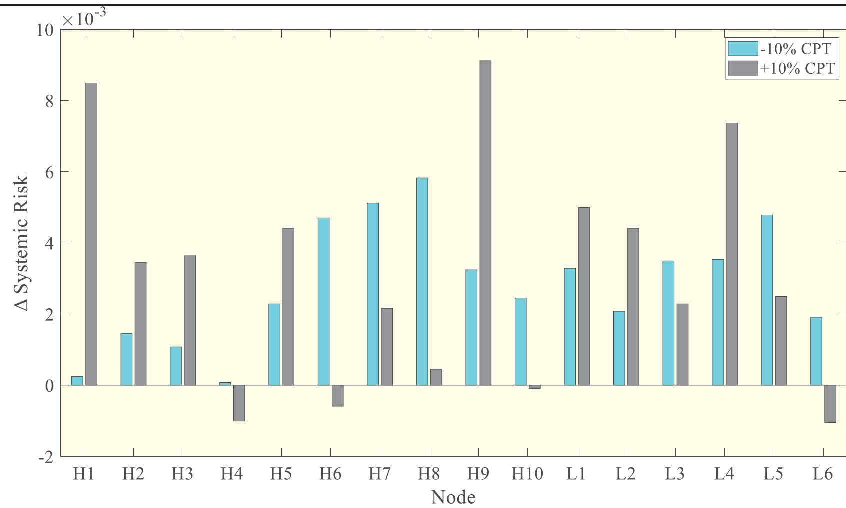

Figure 6.7

(a)-Case 1

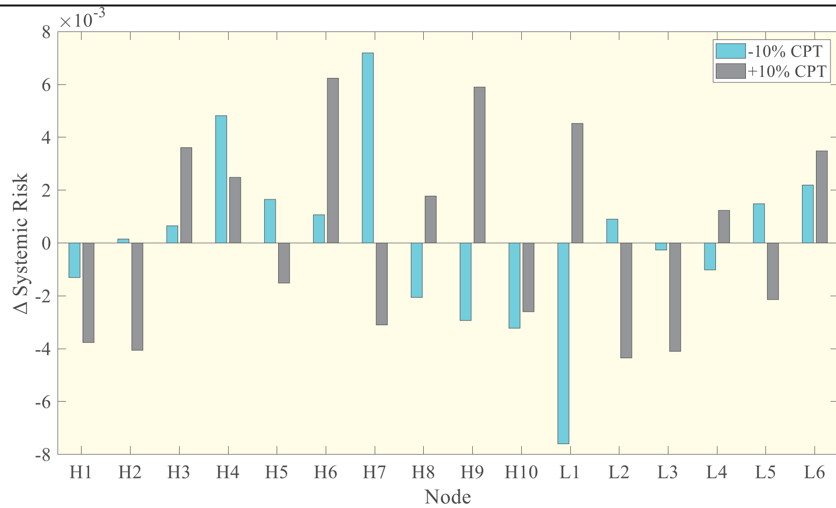

Figure 6.7

(b)-Case 2

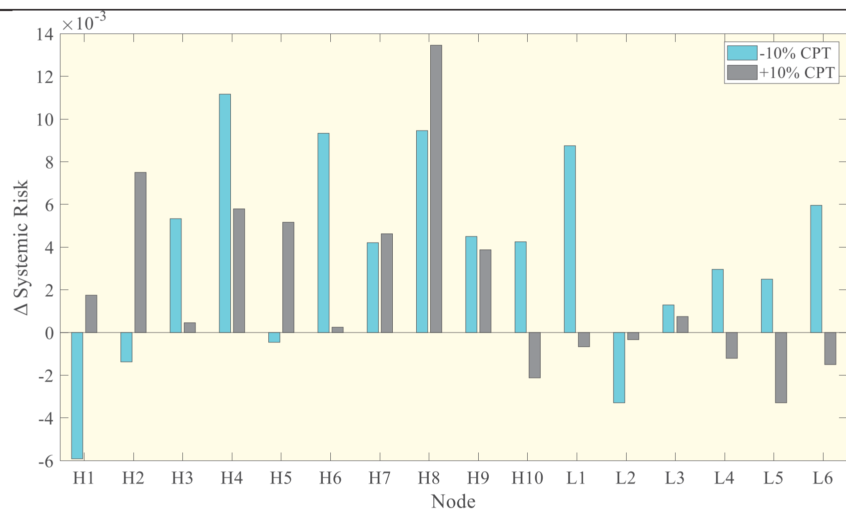

Figure 6.7

(c)-Case 3

Figure 6.7 Sensitivity to CPT perturbation (hazards + losses)

In Case 3, the CPT sensitivity analysis shows a broader and more amplified distribution of responses compared to previous cases, indicating that risk propagation is highly sensitive to changes in the conditional relationships among several Hazard and Loss nodes. Unlike the previous scenarios, where sensitivity was concentrated in a few elements, this case displays multiple high-impact nodes that collectively shape the systemic risk dynamics, often with asymmetric effects.

Among the Hazard nodes, H4 (Not providing precise and real-time data), H7 (Data security problem), H8 (Damage to the product during the process), and H9 (Release of harmful refrigerants due to improper disassembly) exhibit the most significant deviations. H8 stands out as the most critical, demonstrating the highest positive Δ Systemic Risk under increased CPT scaling, implying that strengthening its conditional dependencies considerably increases systemic risk. Its sensitivity suggests that H8 acts as a core amplifier—small probability increases in its hazard pathways have disproportionate effects on overall system severity. Similarly, H4 and H7 exhibit large positive shifts under decreased CPT scaling, indicating that reducing their CPT probabilities results in an escalation of risk. This pattern reflects their stabilizing function, as weakening these links reduces the model's ability to contain risk propagation toward severe loss states. H9 demonstrates sensitivity in both directions, showing an increase in risk under both increased and decreased CPT scaling, implying a fragile equilibrium—any perturbation, whether amplification or reduction, destabilizes the system equilibrium.

At the Loss level, L1 (Loss or injury to the worker), L5 (Loss of sensitive information), and L6 (Environmental loss) exhibit distinct but consistent patterns of asymmetry between the increased and decreased CPT perturbations. L1 shows a reduction in systemic risk when its CPT is decreased, with a negligible effect when increased. L5, conversely, demonstrates an increase in systemic risk when its CPT is decreased, and a reduction when its CPT is increased. L6 similarly displays a pronounced increase in systemic risk under decreased CPT scaling, accompanied by a reduction under increased CPT scaling. These varied patterns indicate that changes in their CPTs induce specific directional shifts in systemic risk, though the overall magnitudes remain moderate compared to the primary Hazard nodes. This collective behavior suggests these nodes operate under related pathways or dependencies, contributing distinctively to the system's downstream response rather than acting as independent amplifiers.

6.4.3.3 Structural sensitivity

The structural sensitivity analysis evaluates how the network's topology—the presence of specific parent–child links—shapes overall risk. For each directed edge in the DAG, we remove the edge (parent → child) while holding all CPTs and other structural elements fixed, then recompute the expected severity of the Risk node. The resulting ΔScore quantifies the edge's leverage on systemic behavior: positive values indicate that removing the edge raises risk (the link acts as a stabilizing or protective coupling in the baseline), whereas negative values indicate that removing the edge lowers risk (the link functions as a risk-amplifying conduit under current conditions).

Figure 6.8 reports the top 20 edges ranked by absolute impact (|ΔScore|) and visualized as green horizontal bars. This ranking surfaces the most consequential dependencies in the model—links whose presence or absence materially redistributes probability mass across high-severity routes. In practice, edges with large positive ΔScore are candidates for preservation or strengthening (they help contain escalation), while those with large negative ΔScore highlight amplifying pathways whose mitigation (through design changes, safeguards, or decoupling) can yield meaningful reductions in systemic risk.

In Case 1, the most influential structural dependencies appear among both Loss and Hazard pathways. A distinct pattern of significant risk amplification is observed for direct links from Loss nodes to the aggregate Risk node: L3 → R, L4 → R, and L2 → R all exhibit substantial negative Δ Systemic Risk upon removal. This indicates that these direct connections are strong amplifiers of systemic risk in the baseline configuration, and their removal substantially alleviates overall vulnerability. Other amplifying pathways include L6 → R, H10 → L6, H9 → L6, and L5 → R, all showing notable reductions in systemic risk when removed.

On the other hand, a prominent group of edges, including H6 → L5, H1 → L3, H2 → L5, and H5 → L5, yield substantial positive Δ Systemic Risk when removed. This indicates that these relationships serve as crucial protective couplings that help absorb uncertainty and limit escalation; eliminating them destabilizes the network and significantly increases overall risk. Other noteworthy protective links include H6 → L3, H9 → L1, CA3 → H10, H2 → L3, H5 → L3, CA2 → H10, CA7 → H9, CA1 → H7, and CA6 → H2. These consistently positive values highlight the importance of these connections in maintaining safety boundaries and overall system resilience.

Case 2 exhibits several highly influential risk-amplifying pathways where edge removal leads to a substantial reduction in systemic risk. L4 → R and L3 → R stand out as the most critical amplifiers. These direct links from specific Loss nodes to the aggregate Risk node are identified as primary drivers of systemic vulnerability. Their removal demonstrates the greatest alleviation of overall risk, suggesting that these loss outcomes have a pronounced and direct impact on the system's severity assessment. Other significant amplifying connections include L2 → R, H4 → L4, H3 → L4, H1 → L4, H2 → L4, and L5 → R.

In contrast, a set of edges acts as protective couplings, where their removal increases systemic risk, implying they help contain or channel risk in the baseline. The edge H1 → L1 shows the largest positive Δ Systemic Risk, indicating it is the most critical protective pathway in Case 2. Its presence is vital for managing H1's influence, and its removal significantly destabilizes the network by allowing risk to propagate more freely or severely elsewhere. Edges linking Control Actions to Hazards are also prominent protective mechanisms: CA4 → H2, CA1 → H5, CA7 → H5, CA8 → H5, and CA4 → H5. The consistent positive impact of removing these control action links underscores their fundamental role in restraining associated hazards (H2, H5) and thereby mitigating systemic risk.

Case 3 demonstrates pronounced risk amplification through direct connections from Loss nodes to the aggregate Risk node. L4 → R, L3 → R, and L5 → R are identified as the most critical amplifiers. Their removal leads to the most significant reductions in systemic risk, indicating that these direct loss outcomes are primary drivers of overall system vulnerability. Another substantial amplifying pathway is L2 → R, reinforcing the pattern that direct propagation from various loss categories to the overall risk assessment significantly elevates systemic severity.

Conversely, a set of edges functions as crucial protective couplings, where their removal increases systemic risk, signifying their role in containing or channeling risk in the baseline.

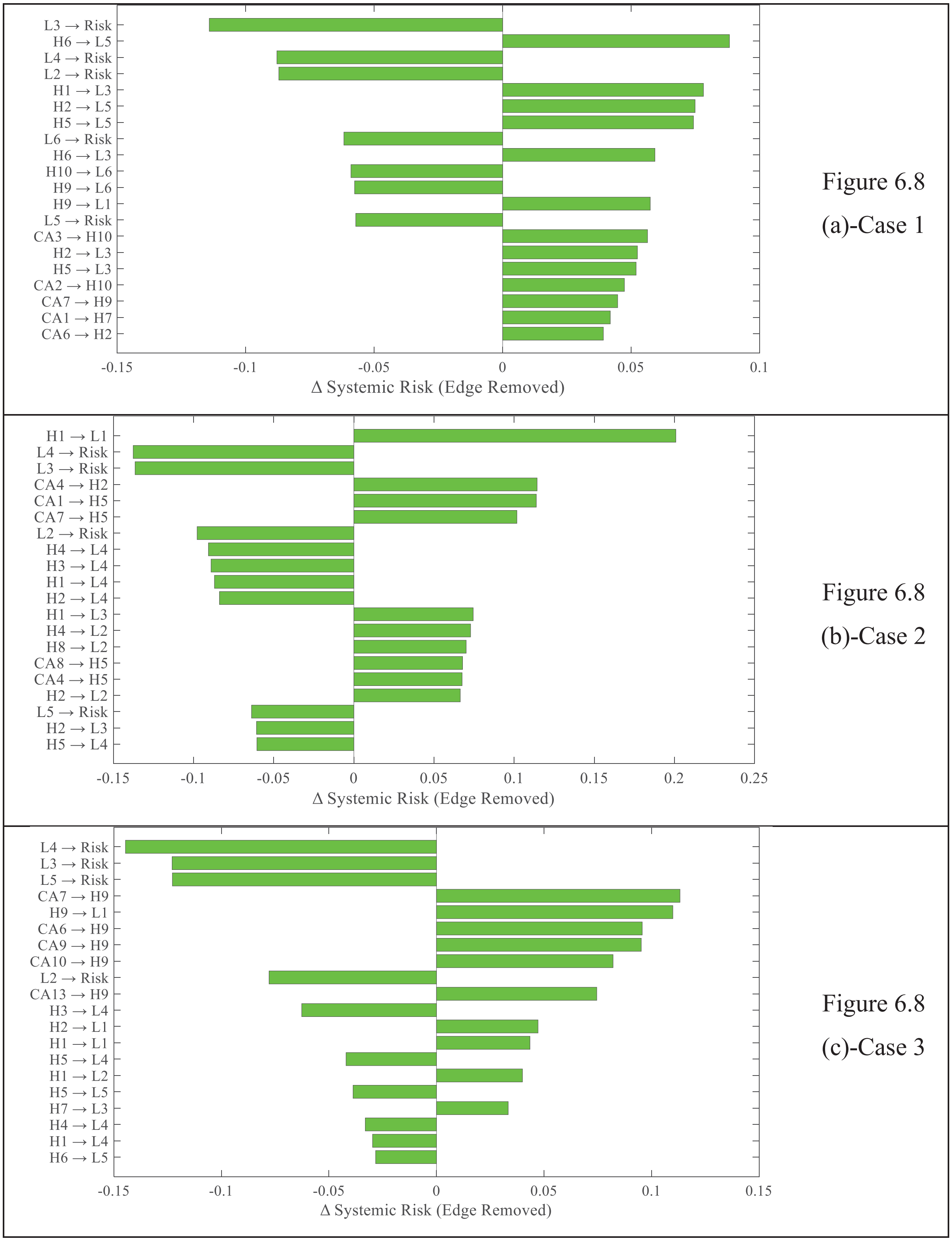

Figure 6.8 Top edges by structural impact

The most prominent protective links are those connecting Control Actions to Hazard nodes: CA7 → H9, H9 → L1, CA6 → H9, CA9 → H9, CA10 → H9, and CA13 → H9.
The concentration of these control action links directed towards H9 (Release of harmful refrigerants) indicates that the system heavily relies on various control mechanisms to manage this specific hazard. Their consistent positive impact upon removal underscores their fundamental role in restraining H9 and preventing broader risk escalation.

6.5 Discussion

A key contribution of BN lies in its ability to probabilistically capture how risks propagate across multiple system layers. Traditional risk analysis often stops at identifying unsafe control actions or hazards, but the hierarchical Bayesian Network allows dependencies to be represented explicitly and quantified through inference. The addition of PSO ensures that these probabilistic relationships are not arbitrarily assigned but are calibrated against both expert-driven priors (STPA-derived) and a plausible systemic risk profile. This dual mechanism strengthens the credibility of the resulting model and reduces reliance on subjective parameterization. One of the recurring challenges in systemic modeling is achieving a balance between transparency for decision-makers and quantitative robustness. STPA-BN-PSO addresses this tension by producing both numerical rankings and intuitive visualizations (e.g., path-weighted networks).
The results obtained across the three distinct case studies compellingly demonstrate the framework's adaptive diagnostic power. In the sequential assembly context (Case 1), systemic vulnerability was primarily centered around planning failures (CA12) and safety-critical losses. Conversely, in the job-shop environment (Case 2), communication and digital connectivity hazards (H6, H7) were identified as the primary drivers of risk. This reflects the increased complexity of the Human-Machine Interface (HMI) in decentralized layouts, where the reliability of information flow is the foundation of system resilience. Disassembly operations (Case 3), in contrast, revealed a convergence of multiple high-impact environmental (L6) and informational (L5) failures. These context-dependent shifts vividly illustrate the

framework's ability to reveal how systemic risk reorganizes under varying operational conditions, providing a level of diagnostic detail that exceeds traditional linear methods.

From a managerial perspective, the STPA-BN-PSO framework offers several strategic advantages for proactive risk management. First, the baseline quantification revealed that nearly one-third of potential outcomes fall into unacceptable risk states, highlighting the urgency of mitigation during wearable deployment. Second, the criticality and path-based analyses provide a data-driven prioritization tool, allowing decision-makers to target the specific control actions that exert the most leverage on the final risk state. Third, the multi-layer sensitivity analyses serve as a "what-if" simulator. They empirically demonstrate that targeted interventions, such as improving worker training reliability (CA6), can yield disproportionate reductions in systemic risk. This alignment between model predictions and the structural logic of the manufacturing system enhances confidence in the framework's actionable recommendations.

Despite its strengths, the STPA-BN-PSO framework has several identifiable limitations. Its structural foundation is directly dependent on the initial STPA output; any omissions at that foundational stage will inevitably propagate into the BN model. Furthermore, while the optimization process successfully reduces subjectivity in parameter estimation, it relies on assumed reference profiles to initialize the calibration. While the current study utilized these synthetic scenarios to demonstrate framework robustness and stability, future empirical validation utilizing diverse industrial datasets will be critical to confirm the framework's external validity across varied operational domains. The promising results point toward multiple directions for future development. Integrating real-time sensor data from wearable devices into BN priors could transform the framework into a semi-autonomous monitoring system capable of adaptive risk assessment. Furthermore, coupling STPA-BN-PSO with multi-criteria decision-making (MCDM) could further align risk mitigation with organizational and sustainability priorities.

A direct quantitative comparison with conventional methods like Fault Tree Analysis or manual Bayesian Networks was excluded due to their inability to model sociotechnical feedback or predict how risk pathways reorganize during the design phase. Conventional tools are fundamentally linear and reductionist, designed for mechanical systems that can be easily decomposed into independent, analyzable components. However, the wearable-enabled environments central to Industry 5.0 are not decomposable in this manner; systemic risks emerge from the complex interactions between humans, software, and physical devices rather than isolated component failures. Furthermore, these traditional tools require historical failure rates that are inherently unavailable in data-scarce early integration stages. In contrast, the STPA-BN–PSO framework uniquely bridges qualitative control logic and probabilistic quantification, capturing the non-linear interdependencies and emergent vulnerabilities that standard linear frameworks are less suited to represent in such highly coupled systems.

When placed in the broader context of hybrid frameworks, STPA-BN-PSO complements alternatives such as STPA-PSO and FRAM-PSO. As summarized in Table 6.7, each method offers a unique contribution: STPA-BN-PSO provides path-based, probabilistic quantification with path-sensitivity; STPA-PSO delivers an early-stage qualitative feedback loop; and FRAM-PSO integrates sustainability criteria into risk optimization.

Taken together, these methods form a layered strategy for Industry 5.0: STPA-PSO for qualitative hazard structuring, STPA-BN–PSO for proactive probabilistic quantification during the design and early integration phases, and FRAM-PSO for managing variability during continuous improvement. This toolkit allows practitioners to select the most appropriate method based on computational effort and industrial suitability. Specifically, the STPA-BN–PSO framework is uniquely suited for data-scarce environments at the design stage, where it provides the path-level diagnostic power necessary to predict how risk propagation pathways will reorganize before the system becomes operational. This fills a critical gap by allowing for safety-guided design in high-reliability industries where probabilistic evidence and systemic foresight are essential.

Table 6.7 Hybrid risk management framework comparison

Feature / Criterion	**STPA-PSO**	**FRAM-PSO**	**STPA-BN-PSO**
Focus	Identification and prioritization of unsafe control actions	Variability propagation and sustainability-driven mitigation	Probabilistic risk and path reorganization across CA–H–L–Risk layers
Limitations	Not capture probabilistic dependencies; High reliance on expert input; Can be time-consuming	High dependence on expert input for variability parameters; Subjectivity in defining damping/amplifying factors	Dependent on foundational STPA quality; Requires reference targets for calibration; Subjectivity in severity weighting
Best application stage	Early system design and safety validation	Both design and improvement stages, especially when sustainability is central	Design and early integration phases (proactive assessment)
Unique contribution	Semi-automated feedback loop for risk prioritization and mitigation	Integration of sustainability criteria into systemic risk optimization	Provides systemic, path-based quantification of risk reorganization in data-scarce environments
Computational effort	Moderate	High	Very high
Data acquisition effort	Requires UCA lists, probabilities, and impact ratings	Requires detailed function mapping, SPCs, and variability distributions	Requires structured reference risk profiles (simulated or expert-derived)
Expert elicitation	High (hazard/UCAs identification, impact weighting)	Very high (function definitions, variability values, SPC impacts, sustainability scoring)	High (STPA priors + some CPT calibration)

Feature / Criterion	STPA-PSO	FRAM-PSO	STPA-BN-PSO
Risk estimation bias	Possible bias in weighting and expert-driven ratings	Subjectivity in expert scoring of SPCs and sustainability pillars	Possible bias from assumed reference profiles and assigned severity weights
Best situations for use	When early design or integration stages require systematic hazard identification and prioritization; best for preliminary safety engineering	When sustainability trade-offs are central, or when decision-makers must balance environmental, economic, and social objectives in risk mitigation	When historical failure data is unavailable (early design stage); suitable for safety-guided design and predicting path reorganization
Industrial suitability	Complex socio-technical sectors (aviation, healthcare, rail, defense) where unsafe control actions must be identified early	Manufacturing, recycling, logistics, or energy sectors under strong sustainability mandates	High-reliability industries where proactive, path-level diagnostic power and probabilistic evidence are essential

6.6 Conclusions

This study introduced the STPA-BN-PSO framework as a probabilistic approach for assessing and managing systemic risks associated with the integration of smart wearables in complex Industry 5.0 manufacturing environments. By leveraging STPA-derived causal structures and calibrating probabilistic relationships through PSO, the methodology provides a robust and interpretable tool for proactive risk quantification during the design phase, where historical failure data is inherently scarce.

The application of the framework across three distinct manufacturing case studies yielded several key findings:

- **Quantitative risk profiling:** The results demonstrate that systemic risk is profoundly context-dependent. The Job-Shop environment (Case 2) exhibited the highest baseline unacceptable risk at 31.5%, while the sequential assembly line (Case 1) showed a lower baseline of 28.0%. This highlights the increased vulnerability created by the complex interdependencies and connectivity requirements of decentralized Industry 5.0 layouts.

- **Adaptive diagnostic power:** The framework successfully identified shifting risk drivers across operational contexts. In sequential operations, risk is primarily driven by planning quality (CA12), whereas in flexible job-shops, digital connectivity and information flow (H4, H5) are the primary amplifiers of systemic vulnerability.
- **Technical stability and rigor:** The PSO calibration process proved to be statistically stable across multiple independent runs. This confirms that the framework reliably identifies consistent model parameters despite the high-dimensional uncertainty inherent in sociotechnical systems.
- **Prioritization of human safety:** By utilizing a probabilistic weighted Risk node, the framework successfully prioritized safety-critical outcomes over technical losses. This ensures that the resulting risk assessments are aligned with the human-centric philosophy of Industry 5.0.

While STPA-BN-PSO advances systemic risk modeling, limitations include the current reliance on synthetic reference profiles for initial calibration and the structural dependence on the initial STPA output. Future research should prioritize extending the framework to integrate real-time sensor data from wearables into the BN priors, move toward semi-autonomous decision-support, and explore hybrid approaches that incorporate multi-criteria decision-making for broader organizational priorities.

In summary, this research establishes the STPA-BN-PSO approach as a powerful and interpretable tool that uniquely equips organizations to anticipate, prioritize, and mitigate the complex systemic vulnerabilities inherent in wearable-enabled manufacturing. Positioned strategically alongside design-oriented tools like STPA-PSO and sustainability-focused methods like FRAM-PSO, STPA-BN-PSO fills a critical operational gap in a comprehensive, layered risk-management stack tailored for the evolving landscape of Industry 5.0.

CONCLUSION

The objective of this thesis was to develop hybrid intelligent methods capable of addressing the systemic risks introduced by integrating multiple smart wearables—notably smart glasses and smart gloves—into modern manufacturing systems. While wearable technologies hold promise for enhancing worker guidance, ergonomics, and system monitoring, their adoption has also revealed new pathways of risk that are difficult to capture using traditional safety and reliability methods. This research has demonstrated that advancing beyond conventional approaches requires frameworks that integrate qualitative systemic modeling with quantitative optimization, enabling the assessment, prioritization, and mitigation of risks in socio-technical environments.

The literature review confirmed that classical methods, such as FMEA and FTA, remain valuable but are constrained by linear cause–and–effect reasoning, and the need to break down systems, which is not possible with complex systems. Systemic approaches such as STAMP–STPA, and FRAM capture feedback loops, variability, and emergent properties, but remain predominantly qualitative and provide limited support for quantitative decision-making. Similarly, Bayesian Networks offer a probabilistic framework but face challenges of parameterization and calibration in real-world contexts. This persistent gap between qualitative systemic insight and quantitative rigor formed the central problem addressed in this thesis.

To bridge this gap, three hybrid frameworks were proposed and validated across case studies in sequential assembly, job-shop assembly, and disassembly. Each method offers distinct strengths and is best suited to different phases of system development and risk management.

The STPA–PSO framework proved most effective during early system design and safety validation, when unsafe control actions must be systematically identified and prioritized before wearables are widely deployed. By combining STPA's structured identification of hazards with PSO's optimization capacity, the framework created a semi-automated feedback loop for risk prioritization and mitigation. Its strength lies in its clarity and direct applicability for preliminary safety engineering, particularly in complex socio-technical sectors such as aviation, healthcare, or defense. However, because the method relies on expert judgment for hazard identification and impact weighting, the results may vary depending on the expertise and context of contributors. Moreover, while the framework effectively leverages qualitative insights, its current formulation limits the explicit modeling of probabilistic dependencies without further integration of quantitative expert elicitation techniques, such as those discussed by O'Hagan et al. (2006), to derive subjective probabilities.

The FRAM–PSO framework was most valuable in contexts where variability propagation and sustainability trade-offs are central. It demonstrated how timing, precision, and performance variability across functions can amplify or dampen risks when multiple wearables interact, while simultaneously enabling mitigation strategies to be evaluated against social, economic, and environmental dimensions. This integration of sustainability into systemic risk analysis represents a novel contribution. FRAM–PSO is particularly well-suited to design and improvement stages in manufacturing, recycling, logistics, and energy sectors, especially under strong sustainability mandates. Yet, its application requires extensive expert elicitation to define functions, variability distributions, and sustainability scoring, which makes it demanding in terms of data and human resources.

The STPA-BN–PSO framework was best suited to the operational phase, when structured data or simulated evidence is available to support calibration. By optimizing conditional probability tables through PSO, STPA-BN–PSO enabled systemic and path-based risk quantification, probabilistic propagation across control actions, hazards, and losses, and powerful sensitivity analyses. It was particularly effective in high-reliability industries such as aerospace, nuclear, and chemical plants, where probabilistic calibration and evidence updating are essential. However, its reliance on priors and deterministic assumptions for risk nodes, and its very high computational and data acquisition effort, make it resource-intensive.

These findings yield three conclusions. First, the integration of multiple wearables creates systemic couplings that reshape the risk landscape in ways that demand hybrid systemic–quantitative analysis. Second, the three proposed frameworks are not alternatives but complements: STPA–PSO provides structure and early safety validation, FRAM–PSO captures variability and sustainability trade-offs, and STPA-BN–PSO delivers probabilistic depth and sensitivity analysis once data is available. Third, by embedding sustainability principles into systemic modeling, this research demonstrated that risk management can move beyond compliance toward alignment with broader industrial and societal objectives.

Overall, this thesis advances the state of systemic risk assessment by showing how risk models can be hybridized with metaheuristic optimization to bridge the gap between qualitative insights and quantitative rigor. It contributes theoretically by extending STPA, FRAM, and BN into hybrid intelligent frameworks; methodologically by validating them across assembly and disassembly case studies with multiple wearables; and practically by providing tools that can achieve measurable reductions in systemic risk while supporting sustainable technology adoption. More broadly, this work reaffirms the vision of Industry 5.0, where humans and advanced technologies collaborate rather than compete. By equipping researchers and decision-makers with rigorous methods to assess and manage the risks of human–machine collaboration, this thesis contributes to the safe, reliable, and sustainable integration of wearable technologies in the factories of the future.

RECOMMENDATIONS

The limitations of this dissertation point to several important directions for future research and practical application.

1. One important limitation was the reliance on simulated case studies. Next step, therefore, is the validation of the proposed methodologies with real-world data from industrial partners or an infrastructure like CEOSNet. Such validation would not only strengthen the credibility of the models but also shed light on the practical challenges of implementation in dynamic manufacturing environments.
2. Another priority lies in the improvement of expert elicitation and tailored weighting techniques. Building on the existing structured approach, future work could benefit from adopting formalized elicitation protocols that are already well-established and employed in various fields for quantifying expert judgment, to further strengthen the consistency and transparency of probability estimates and impact ratings in systemic risk assessment. Such practices may promote greater consistency in model calibration, as they establish clear guidelines for the integration and weighting of expert judgments.
3. The scope of application also remains restricted. This dissertation focused on sequential assembly, job-shop assembly, and disassembly processes, yet the proposed frameworks may hold broader relevance. Future studies should test them across diverse industries, task complexities, and combinations of wearable technologies. Moreover, ergonomic and usability aspects were not addressed in depth. Integrating ergonomic evaluation with systemic risk assessment would allow for a more holistic understanding of how wearables influence both system performance and worker well-being.
4. A further avenue for research is to move beyond short-term impacts. Current analyses focused primarily on immediate performance and safety outcomes; however, there is increasing regulatory and societal interest in long-term value creation. Future studies should therefore adopt extended time horizons and include long-term key performance indicators that capture sustainable impacts on productivity, safety, and worker health.
5. Finally, future work should explore alternative optimization algorithms and further validation of computational strategies. Comparing PSO with other metaheuristics or

hybrid learning approaches would help identify the most effective methods for calibrating systemic models under uncertainty. Such comparisons would also clarify the trade-offs between computational efficiency, accuracy, and interpretability.

By addressing these research directions, the frameworks developed in this dissertation can be further refined and adapted to meet the evolving needs of Industry 5.0. This, in turn, will ensure that wearable integration in manufacturing advances not only safety and efficiency but also sustainability and human-centered innovation.

ANNEX I

LIST OF PUBLICATIONS RELATED TO THE THESIS

Peer-reviewed journal papers

1- Karevan, A. & Nadeau, S., 2026. Integrating smart glasses and smart gloves in hybrid assembly: an STPA-based risk management framework. *Robotics and Computer-Integrated Manufacturing*. 100, 103253. https://doi.org/10.1016/j.rcim.2026.103253

2- Karevan, A. & Nadeau, S., 2025. FRAM-PSO: Sustainability-driven framework for complex systems risk mitigation. *Computers & Industrial Engineering*. 210, 111560. https://doi.org/10.1016/j.cie.2025.111560

3- Karevan, A. & Nadeau, S., 2024. A comprehensive STPA-PSO framework for quantifying smart glasses risks in manufacturing. *Heliyon,* 10, 9, e30162. https://doi.org/10.1016/j.heliyon.2024.e30162

4- Karevan, A. & Nadeau, S., Submitted. STPA-BN–PSO: a hybrid probabilistic framework for managing systemic risks in human-centric wearables-enabled manufacturing. *Computers & Industrial Engineering*. (Submitted on 02/022026).

Peer-reviewed conference papers

1- Karevan, A. & Nadeau, S., 2024. Fostering AI-human collaboration in Industry 5.0 manufacturing. *Proceedings of the 22nd Congress of the International Ergonomics Association*, Volume 2. IEA 2024. Springer Series in Design and Innovation, vol 40. Springer. https://doi.org/10.1007/978-981-96-8908-8_69

2- Karevan, A. & Nadeau, S., 2024. FRAM effectiveness in the era of Industry 4.0: A dual perspective review. *IISE Annual Conference*. Proceedings, 1-6. Canada. https://doi.org/10.21872/2024IISE_6792

3- Karevan, A. & Nadeau, S., 2023. The role of Industry 5.0 in reducing the risk of human error in manufacturing- a critical literature review. *CIGI-QUALITA MOSIM 2023*, 1-8. Canada. https://doi.org/10.60662/00a1-5g45

Vulgarization activities

1- Karevan, A. & Nadeau, S. 2025, Making manufacturing smarter, safer and more sustainable, *Substance article ÉTS*, [Link]

2- Karevan, A. 2025, PSO-STPA model: case study of an Industry 4.0 plant using smart glasses, 30 minutes online presentation, *IEA Resilience Engineering Committee*, [Link]

3- Karevan, A. 2025, Risks of using smart glasses in an Industry 5.0 plant, 3-minute presentation, *CAÉC (Congrès Annuel des Étudiants Chercheurs) ÉTS*

4- Karevan, A. 2025, Empowering humans, not replacing them, 3-minute presentation, *3Minutes Thesis ÉTS*

5- Karevan, A. 2024, Wearable risks in manufacturing, 10-minute presentation, *CAÉC (Congrès Annuel des Étudiants Chercheurs) ÉTS*

ANNEX II

CONFERENCE PRESENTATION – CIGI QUALITA MOSIM 2023

The Role of Industry 5.0 in Reducing the Risk of Human Error in Manufacturing- A Critical Literature Review

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Abstract

With technological advances in the modern workplace, no illustration would be complete without mentioning those related to IoTs and especially wearable devices. Industry 5.0 is expected to enhance the relationship between machines and humans as part of the fifth industrial revolution by making it easier for humans to use intelligent machines. Operators can use IoTs to reduce human errors; however, the use of this technology can also add new risks to the production system. Human reliability analysis must therefore be used to attempt to estimate the extent to which human error contributes to both qualitative and quantitative risks. In this study, a critical review of the existing literature is presented based on PRISMA. Based on the inclusion and exclusion criteria, 22 articles were considered relevant for review. Several keyword combinations in English were used, including human error, Industry 5.0, IoT, wearables, complex systems, and manufacturing. Scopus and Web of Science were used to find such keywords from 2013 to 2023. The results demonstrate the need for a reliable and comprehensive model to assess the human error risks related to using IoTs in manufacturing. A basis for future research will be provided by the results of this study.

***Keywords**:* Critical review, Human error, Industry 5.0, Complex systems, Risk analysis

1 Introduction

Over the past decade or so, manufacturing companies have been getting more aware of the great benefits provided by Industry 4.0 (I4.0) and data science, and armed with that knowledge, they have moved toward this industry (Angelopoulou et al., 2020). Modern manufacturing methods increasingly involve fewer human interventions, thanks to the use of new technologies such as wireless sensor networks, big data, embedded systems, and cloud computing (Angelopoulou et al., 2020; Jasiulewicz-Kaczmarek & Gola, 2019). One of the main motivations underlying the use of digital technologies is the time and cost reductions they bring (Stahn et al., 2022).

However, there is little emphasis on human performance, despite the German definition of Industry 4.0, which places humans at the center. Industry 4.0 systems are complex, and neglecting the human element could have adverse effects on their performance (Angelopoulou et al., 2020). Furthermore, from an economic perspective, some modern equipment could be expensive (Reiman et al., 2021). Even though mass production is the main aim and focus of Industry 4.0, it does not appear to be environmentally friendly. Also, it is not human-centered. Consequently, because of its technology-driven nature, Industry 4.0 has led to some concerns regarding job losses due to the integration of digital, smart, connected, and autonomous technologies (Demir & Cicibaş, 2019). The increased complexity of manufacturing and the increased demand for human operators' skills are expected to result from this mass customization (Torres et al., 2021b).

All these issues led to the introduction of Industry 5.0 (I5.0) less than a decade after Industry 4.0 came to be. The former aims to help factories return to maximum productivity and to make effective use of modern technology (Nahavandi, 2019). There is now a need not just for intelligent machines, but also for humans to be able to use the underlying technologies (Reiman et al., 2021).

A key component of Industry 5.0 is the idea that humans can combine their innovation and knowledge with the productivity of machines and equipment as well as their speed of execution, such as collaborative robots, to achieve the most efficient results. Using robots, humans can perform their most valuable tasks and responsibilities more efficiently while improving safety, productivity, and performance (Gaiardelli et al., 2021). By combining human intelligence and creativity with intelligent, precise, efficient machines, the fifth industrial revolution focuses on bringing humans back into production (Sharma et al., 2020).

The Internet of Things (IoT) could be considered one of the main foundations of these technologies. IoT can collect data from the environment and communicate with other objects. It can thus be used in numerous industries, based on the specifications of the latter (Naeini & Nadeau, 2022b). Sensors connected to outputs, inputs, components, materials, or tools in manufacturing are known as the Internet of Things (Riso, 2021). IoT enables digital devices equipped with sensors to connect and transmit, store, and process data seamlessly in real-time (Riso, 2021). By integrating IoT with factory processes, manufacturers can reduce human decision-making and create 'smart factories' with highly connected and digitalized factories (Riso, 2021).

Electronic monitoring systems and wearable computing devices are also part of the IoT. These devices are used for a variety of purposes, including monitoring work processes and employee performance, which ultimately guides management decisions (Riso, 2021). Applications installed on mobile operating systems (OS) can be used on wearable devices to provide additional functionality beyond health and fashion (Kim & Choi, 2021). It is near-impossible to find an illustration symbolizing current changes in the workplace today that does not include wearable technology, such as data glasses or smartwatches (Krzywdzinski et al., 2022), among others.

Although robots can reduce human errors, they cannot eliminate them completely. In fact, they may add new threats to the system, such as the inability of workers to make optimal use of machinery (Reiman et al., 2021). It is expected that Industry 5.0 will refine the relationship between machines and humans as part of the fifth industrial revolution. The precision of technology and human creativity and intelligence are more closely combined in this revolution than they are separate entities (Raya, 2022).

Human reliability, on the other hand, is strongly correlated with manufacturing costs, safety, and performance (Aalipour et al., 2016). Human error can lead to wrong actions and decisions and increase production costs (Mannan, 2013; Singh & Kumar, 2015). An interesting fact is that between 50% and 90% of incidents reported in the industry relate to human errors (Castiglia & Giardina, 2013).

Qualitative and quantitative methods are used in human reliability analysis to determine the extent of human contribution to risks (Bell & Holroyd, 2009). It has been possible to estimate the probability of human error using numerous methodologies (Kirwan, 1992; Torres et al., 2021a). Despite this, little research has been conducted on the risks associated with IoT use in complex systems (Naeini & Nadeau, 2022b).

The main aim of this paper is to conduct a critical literature review to analyze the literature on the risk of using IoTs in the manufacturing process, and to find the gap for future studies.

This paper is organized as follows: Section 2 describes the methodology of the literature review. Section 3 presents the results, while the discussion is conducted in Section 4. Finally, the conclusion is given in Section 5.

2 Methodology

Literature searches were conducted using Scopus and the Web of Science (WOS). There are more than a thousand titles and journals in these two databases, making them among the most popular search engines among researchers. These databases also index a wide range of sources, including scholarly articles, books, conference papers, and other published works. Furthermore, they provide access to a variety of citation metrics, making it easier to evaluate the impact of a particular research paper (Zorzenon et al., 2022).

In this study, the PRISMA, Preferred Recording Items for Systematic Reviews and Meta-Analyses, 2020 statement was used to conduct a systematic review of the literature (Page et al., 2021).

As can be seen in Table 1, different categories were used to achieve the most effective results. Each keyword, if it has any abbreviations, was applied for the research term. For example, we used both “OHS” and “Occupational Health and Safety”.

Table-AII-1 Keywords

			
Human error	Manufacturing	Risk	Industry 5.0
Human reliability	Industry	Risk analysis	Industry 4.0
OHS	Assembly	Risk management	IoT
	Disassembly		Wearable
	Production		Glass
	Complex systems		Glove

The literature analysis was conducted using the search string presented in Table 2, which was used to search through the mentioned databases from January 2013 until March 2023.

Table-AII-2 Definition of the search strings

Significant term	**Search term**
Human error	[“human error” OR “human reliability” OR “Occupational Health and Safety” OR “OHS”]
AND	
Manufacturing	[“manufacturing” OR “complex system” OR “industry” OR “production” OR “assembly” OR “disassembly”].
AND	
Risk	[“Risk” OR “risk analysis” OR “risk management”]
AND	
Industry 5.0	[“Industry 5.0” OR “I5.0” OR “Industry 40” OR “I4.0” OR “wearable” OR “glass” OR “glove” OR” IoT” OR “Internet of Thing”]

In this review, we only focus on English-written documents. Also, the search period is from January 2013 until March 2023. Figure 1 shows the PRISMA flowchart. The exclusion criteria are presented in Table 3.

Table-AII-3 Exclusion criteria

Criteria	**Description**
Language	If the language of the document was other than English
Source type	If the document was not a journal paper, conference paper, or review paper
Availability	If the document was not available to read
Eligibility	If the document was not related to this study

For the eligibility criteria, different situations may be considered as shown in Table 4. This table outlines the various factors that must be taken into consideration when determining eligibility.

Table-AII-4 Eligibility criteria

Scope	• Manufacturing • Assembly/disassembly • Industrial plants
Risk type	• Human error • Industrial equipment failure
Other	• Using IoTs or wearables

3 Results

3.1 Initial results of the literature search

Searching keywords in the databases yielded 95 documents in Scopus and 37 in WOS. A spreadsheet was used to exclude 23 duplicate papers. Out of 109 remaining documents, 8 of them were not in English, and 9 of them were not available for download.

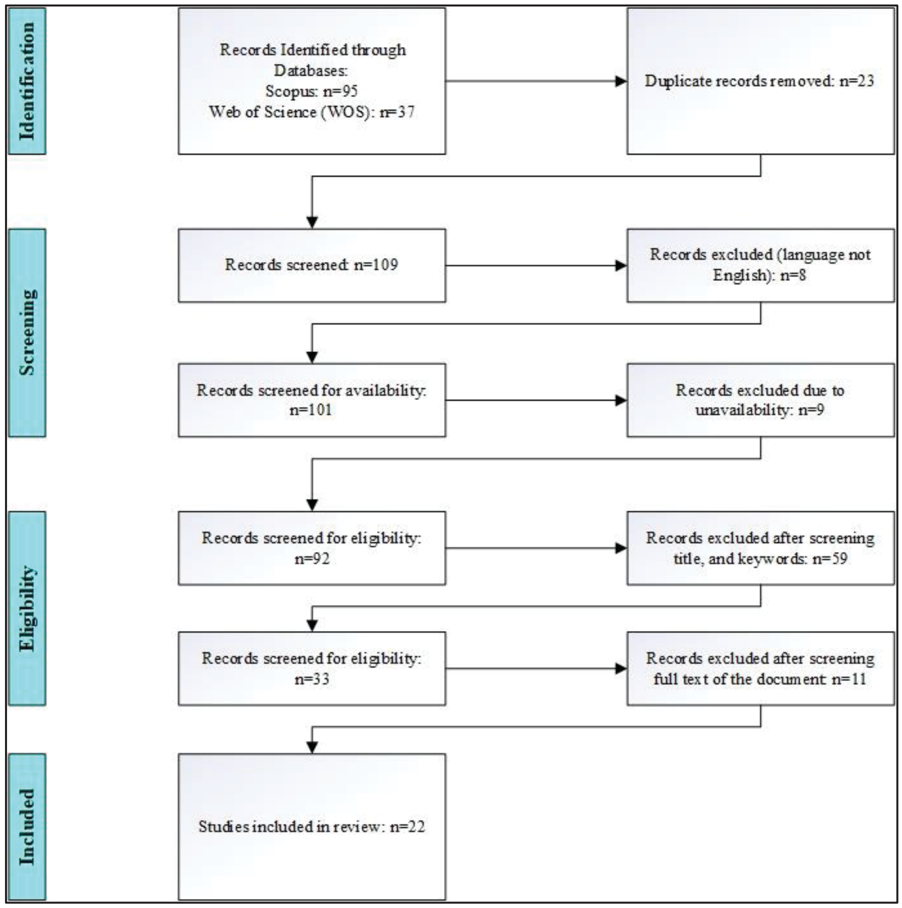

Figure-AII-1 PRISMA flowchart for this study

A first screening of the 92 documents revealed that 59 were unrelated to this study based on their title and keywords. After reading their full texts, 11 papers were also excluded. The remaining 22 papers went through a full-text analysis to extract relevant data. Descriptive statistics were used to analyze the data and results were reported.

The following facts are taken from the papers included in this review. As shown in Figure 2, the most common type of documents are journal articles and review papers, which compose 68% of all documents. Conference papers make up approximately one-third of the documents.

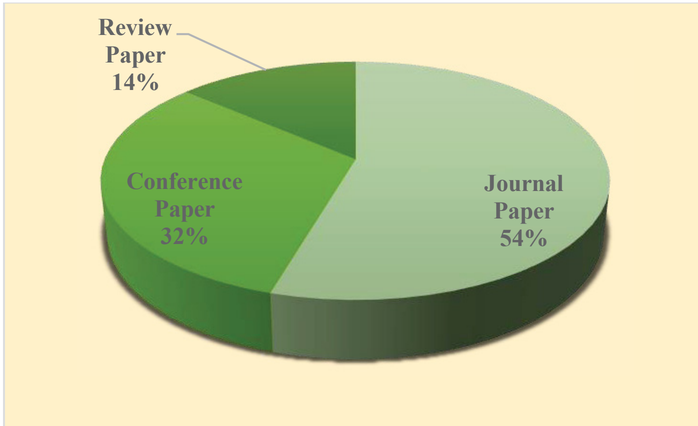

Figure-AII-2 Document type

Table 5 lists the journals and the number of papers that they published and linked to this study. Except for "Computers and Industrial Engineering", "Robotics and Computer-Integrated Manufacturing", and "Safety Science", which each had two articles in this review, other journals had one paper in this review. Additionally, Figure 3 shows that more than two-thirds of the papers were published in "Elsevier" and "Springer". This indicates that "Elsevier" and "Springer" are the leading publishers in this field.

Table-AII-5 Journal title

Journal Title	Frequency
Computers and Industrial Engineering	2
Robotics and Computer-Integrated Manufacturing	2
Safety Science	2
Advanced Intelligent Systems	1
Process Safety and Environmental Protection	1
CIRP Journal of Manufacturing Science and Technology	1
Complexity	1
Heliyon	1
International Journal of Environmental Research and Public Health	1
Safety	1
Smart and Sustainable Manufacturing Systems	1
SN Applied Sciences	1

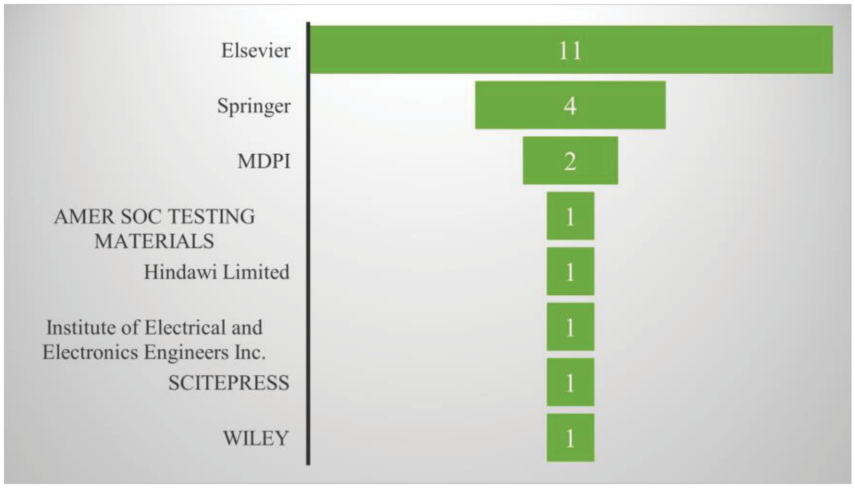

Figure-AII-3 Publishers

Figure 4 also provides a detailed overview of the publications used in the study, in order of their year of publication. There is no doubt that the trendline from 2018 is upward. This indicates a positive outlook for the future.

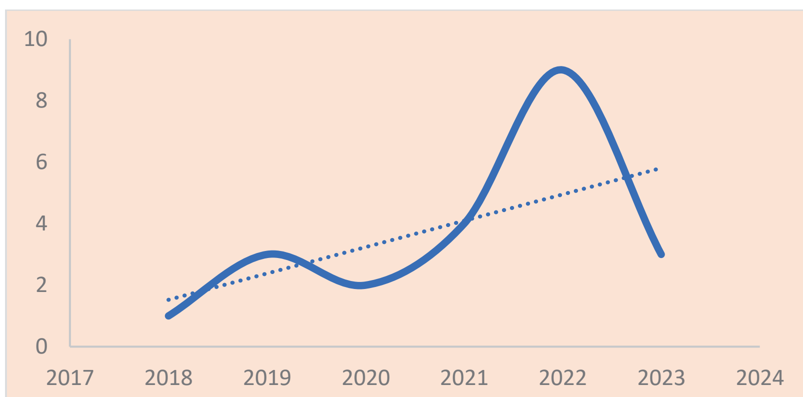

Figure-AII-4 Papers published each year

Our keyword network analysis was performed using VOSviewer software, as shown in Figure 5. As shown by the nodes and their sizes, each word was cited a proportionate number of times. If the words appear in the same article, the nodes are connected. Increasing co-citations intensified the connection between two nodes. By analyzing the included papers, 293 keywords were found. In order to qualify as a co-citation, each word had to be mentioned at least two times, which made 52 keywords. It is demonstrated that, OHS, Industry 4.0, accident prevention, and industrial hygiene are the most used keywords in these references.

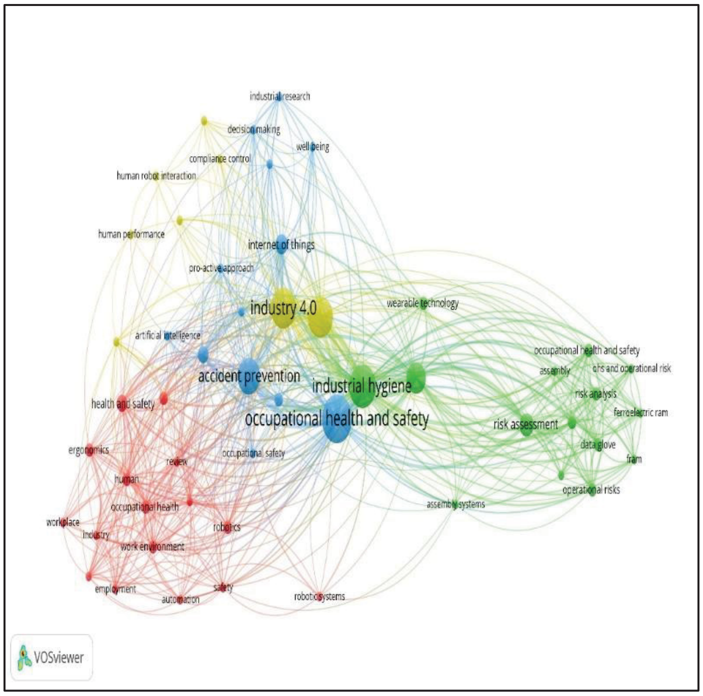

Figure-AII-5 Bibliometric analysis of the keywords with VOSviewer program

Figure 6 shows the geographic distribution of the articles included in the study. Overall, the study includes 22 articles from 12 countries. A majority of publications were published in Canada (n = 5), followed by Brazil, Italy (n = 3), Portugal, and the United States (n = 2). There is one article from each of the following countries: Algeria, Belgium, France, Poland, Slovakia, Spain, and Turkey.

Figure-AII-6 Geographical distribution

3.2 Depth results of the included documents

In this section, the included papers were analyzed by their main objectives presented in Table 6.

Table-AII-6 Main objectives of the included papers

Reference	Main objectives
(Arana-Landín, Laskurain-Iturbe, Iturrate, & Landeta-Manzano, 2023)	An examination of the impact of Industry 4.0 technologies on OHS risks, with particular focus on new emerging risks.
(Mofidi Naeini & Nadeau, 2023)	To analyze OHS and operational risk related to Industry 4.0 assembly, integrate FRAM and STPA by using two case studies in order to support their model.
(Zarei, Khan, & Abbassi, 2023)	Human factors analysis can be enhanced by integrating artificial intelligence and expert systems. This review mainly examined the application of machine learning and deep learning techniques as well as knowledge/data-driven modeling to Human factors analysis. A number of myths, misapplications, and critical concerns were highlighted in this work.
(El Helou et al., 2022)	An image processing and analysis system for machine inspection and conformity control of machined parts is proposed in this paper using smart vision technologies embedded in industrial robots. An agile and customized configuration is enabled by the solution's modular user interface for human–machine interactions.
(Hayat & Reda, 2022)	Emphasize the importance of integrating the spatial dimension into the monitoring of individual and continuous occupational risk exposure.
(Teixeira, Ferreira, & Gonçalves, 2022)	A smart sole solution that collects workers' postural data and alerts them, when necessary, ultimately supporting their wellbeing

Reference	Main objectives
(Mofidi Naeini & Nadeau, 2022c)	Analyzing the risks associated with introducing a data glove to an assembly system and reducing them through STPA.
(Zorzenon et al., 2022)	This study examined the impact of Industry 4.0 technologies on occupational safety and health; it also examined the impact of Industry 4.0 technologies on safety and health management systems in a company, as well as identifying potential risks associated with them.
(Patel, Chesmore, Legner, & Pandey, 2022)	In order to address OHS and productivity, they intend to provide a comprehensive analysis of commercial wearables and connected worker solutions. As well as to include technologies that already exist or can be used in a variety of work environments.
(Mofidi Naeini & Nadeau, 2022a)	Applying FRAM to analyze the OHS and operational risks of using data gloves in assembly with two different case studies to support the model.
(Gualtieri, Rauch, & Vidoni, 2022)	As part of this work, guidelines for developing safe human-robot collaborative assemblies are developed, focusing specifically on the system's features. In this work, a set of structured guidelines is presented to simplify the design process for the features defining a CAS from the perspective of preventing mechanical hazards. The digital twin model and laboratory case study are used to validate these results.
(Di Pasquale, De Simone, Radano, & Miranda, 2022)	Discuss how wearable devices can be used to monitor worker safety and health by focusing on physiological and movement variables or signals and how those relate to workers' conditions such as fatigue or stress.
(Bavaresco, Arruda, Rocha, Barbosa, & Li, 2021)	The study outlines the impact of IoT on occupational well-being for the period 2009 to 2019.

Reference	**Main objectives**
(Silva, Coelho, & Delabrida, 2021)	Several promising solutions are presented to support human activities in confined spaces in this work, which examines technologies used in the industry. The purpose of this project is to analyze and develop augmented reality devices for these environments under these perspectives.
(Pauliková, Gyurák Babeľová, & Ubárová, 2021)	In addition to identifying positive effects, the research was aimed at identifying negative effects in human–cobot interactions (HCI) while meeting the requirements for health and safety at work as well as ensuring the production process meets quality standards. We conducted this research to determine which negative effects may be caused by HCI, and then propose preventive and corrective measures based on this identification.
(Lolli et al., 2021)	Through the use of a multi-criteria approach, occupational risk is assessed. It is indeed possible to assess the dynamic, individual, and integrated risk that a worker is subjected to over time by using a TOPSIS approach after pre-processing the time series using a segmentation algorithm.
(Adem, Çakit, & Dağdeviren, 2020)	In this study, they are investigating three objectives: investigating OHS risks that may arise with Industry 4.0 integration in production environments; identifying and categorizing these risks; and prioritizing them.
(Polak-Sopinska, Wisniewski, Walaszczyk, Maczewska, & Sopinski, 2020)	List some recommendations regarding the integration of OHS into manufacturing in the context of Industry 4.0 and its effects.
(Barata & da Cunha, 2019)	Provide a comprehensive solution for their adoption in OHS

Reference	Main objectives
(Brocal et al., 2019)	Human-Machine Interactions and Human-Robot Interactions are examples of complex systems that are linked to emerging risk management. The objective of this paper is to propose an organizational and human performance approach to improve risk management associated with such complex systems.
(Adriaensen et al., 2019)	For an assessment of the abruptly changing hazards introduced by Industry 4.0, this paper proposes a new paradigm and safety method based on complexity thinking and theories derived from complex adaptive systems. In spite of this, this review demonstrates that no single solution-fits-all approach exists.
(Badri et al., 2018)	In this article, the authors aim to provoke reflection regarding OHS integration into Industry 4.0 by raising related questions. They discuss the challenges and opportunities of integrating OHS into Industry 4.0 and how this can create new risks and opportunities.

Based on the table above, most papers aimed to investigate the use of IoTs on OHS. Occupational health and safety risks can be reduced through Industry 4.0 applications such as the Internet of Things, Robotics, and Virtual and Augmented Reality (Arana-Landín et al., 2023). However, just 13% of the papers analyzed the risk of using IoTs in manufacturing.
As shown in Table 7, we intend to extract information from the literature and to accomplish the study's primary objective. The three parameters that were investigated involved the type of IoT being used, quantitative or qualitative methods of assessing risk, and approaches for analyzing risk. By examining these parameters, we were able to gain a better understanding of the risks associated with IoT technology and the potential solutions that can be implemented to mitigate those risks.

Table-AII-7 Included paper's specifications

Reference	IoT used	Qualitative /Quantitative	Risk analysis method
(Hayat & Reda, 2022)	A system that measures occupational health risk exposure to follow digital workplace transformation	Qualitative	N/A
(Mofidi Naeini & Nadeau, 2023)	Data glove		FRAM/STPA
(Bavaresco et al., 2021)	Various		N/A
(Barata & da Cunha, 2019)	Structured sensors		N/A
(Teixeira et al., 2022)	Smart soles		N/A
(Arana-Landín et al., 2023)	N/A		N/A
(Mofidi Naeini & Nadeau, 2022c)	Data glove		STPA
(Adriaensen et al., 2019)	N/A		Comparaison of different methods
(Silva et al., 2021)	AR glasses		N/A
(Zorzenon et al., 2022)	N/A		N/A
(Badri et al., 2018)	N/A		N/A
(Zarei et al., 2023)	Data-driven models		N/A
(Patel et al., 2022)	Various		N/A
(Mofidi Naeini & Nadeau, 2022a)	Data glove		FRAM
(Di Pasquale et al., 2022)	Various		N/A
(Brocal et al., 2019)	N/A		N/A

Reference	IoT used	Qualitative /Quantitative	Risk analysis method
(El Helou et al., 2022)	Smart vision system embedded in industrial robot	Qualitative	N/A
(Polak-Sopinska et al., 2020)	N/A		N/A
(Pauliková et al., 2021)	Cobots	Quantitative	N/A
(Gualtieri et al., 2022)	Digital twin		N/A
(Lolli et al., 2021)	N/A		Fuzyy TOPSIS
(Adem et al., 2020)	N/A		Hesitant Fuzzy AHP

Additionally, we were able to gain insights into the current state of the industry and identify potential areas for further study.
According to the above table, only 18% of the papers analyzed the risk quantitively, and the rest were qualitative. From another perspective, just three of them (13%) analyzed the risk of using wearables (IoTs) with a risk management method (FRAM and STPA); however, they are qualitative approaches.

4 Discussion

By combining human intelligence and creativity with intelligent, precise, efficient machines, the fifth industrial revolution focuses on bringing humans back into production (Sharma et al., 2020). A key element of Industry 5.0 is human-machine collaboration (Raya, 2022). By assigning repetitious tasks to these new technologies, Industry 5.0 can improve production quality by empowering humans to think critically and creatively (Maddikunta et al., 2022). Using fully digitalized tools and a set of fully computerized tools, humans will be able to create a unique product in manufacturing with minimal efficiency and input from humans (Javaid & Haleem, 2020).

This revolution helps industries to be more sustainable. In such a way, besides achieving economic objectives, this concept aims to ensure that human (worker) remains at the center of the production process; and is Environment-friendly because it uses renewable energy and wastes less (Javaid & Haleem, 2020; Xu et al., 2021).

By linking manufacturing resources with the IoT, the entire production process can be monitored and optimized. Wearables will enhance and expand the potential of IoT in the industrial environment (Hao & Helo, 2017). The goal of wearable technology in the workplace is to provide employees with situation-specific information, thus enabling them to maximize their performance, while also collecting and feeding data to the company's IT systems. Wearables function as interfaces that provide employees with relevant information and enable them to use both hands (Krzywdzinski et al., 2022). The IoT is characterized by wearable technologies, which have been shown to enhance employee productivity by 8.5 % and improve life as well as job satisfaction by 3.5 % (Hao & Helo, 2017; Nadeau et al., 2021).

It is critical to design a workplace based on the physical and cognitive needs of workers, with a suitable balance between humans and machines (Alogla & Alruqi, 2021). Even so, human errors will continue to be a part of the industry. Humans are susceptible to cognitive and operational errors caused by long-term stress, for example. The consequences of human error in emergencies can include death, injury, disruption, and psychological effects; there can be environmental consequences as well (Abbassinia et al., 2020). The proportion of worker errors can be reduced by designing prevention systems (Alogla & Alruqi, 2021).

Several factors can lead to human error, including inadequate operator qualifications, inaccuracy of the operator during work, inattention, and misunderstanding of instructions (Stojiljkovic et al., 2018). Human errors can be reduced by these new technologies, but they are not necessarily eliminated entirely. Indeed, they might have the opposite effect, leading workers to make inefficient use of machinery (Reiman et al., 2021). Thus, it is essential to analyze the risk of using these IoTs in the process (Naeini & Nadeau, 2022a). Also, the usability of FRAM and STPA was demonstrated in this type of problem (Naeini & Nadeau, 2022a, 2022c, 2023).

After analyzing the literature presented in section 3, it was concluded that unless there is a significant increase in papers that discuss the use of IoTs in manufacturing and complex

systems, few studies have explored the risks associated with the use of these technologies. Furthermore, no quantitative study has been found that analyzes these risks.
The results of this work provide a basis for researchers to analyze this gap and assess the human error risks associated with the use of IoT in complex systems.
The following limitations were demonstrated in this study:

- Language: All publications used in this study are in English. This means that any studies published in other languages were not considered, which could lead to an incomplete or inaccurate representation of the research subject.
- Database: Only Scopus and Web of Science databases were used in this study. Moreover, citations from these databases were carefully analyzed to gain deeper insights into the study's findings.
- Period: Results from 2013-2023 were analyzed. The analysis revealed a clear trend in the findings over the ten years, allowing for a deeper understanding of the data.

5 Conclusions

By making intelligent machines easier to use, Industry 5.0 will facilitate man-machine communication. IoTs and particularly wearable technologies have become such an integral part of the modern workplace that creating an illustration without them today would be impossible. Although IoTs can facilitate production processes and have many benefits, they can also pose several risks to workers. This study reviews the current literature in that regard.
As part of the review, we aim to analyze the literature to identify gaps in assessing the risks associated with the use of IoTs, such as wearables, in complex systems such as manufacturing. Based on the PRISMA statement method, and by defining exclusion criteria, 22 papers were included for further analysis.
This study shows that during the past five years, IoT use has increased in the manufacturing sector. Also, some studies have analyzed the impact of evolving technologies on OHS. However, very few studies have focused on the human error risk of using these technologies in manufacturing. Interestingly no study quantifies these risks. Therefore, it is crucial to

examine the risks of including these technologies in complex systems, and more studies should be done in this area.

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References

Aalipour, M., Ayele, Y. Z., & Barabadi, A. (2016). Human reliability assessment (HRA) in maintenance of production process: a case study. International Journal of System Assurance Engineering and Management, 7(2), 229-238.

Abbassinia, M., Kalatpour, O., Motamedzade, M., Soltanian, A., & Mohammadfam, I. (2020). Dynamic human error assessment in emergency using fuzzy Bayesian CREAM. Journal of Research in Health Sciences, 20(1), e00468.

Adem, A., Çakit, E., & Dağdeviren, M. (2020). Occupational health and safety risk assessment in the domain of Industry 4.0. SN Applied Sciences, 2, 1-6.

Adriaensen, A., Decré, W., & Pintelon, L. (2019). Can complexity-thinking methods contribute to improving occupational safety in industry 4.0? A review of safety analysis methods and their concepts. Safety, 5(4), 65.

Alogla, A. A., & Alruqi, M. (2021). Aircraft assembly snags: human errors or lack of production design? Aerospace, 8(12), 391.

Angelopoulou, A., Mykoniatis, K., & Boyapati, N. R. (2020). Industry 4.0: The use of simulation for human reliability assessment. Procedia Manufacturing, 42, 296-301.

Arana-Landín, G., Laskurain-Iturbe, I., Iturrate, M., & Landeta-Manzano, B. (2023). Assessing the influence of industry 4.0 technologies on occupational health and safety [Article]. Heliyon, 9(3), Article e13720. https://doi.org/10.1016/j.heliyon.2023.e13720

Badri, A., Boudreau-Trudel, B., & Souissi, A. S. (2018). Occupational health and safety in the industry 4.0 era: A cause for major concern? Safety science, 109, 403-411.

Barata, J., & da Cunha, P. R. (2019). Safety Is the New Black: The Increasing Role of Wearables in Occupational Health and Safety in Construction. In W. Abramowicz & R. Corchuelo (Eds.), 22nd International Conference on Business Information Systems, BIS 2019 (Vol. 353, pp. 526-537): Springer Verlag.

Bavaresco, R., Arruda, H., Rocha, E., Barbosa, J., & Li, G. P. (2021). Internet of Things and occupational well-being in industry 4.0: A systematic mapping study and taxonomy [Article]. Computers and Industrial Engineering, 161, Article 107670. https://doi.org/10.1016/j.cie.2021.107670

Bell, J., & Holroyd, J. (2009). Review of human reliability assessment methods. Health & Safety Laboratory, 78.

Brocal, F., González, C., Komljenovic, D., Katina, P. F., & Sebastián, M. A. (2019). Emerging risk management in industry 4.0: an approach to improve organizational and human performance in the complex systems. Complexity, 2019.

Castiglia, F., & Giardina, M. (2013). Analysis of operator human errors in hydrogen refuelling stations: Comparison between human rate assessment techniques. International Journal of Hydrogen Energy, 38(2), 1166-1176.

Demir, K. A., & Cicibaş, H. (2019). The next industrial revolution: industry 5.0 and discussions on industry 4.0. Industry, 4, 247-260.

Di Pasquale, V., De Simone, V., Radano, M., & Miranda, S. (2022). Wearable devices for health and safety in production systems: a literature review. IFAC-PapersOnLine, 55(10), 341-346.

El Helou, M., Benfriha, K., Al-Ahmari, A. M., Wardle, P., Talhi, E., Loubère, S., El Zant, C., & Charrier, Q. (2022). A Modular Smart Vision System for Industrial Inspection and Control of Conformity.

Gaiardelli, S., Spellini, S., Lora, M., & Fummi, F. (2021). Modeling in Industry 5.0: What Is There and What Is Missing: Special Session 1: Languages for Industry 5.0. 2021 Forum on specification & Design Languages (FDL),

Gualtieri, L., Rauch, E., & Vidoni, R. (2022). Development and validation of guidelines for safety in human-robot collaborative assembly systems. Computers & Industrial Engineering, 163, 107801.

Hao, Y., & Helo, P. (2017). The role of wearable devices in meeting the needs of cloud manufacturing: A case study. Robotics and Computer-Integrated Manufacturing, 45, 168-179.

Hayat, H., & Reda, G. A. (2022). An IoT and spatial Big data based architecture for monitoring Occupational Health Risks exposure. 1st International Conference on Big Data, IoT, Web Intelligence and Applications, BIWA 2022,

Jasiulewicz-Kaczmarek, M., & Gola, A. (2019). Maintenance 4.0 technologies for sustainable manufacturing-an overview. IFAC-PapersOnLine, 52(10), 91-96.

Javaid, M., & Haleem, A. (2020). Critical components of Industry 5.0 towards a successful adoption in the field of manufacturing. Journal of Industrial Integration and Management, 5(03), 327-348.

Kim, D., & Choi, Y. (2021). Applications of smart glasses in applied sciences: A systematic review. Applied Sciences, 11(11), 4956.

Kirwan, B. (1992). Human error identification in human reliability assessment. Part 1: Overview of approaches. Applied ergonomics, 23(5), 299-318.

Krzywdzinski, M., Pfeiffer, S., Evers, M., & Gerber, C. (2022). Measuring work and workers: Wearables and digital assistance systems in manufacturing and logistics.

Lolli, F., Coruzzolo, A. M., Alessandro, G., Balugani, E., Butturi, M. A., Marinello, S., & Marinelli, S. (2021). The Dynamic, Individual and Integrated Risk Assessment: A Multi-criteria Approach Using Big Data. Advances in Safety Management and Human Performance: Proceedings of the AHFE 2021 Virtual Conferences on Safety Management and Human Factors, and Human Error, Reliability, Resilience, and Performance, July 25-29, 2021, USA,

Maddikunta, P. K. R., Pham, Q.-V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., Ruby, R., & Liyanage, M. (2022). Industry 5.0: A survey on enabling technologies and potential applications. Journal of Industrial Information Integration, 26, 100257.

Mannan, S. (2013). Lees' Process Safety Essentials: Hazard Identification, Assessment and Control. Butterworth-Heinemann.

Nadeau, S., Bruder, R., & Hof, L. (2021). Using Smart Glasses in assembly/disassembly: Current state of the art. Travail et Santé, 37(2), 2-6.

Naeini, A. M., & Nadeau, S. (2022a). Application of FRAM to perform Risk Analysis of the Introduction of a Data Glove to Assembly Tasks. Robotics and Computer-Integrated Manufacturing, 74, 102285.

Naeini, A. M., & Nadeau, S. (2022b). Comparing FRAM and STAMP for occupational health and safety (OHS) and operational risks analysis: The case of data gloves in assembly 4.0 production. Safety and Health at Work, 13, S89.

Naeini, A. M., & Nadeau, S. (2022c). STPA systemic approach for OHS and operational risk analysis of data glove use in 4.0 assembly. CIRP Journal of Manufacturing Science and Technology, 39, 317-331.

Naeini, A. M., & Nadeau, S. (2023). Proposed integrated FRAM/STPA risk analysis of data gloves in assembly 4.0 system. Robotics and Computer-Integrated Manufacturing, 81, 102523.

Nahavandi, S. (2019). Industry 5.0—A human-centric solution. Sustainability, 11(16), 4371.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. International journal of surgery, 88, 105906.

Patel, V., Chesmore, A., Legner, C. M., & Pandey, S. (2022). Trends in workplace wearable technologies and connected-worker solutions for next-generation occupational safety, health, and productivity. Advanced Intelligent Systems, 4(1), 2100099.

Pauliková, A., Gyurák Babeľová, Z., & Ubárová, M. (2021). Analysis of the impact of human–cobot collaborative manufacturing implementation on the occupational health and safety and the quality requirements. International Journal of Environmental Research and Public Health, 18(4), 1927.

Polak-Sopinska, A., Wisniewski, Z., Walaszczyk, A., Maczewska, A., & Sopinski, P. (2020). Impact of industry 4.0 on occupational health and safety. Advances in Manufacturing, Production Management and Process Control: Proceedings of the AHFE 2019 International Conference on Human Aspects of Advanced Manufacturing, and the AHFE International Conference on Advanced Production Management and Process Control, July 24-28, 2019, Washington DC, USA 10,

Raya, M. (2022). IMPLANTATION ET TECHNOLOGIES DE CONCEPTION EN CONTEXTE D'INDUSTRIE 5.0 : LE CAS DU SECTEUR AÉRONAUTIQUE ÉCOLE DE TECHNOLOGIE SUPÉRIEURE].

Reiman, A., Kaivo-oja, J., Parviainen, E., Takala, E.-P., & Lauraeus, T. (2021). Human factors and ergonomics in manufacturing in the industry 4.0 context–A scoping review. Technology in Society, 65, 101572.

Riso, S. (2021). Digitisation in the workplace.

Sharma, I., Garg, I., & Kiran, D. (2020). Industry 5.0 and smart cities: A futuristic approach. European Journal of Molecular & Clinical Medicine, 7(08), 2515-8260.

Silva, T. R., Coelho, B. N., & Delabrida, S. E. (2021). Promising Technologies and Solutions for Supporting Human Activities in Confined Spaces in Industry. ICEIS (2),

Singh, S., & Kumar, R. (2015). Evaluation of human error probability of disc brake unit assembly and wheel set maintenance of railway bogie. Procedia Manufacturing, 3, 3041-3048.

Stahn, C., Hartmann, V., & Koczy, A. (2022). Working world 4.0: will everything remain different?!" AWA" project examines the changes of digitalization on a company level. Procedia Computer Science, 200, 969-975.

Stojiljkovic, E., Bijelic, B., & Cvetkovic, M. (2018). Application of HEART technique for human reliability assessment–a Serbian experience. Facta Universitatis. Series: Working and Living Environmental Protection, 187-196.

Teixeira, D., Ferreira, J., & Gonçalves, R. (2022). Monitoring of shop-floor workers postural stability through the use of smart soles. 10th IFAC Conference on Manufacturing Modelling, Management and Control, MIM 2022, Torres, Y., Nadeau, S., & Landau, K. (2021a). Application of SHERPA (Systematic Human Error Reduction and Prediction Approach) as an alternative to predict and prevent human error in manual assembly. Congress of the International Ergonomics Association,

Torres, Y., Nadeau, S., & Landau, K. (2021b). Classification and quantification of human error in manufacturing: a case study in complex manual assembly. Applied Sciences, 11(2), 749.

Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. Journal of Manufacturing Systems, 61, 530-535.

Zarei, E., Khan, F., & Abbassi, R. (2023). How to account artificial intelligence in human factor analysis of complex systems? Process safety and environmental protection.

Zorzenon, R., Lizarelli, F. L., & Daniel, B. d. A. (2022). What is the potential impact of industry 4.0 on health and safety at work? Safety science, 153, 105802.

ANNEX III

CONFERENCE PRESENTATION - IISE ANNUAL CONFERENCE & EXPO 2024

FRAM effectiveness in the era of Industry 4.0: A dual perspective review

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Abstract

The advent of Industry 4.0 has ushered in a new era of greater system sophistication, which goes beyond the capabilities of traditional risk analysis methods. In response, researchers have turned to systemic methods that are more suitable. The Functional Resonance Analysis Method (FRAM), along with other systemic methods, stands out for its ability to analyze accidents, regular performance, and risks by considering the entire system as the unit of analysis. FRAM's unique focus on understanding how everyday variability combines to produce unexpected results distinguishes it from conventional methods as well as its focus on what went wrong and analysis capacity of what went right. In this regard, there are two opposing perspectives regarding FRAM's applicability to Industry 4.0. While the first focuses on the advantages of this method, the second argues that FRAM may not align well with industry 4.0 systems. This study delves into the performance of FRAM within the context of Industry 4.0, including its ability to address human error. This investigation examines the application of FRAM in the dynamic landscape of Industry 4.0, leveraging a comprehensive literature analysis to provide an in-depth understanding of the method's strengths and limitations in contemporary industrial systems. Drawing on evidence from successful documented applications, this study argues that FRAM can be effectively utilized in complex systems employing Industry 4.0 applications, countering claims of misalignment and emphasizing FRAM's applicability for Industry 4.0 contexts.

Keywords: Functional Resonance Analysis Method (FRAM), Industry 4.0, Risk management, Systemic methods

1 Introduction

Various perspectives exist regarding human error, encompassing the mechanistic, individual, interactionist and systems perspectives [1]. Systemic methods are distinct from human error methods as they focus on analyzing accidents and normal performance by considering the entire system as the unit of analysis, rather than solely focusing on human behavior. These methods, such as AcciMap, STAMP (System Theoretic Accident Model and Process), CWA (Cognitive work analysis), EAST (Event Analysis of Systemic Teamwork), Net-HARMS (Networked Hazard Analysis and Risk Management System), and FRAM, take into account the complexity of sociotechnical systems and help identify conditions or components that contribute to both failures and normal performance [1, 2]. As part of systems thinking, one emphasizes interactions and relationships, considers multiple perspectives, and recognizes patterns of cause and effect by looking at the world through the lens of systems. A system is the primary unit of analysis in systems thinking, and individual components can only be understood within the context of the system as a whole. In other words, accidents and failures cannot be attributed exclusively to one component's actions (e.g., human error). Instead, the focus is on examining how interactions between components within the system led to the failure; thus, the system as a whole is considered responsible [1].

In 2004, Erik Hollnagel introduced FRAM [3]. In the years since then, the method has continuously been used to analyze and assess complex social-technical systems for risks [4, 5]. Patriarca et al. [5] reported that FRAM is used primarily in the aviation industry, healthcare, and industrial processes, which include more than 51% of all FRAM papers. Among others, FRAM has been successfully applied as a retrospective and prospective method by resilience engineering [6, 7]. FRAM can provide safety assurance and an understanding of how the system can maintain safety in dynamic operational environments [8]. In many industries, such as maritime accidents [9], offshore drilling [10], coal mine accidents [11], software engineering [12], and healthcare [13], FRAM is being implemented. Typically, FRAM is used in high-risk environments, but it has also been used in other industries like manufacturing [14]. FRAM focuses on understanding how everyday variability may combine to produce unexpected and undesirable results rather than tracing the proliferation of failures or malfunctions [15]. In addition to concentrating on what went wrong, FRAM is the only method for determining what went right [15]. FRAM will examine how these functional differences might resonate together to create unwanted events based on the variability in performance. It has been shown that FRAM can produce positive outcomes in emerging events [16]. In contrast to traditional methods, it is not a decomposition method [3].

On the other hand, some scholars, like Holman and colleagues (2020) have raised doubts about whether the FRAM works well for Industry 4.0 systems [17]. They worry that the complex interactions and timing in these systems might not fit FRAM's traditional approach. Moreover, FRAM is a qualitative method and researchers are making efforts to quantify this method in different areas [18-20], but no solution yet stands out. Finally, studying complex systems requires extensive input data, which, like for every systemic method, is among the disadvantages of using FRAM [21, 22].

Thus, there are two different perspectives about FRAM’s effectiveness in dealing with Industry 4.0 systems. These dual perspectives motivate authors to analyze this problem. The remainder of the paper is structured as follows: Section two presents the methodology employed in this study. Section three outlines the results obtained from the analysis. Section four provides a discussion of the findings. Finally, Section five presents the conclusions.

2 Methodology

In adherence to transparent and comprehensive reporting standards, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines were followed to ensure the accuracy of the literature review process. The systematic review aimed to identify relevant studies about FRAM, Industry 5.0, Industry 4.0, IoT (Internet of Things), Wearable, Glasses, Glove, and Human-Robot Interaction. To ensure a comprehensive search of the literature, two widely recognized and authoritative databases, Scopus and Web of Science

(WOS), were selected for their extensive coverage of scholarly publications across various disciplines [18, 23]. Exclusion criteria were established as a priori to refine the search results and exclude irrelevant or redundant studies. These criteria were informed by the research objectives and were systematically applied during the screening process. During the screening process, exclusion criteria were strictly enforced. For instance, non-English documents were excluded. Similarly, documents that were not available to read or were unrelated to the study's objectives were also eliminated. Additionally, studies published outside the timeframe of 2011-2024 were not considered for inclusion. These criteria ensured a rigorous and focused approach to selecting relevant literature for the study. By adhering to predefined exclusion criteria, we aimed to maintain the relevance and quality of the studies included in our systematic review while minimizing the risk of bias and ensuring the reliability of our findings.

3 Results

In this section, the literature analysis results are presented. Firstly, the PRISMA flowchart depicting the systematic review process is provided in Figure 1. The initial search using the specified keywords yielded 47 documents from Scopus and 38 documents from WOS, totaling 85 documents in the initial stage. As a result of a thorough review, 26 duplicated documents were identified and removed, while one document was excluded due to its language being Chinese. Additionally, three documents were inaccessible, resulting in a pool of 55 documents subjected to further analysis for eligibility. Initially, each document's keywords and titles were examined, leading to the exclusion of 35 additional documents. Subsequently, following a thorough evaluation of their abstracts, eight more documents were deemed irrelevant to the scope of the present study and thus removed from consideration. Ultimately, 12 documents remained for comprehensive analysis in alignment with the study's objective and research question.

These documents represent the subset of literature deemed most pertinent to our investigation, forming the basis for our subsequent analysis and discussion. Utilizing VOSviewer software, the keyword network analysis was performed, as depicted in Figure 2. The visual depiction of nodes and their sizes reflects the frequency of citation for individual words. Nodes become interconnected when words co-occur within the same article, with the strength of the connection intensifying with greater co-citations. The analysis reveals that "Internet of Things," "FRAM," "Industry 4.0," "risk assessment," "system thinking," and "analysis method" emerge as the most frequently used keywords across the references examined. This finding underscores their significance and prevalence within the literature under review.

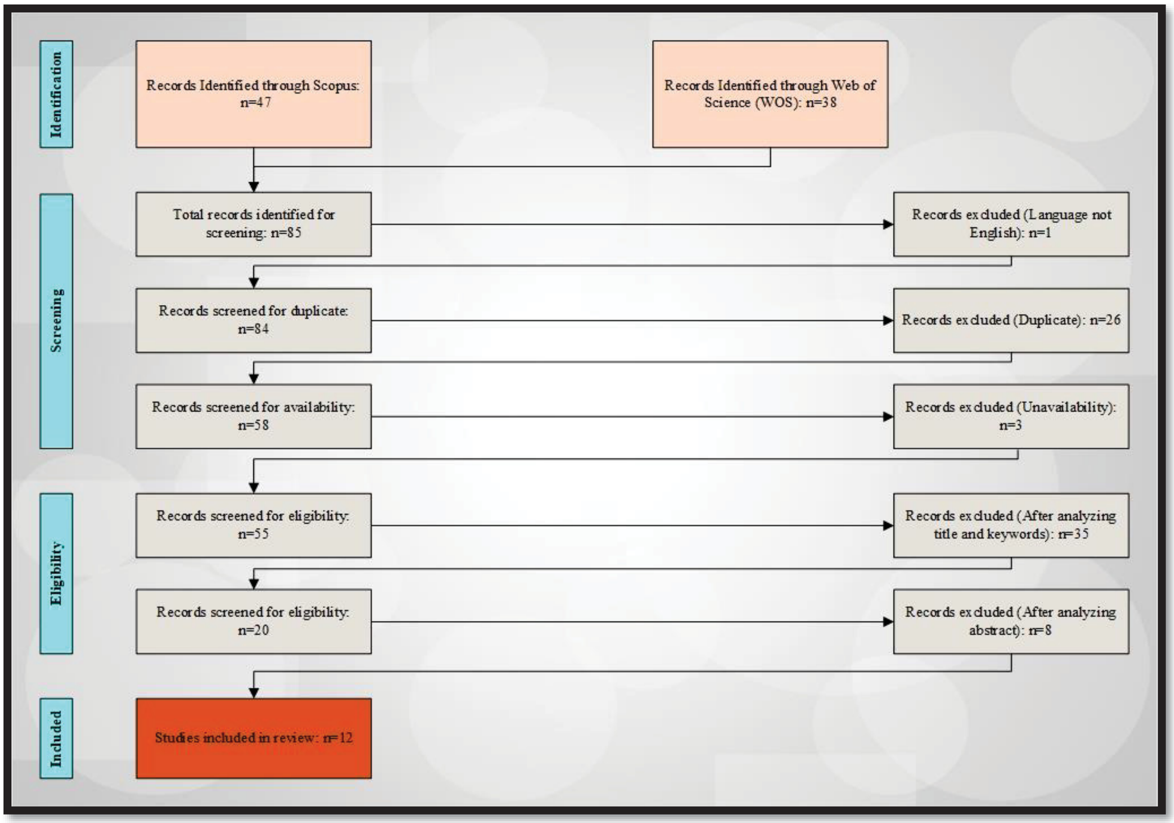

Figure-AIII-1 PRISMA flowchart

Upon reviewing the included papers, it becomes evident we find that there are instances where FRAM has proven useful in analyzing complex systems, including those related to human error in Industry 4.0. For instance, Mofidi Naeini & Nadeau (2023) aimed to integrate FRAM and STPA to analyze occupational health and safety (OHS) as well as operational risks associated with the introduction of data gloves to assembly operations in the manufacturing industry [24]. Adriaensen et al. (2023) introduced a framework that combines FRAM and interdependence analysis for Cobots, targeting safety analysis within the manufacturing industry [25]. Similarly, Mofidi Naeini & Nadeau (2022) applied FRAM to assess OHS and operational risks related to the use of data gloves in assembly processes within the manufacturing sector [16].

Additionally, Adriaensen et al. (2022) evaluated co-agency in human-robot interactions, particularly focusing on safety analysis for collaborative robots in manufacturing [26]. Chacón, Ponsa, & Angulo (2020) utilized FRAM and simulated scenarios to enhance the performance of human operators and supervisors in working with Cobots in manufacturing [27]. Zúñiga et al. (2023) combined discrete-event simulation, FRAM, and work domain analysis to enhance manufacturing systems [28].Zhou, Matsubara, & Takada (2023) introduced a semi-quantitative FRAM method to improve the reliability of healthcare services, specifically for diabetic patients [29]. Moreover, Diop, Abdul-Nour, & Komljenovic (2022) addressed inadequacies in risk management approaches for Industry 4.0 and Industry 5.0 within the manufacturing industry [30]. Salehi et al. (2022) enhanced FRAM by integrating it with reinforcement learning to explore complex system operations in the health industry [31]. Liu et al. (2021) evaluated the ergonomic reliability of medical equipment design during operation using FRAM-Moran's and CREAM methods within the medical equipment field [32]. Holman et al. (2020) outlined requirements for future modeling approaches and presented a manifesto for the future of the discipline within social science [17]. Additionally, Rosa, Carvalho, & Haddad (2020) identified potential risks and improved work processes to minimize losses with the application of FRAM and AHP within the construction industry [33]. Despite inherent limitations such as its qualitative nature and complexity, as highlighted by Karevan & Nadeau (2023), FRAM remains a robust systemic methodology capable of effectively navigating the multifaceted challenges posed by Industry 4.0 systems [18].

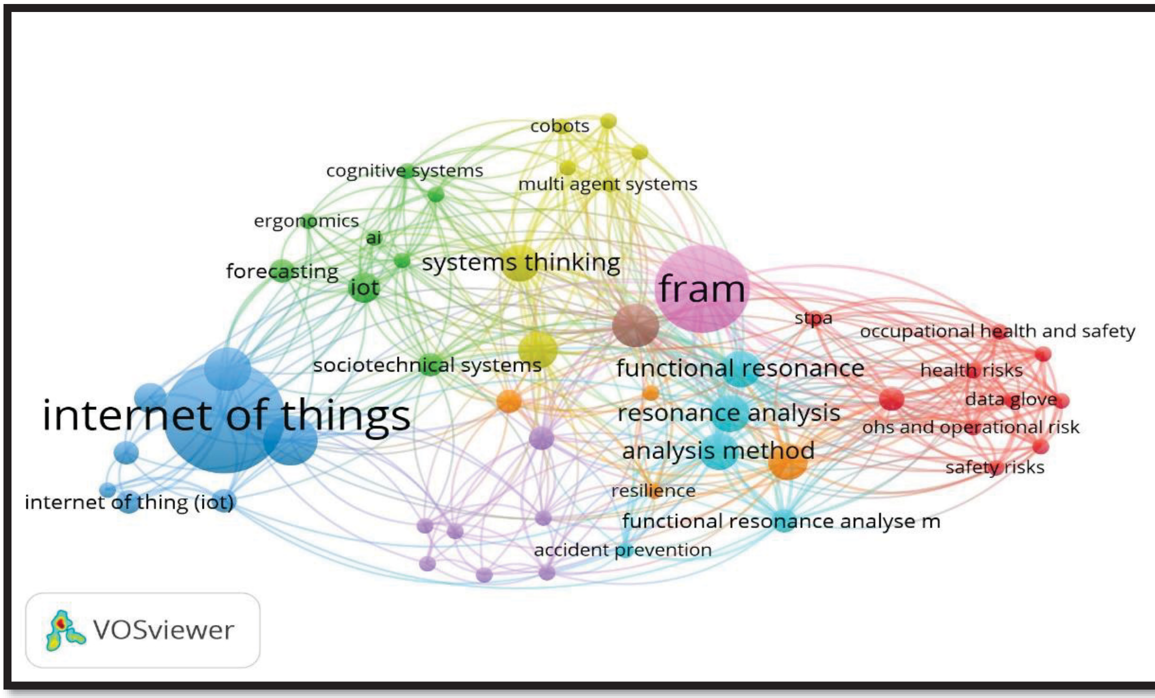

Figure-AIII-2 Bibliometric analysis of the keywords

4 Discussion

Despite the concerns raised by Holman and colleagues (2020) regarding the alignment of FRAM with Industry 4.0 systems, recent studies have demonstrated its adaptability and efficacy in managing complexities inherent in modern industrial landscapes. Notably, empirical evidence underscores FRAM's utility in addressing various aspects of Industry 4.0 systems, particularly in the realms of risk analysis, performance optimization, and organizational resilience. For instance, [16] conducted a thorough risk analysis using FRAM to evaluate the introduction of data gloves into a complex system, emphasizing its capability to effectively assess and mitigate potential risks associated with new technologies. Similarly, [34] applied FRAM to detect subtle signals within complex systems, highlighting its role in facilitating informed decision-making and enhancing situational awareness in dynamic environments. Furthermore, FRAM's versatility extends beyond traditional manufacturing domains into critical sectors like healthcare. [29] demonstrated how FRAM can be useful in designing personalized healthcare services for individuals with diabetes, emphasizing its capacity to accommodate diverse system requirements and user needs. Moreover, [27] focused on evaluating risk management strategies for emerging safety risks in Industry 4.0 contexts, affirming FRAM's significance alongside complementary methodologies like STAMP in addressing complex organizational challenges. The convergence of successful applications and case studies underscores FRAM's relevance in navigating the complexities of Industry 4.0 environments. Its ability to analyze interactions, variability, and unexpected outcomes aligns seamlessly with the evolving demands of modern industrial systems driven by IoT devices, cyber-physical integration, and advanced automation technologies.

5 Conclusion

In conclusion, the advent of Industry 4.0 has necessitated a paradigm shift in risk analysis methodologies, prompting researchers to explore systemic approaches better suited to the complexities of modern industrial systems. Among these methodologies, FRAM emerges as a standout solution for comprehensively analyzing accidents, regular performance, and risks within Industry 4.0 environments. Despite debates surrounding its alignment with Industry 4.0 systems, our investigation into the performance of FRAM has revealed its efficacy in addressing the multifaceted challenges inherent in contemporary industrial landscapes. Through an examination of documented applications and comprehensive literature analysis, our study underscores FRAM's ability to navigate the dynamic landscape of Industry 4.0, including its unique capacity to address human error—a critical consideration in complex socio-technical systems. In essence, our study highlights FRAM as a valuable tool for enhancing operational resilience, optimizing performance, and mitigating risks in Industry 4.0 contexts. By leveraging its systemic perspective and analytical capabilities, organizations can proactively identify and address potential vulnerabilities, fostering a culture of continuous improvement and adaptive governance in an increasingly interconnected and dynamic industrial landscape.

Acknowledgements

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References

[1] G. J. Read, S. Shorrock, G. H. Walker, and P. M. Salmon, "State of science: Evolving perspectives on ‘human error’," Ergonomics, vol. 64, no. 9, pp. 1091-1114, 2021.

[2] A. Karevan and S. Nadeau, "A comprehensive STPA-PSO Framework for quantifying smart glasses risks in manufacturing," Heliyon, vol. 10, no. 9, 2024, doi: 10.1016/j.heliyon.2024.e30162.

[3] E. Hollnagel and O. Goteman, "The functional resonance accident model," Proceedings of cognitive system engineering in process plant, vol. 2004, pp. 155-161, 2004.

[4] Y. Guo, Y. Jin, S. Hu, Z. Yang, Y. Xi, and B. Han, "Risk evolution analysis of ship pilotage operation by an integrated model of FRAM and DBN," Reliability Engineering & System Safety, p. 108850, 2022.

[5] R. Patriarca et al., "Framing the FRAM: A literature review on the functional resonance analysis method," Safety Science, vol. 129, p. 104827, 2020.

[6] K. Lundblad, J. Speziali, R. Woltjer, and J. Lundberg, "FRAM as a risk assessment method for nuclear fuel transportation," in Proceedings of the 4th International Conference Working on Safety, 2008, vol. 1, pp. 223-1.

[7] A. Yousefi, M. Rodriguez Hernandez, and V. Lopez Peña, "Systemic accident analysis models: A comparison study between AcciMap, FRAM, and STAMP," Process Safety Progress, vol. 38, no. 2, p. e12002, 2019.

[8] D. Smith, B. Veitch, F. Khan, and R. Taylor, "Understanding industrial safety: Comparing Fault tree, Bayesian network, and FRAM approaches," Journal of Loss Prevention in the Process Industries, vol. 45, pp. 88-101, 2017.

[9] E. Salihoglu and E. B. Beşikçi, "The use of Functional Resonance Analysis Method (FRAM) in a maritime accident: A case study of Prestige," Ocean Engineering, vol. 219, p. 108223, 2021.

[10] J. E. França, E. Hollnagel, I. J. dos Santos, and A. N. Haddad, "Analysing human factors and non-technical skills in offshore drilling operations using FRAM (functional resonance analysis method)," Cognition, Technology & Work, vol. 23, no. 3, pp. 553-566, 2021.

[11] W. Qiao, X. Li, and Q. Liu, "Systemic approaches to incident analysis in coal mines: Comparison of the STAMP, FRAM and “2–4” models," Resources Policy, vol. 63, p. 101453, 2019.

[12] E. A. de Carvalho, J. O. Gomes, A. Jatobá, M. F. da Silva, and P. V. R. de Carvalho, "Employing resilience engineering in eliciting software requirements for complex systems: experiments with the functional resonance analysis method (FRAM)," Cognition, Technology & Work, vol. 23, no. 1, pp. 65-83, 2021.

[13] P.-F. Cheng, D.-P. Li, J.-Q. He, X.-H. Zhou, J.-Q. Wang, and H.-Y. Zhang, "Evaluating surgical risk using FMEA and MULTIMOORA methods under a single-valued trapezoidal neutrosophic environment," Risk Management and Healthcare Policy, vol. 13, p. 865, 2020.

[14] A. Melanson and S. Nadeau, "Resilience engineering for sustainable prevention in the manufacturing sector: A comparative study of two methods of risk analysis," American Journal of Industrial and Business Management, vol. 9, no. 1, pp. 267-281, 2019.

[15] A. Hulme, N. A. Stanton, G. H. Walker, P. Waterson, and P. M. Salmon, "What do applications of systems thinking accident analysis methods tell us about accident causation? A systematic review of applications between 1990 and 2018," Safety science, vol. 117, pp. 164-183, 2019.

[16] A. Mofidi Naeini and S. Nadeau, "Application of FRAM to perform Risk Analysis of the Introduction of a Data Glove to Assembly Tasks," Robotics and Computer-Integrated Manufacturing, vol. 74, p. 102285, 2022.

[17] M. Holman, G. Walker, T. Lansdown, and A. Hulme, "Radical systems thinking and the future role of computational modelling in ergonomics: An exploration of agent-based modelling," Ergonomics, vol. 63, no. 8, pp. 1057-1074, 2020.

[18] A. Karevan and S. Nadeau, "The role of industry 5.0 in reducing the risk of human error in manufacturing-a critical literature review," 2023.

[19] R. Patriarca, G. Di Gravio, F. Costantino, and M. Tronci, "The Functional Resonance Analysis Method for a systemic risk based environmental auditing in a sinter plant: A semi-quantitative approach," Environmental Impact Assessment Review, vol. 63, pp. 72-86, 2017.

[20] H. Slim and S. Nadeau, "A mixed rough sets/fuzzy logic approach for modelling systemic performance variability with FRAM," Sustainability, vol. 12, no. 5, p. 1918, 2020.

[21] A. B. Toroody, M. M. Abaei, and R. Gholamnia, "Conceptual compression discussion on a multi-linear (FTA) and systematic (FRAM) method in an offshore operation’s accident modeling," International journal of occupational safety and ergonomics, vol. 22, no. 4, pp. 532-540, 2016.

[22] G. Praetorius, A. Graziano, J.-U. Schröder-Hinrichs, and M. Baldauf, "Fram in FSA—Introducing a function-based approach to the formal safety assessment framework," in Advances in Human Aspects of Transportation: Proceedings of the AHFE 2016 International Conference on Human Factors in Transportation, July 27-31, 2016, Walt Disney World®, Florida, USA, 2017: Springer, pp. 399-411.

[23] R. Zorzenon, F. L. Lizarelli, and B. d. A. Daniel, "What is the potential impact of industry 4.0 on health and safety at work?," Safety science, vol. 153, p. 105802, 2022.

[24] A. Mofidi Naeini and S. Nadeau, "Proposed integrated FRAM/STPA risk analysis of data gloves in assembly 4.0 system," Robotics and Computer-Integrated Manufacturing, vol. 81, p. 102523, 2023.

[25] A. Adriaensen, L. Pintelon, F. Costantino, G. Di Gravio, and R. Patriarca, "Systems-theoretic interdependence analysis in robot-assisted warehouse management," Safety Science, vol. 168, p. 106294, 2023.

[26] A. Adriaensen, N. Berx, L. Pintelon, F. Costantino, G. Di Gravio, and R. Patriarca, "Interdependence Analysis in collaborative robot applications from a joint cognitive functional perspective," International Journal of Industrial Ergonomics, vol. 90, p. 103320, 2022.

[27] A. Chacón, P. Ponsa, and C. Angulo, "On cognitive assistant robots for reducing variability in industrial human-robot activities," Applied Sciences, vol. 10, no. 15, p. 5137, 2020.

[28] E. R. Zúñiga, N. Yasue, T. Hirose, H. Nomoto, and T. Sawaragi, "An Integrated discrete-event simulation with functional resonance analysis and work domain analysis methods for industry 4.0 implementation," Decision Analytics Journal, p. 100323, 2023.

[29] Z. Zhou, Y. Matsubara, and H. Takada, "Developing Reliable Digital Healthcare Service Using Semi-Quantitative Functional Resonance Analysis," Computer Systems Science & Engineering, vol. 45, no. 1, 2023.

[30] I. Diop, G. Abdul-Nour, and D. Komljenovic, "Asset and Risk Management Approach in the Context of Complexity in Industry 4.0/5.0 Systems," in World Congress on Engineering Asset Management, 2022: Springer, pp. 508-520.

[31] V. Salehi, T. Tran, B. Veitch, and D. Smith, "A reinforcement learning development of the FRAM for functional reward-based assessments of complex systems performance," International Journal of Industrial Ergonomics, vol. 88, p. 103271, 2022.

[32] X. Liu et al., "Evaluation of the Operation Process of Medical Equipment to Enhance Ergonomic Reliability Based on FRAM–Moran's I and CREAM," Applied Sciences, vol. 12, no. 1, p. 200, 2021.

[33] L. V. Rosa, P. V. Carvalho, and A. N. Haddad, "FRAM-AHP: A Resilience Engineering Approach for Sustainable Prevention," Occupational and Environmental Safety and Health II, pp. 123-131, 2020.

[34] M. Yu, H. Pasman, M. Erraguntla, N. Quddus, and C. Kravaris, "A framework to identify and respond to weak signals of disastrous process incidents based on FRAM and machine learning techniques," Process Safety and Environmental Protection, vol. 158, pp. 98-114, 2022.

ANNEX IV

CONFERENCE PRESENTATION - 22ND TRIENNAL CONGRESS IEA 2024

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 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 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 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 work of Karevan & Nadeau (2024), 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 process [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.

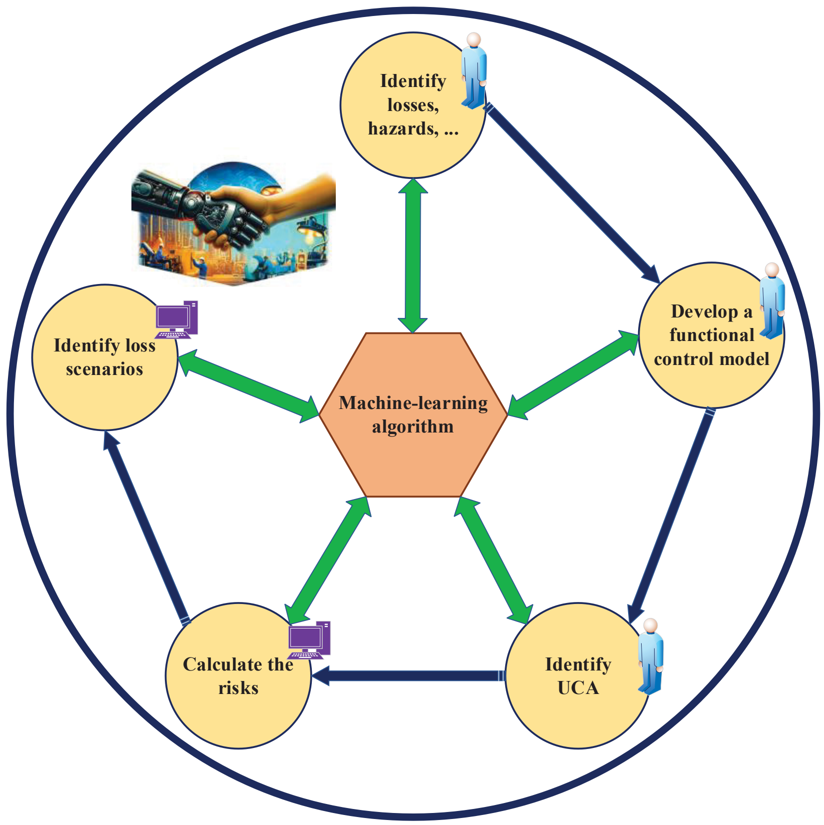

Figure-AIV-1 Methodology process

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-AIV-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, and 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.

Table-AIV-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

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.

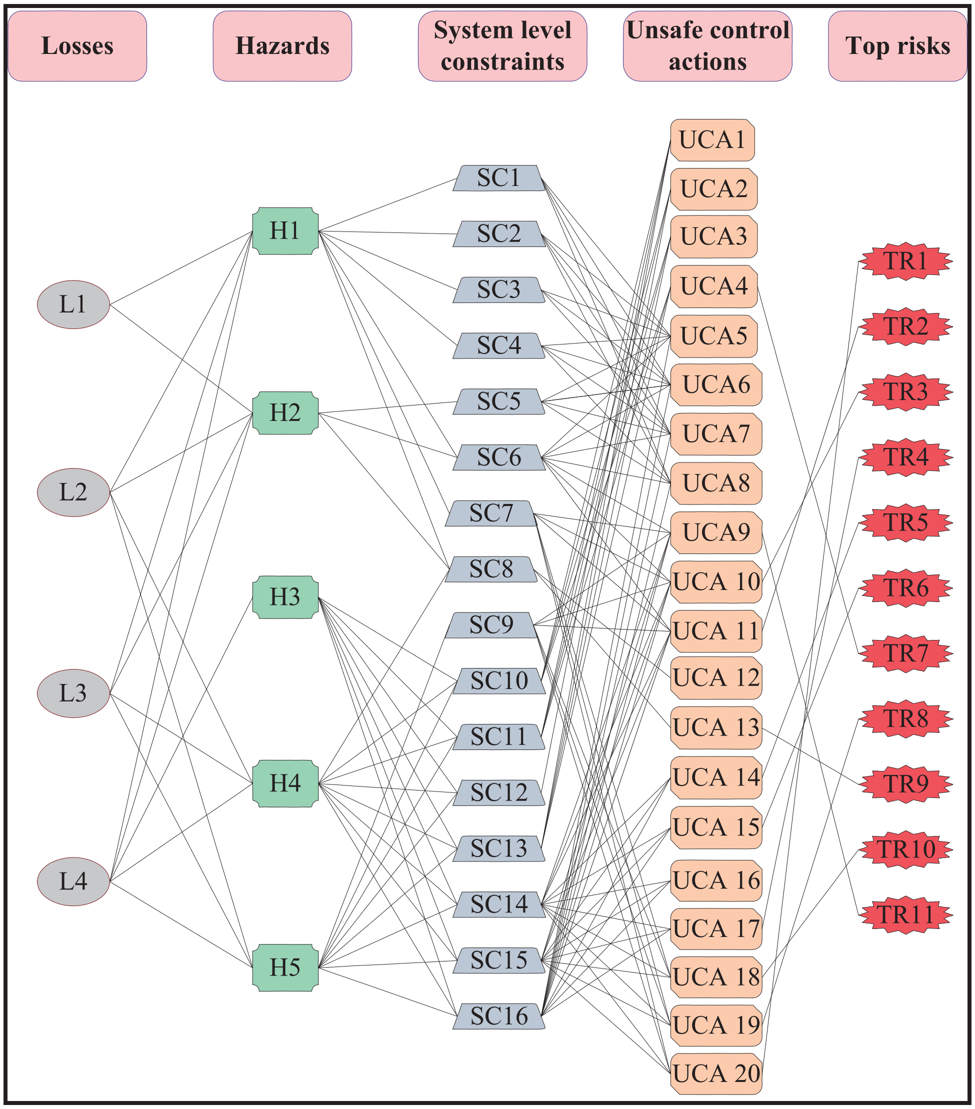

Figure-AIV-2 STPA-PSO graph

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.

Table-AIV-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

Acknowledgments

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References

1. Karevan, A. and S. Nadeau. The Role of Industry 5.0 in Reducing the Risk of Human Error in Manufacturing A Critical Literature Review. in CIGI QUALITA MOSIM 2023. 2023. Trois rivier, Quebec.
2. Commission, E., et al., Industry 5.0 : towards a sustainable, human-centric and resilient European industry. 2021: Publications Office of the European Union.
3. Selvaraj, A., Role of humans in Industry 5.0. Columbus.[Online] October, 2019. 10.
4. Sahoo, S. and C.-Y. Lo, Smart manufacturing powered by recent technological advancements: A review. Journal of Manufacturing Systems, 2022. 64: p. 236-250.
5. Karevan, A. and S. Nadeau. FRAM effectiveness in the era of Industry 4.0: A dual perspective review. in IISE Annual Conference. Proceedings. 2024. Institute of Industrial and Systems Engineers (IISE).
6. Osmëni, T. and M. Ali. Contemporary Generation: Artificial Intelligence Contribution to Manufacturing. in 2022 International Conference on Computing, Networking, Telecommunications & Engineering Sciences Applications (CoNTESA). 2022. IEEE.
7. Chadha, U., et al., A survey of machine learning in friction stir welding, including unresolved issues and future research directions. Material Design & Processing Communications, 2022. 2022.
8. Karevan, A. and S. Nadeau, A comprehensive STPA-PSO Framework for quantifying smart glasses risks in manufacturing. Heliyon, 2024. 10(9).

ANNEX V

PROOF OF SUBMISSION – COMPUTERS & INDUSTRIAL ENGINEERING

Computers & Industrial Engineering

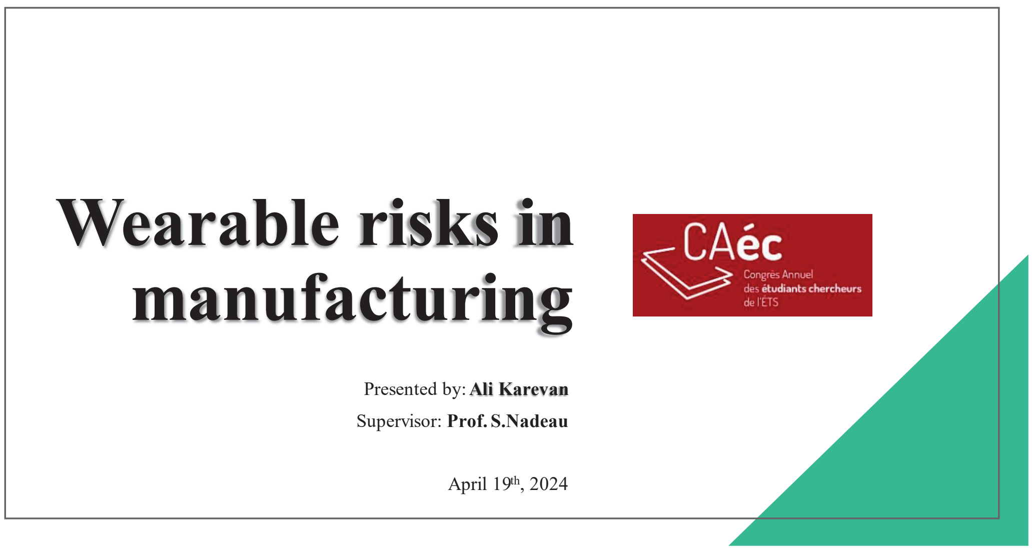
STPA-BN–PSO: a hybrid probabilistic framework for managing systemic risks in human-centric wearables-enabled manufacturing

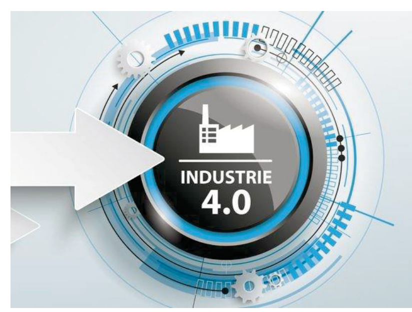
--Manuscript Draft--

Manuscript Number:	CAIE-D-26-00766
Article Type:	Research Paper
Keywords:	BN; PSO; Systemic risk; STPA; Industry 5.0; Wearables-enabled manufacturing
Corresponding Author:	Sylvie Nadeau, Eng., Ph.D. École de technologie supérieure Montréal, QC CANADA
First Author:	Ali Karevan
Order of Authors:	Ali Karevan
	Sylvie Nadeau
Abstract:	The integration of smart wearables into manufacturing promises enhanced worker support but introduces poorly understood systemic risks. Traditional methods often fail to capture the uncertainty and interdependencies of these sociotechnical systems, particularly during the design and early integration phases, where data is scarce. To address this, this study develops a hybrid STPA-BN–PSO framework to resolve the parameterization gap. The BN structure is derived from Systems-Theoretic Process Analysis (STPA) to capture hierarchical control logic, while PSO is used to calibrate weighted conditional probability tables. The framework is applied to three case studies: assembly line, job-shop, and disassembly line. Quantitative results demonstrate that baseline unacceptable risk is context-dependent, reaching 31.5% in the job-shop compared to 28.0% in sequential assembly. Criticality analysis identifies that risk is driven by planning quality in sequential assembly (CA12, ΔRisk=0.181) and digital information quality in flexible job shops (H4, ΔRisk=0.286). Furthermore, multi-faceted sensitivity analyses reveal how risk-propagation pathways reorganize in response to operational layout. The performance of this framework is compared with recently developed STPA-PSO and FRAM-PSO methodologies, demonstrating its unique capability for path-based probabilistic quantification. The findings confirm that STPA-BN–PSO provides a quantitatively rigorous, safety-centric tool for the proactive assessment of emergent risks in Industry 5.0 settings.

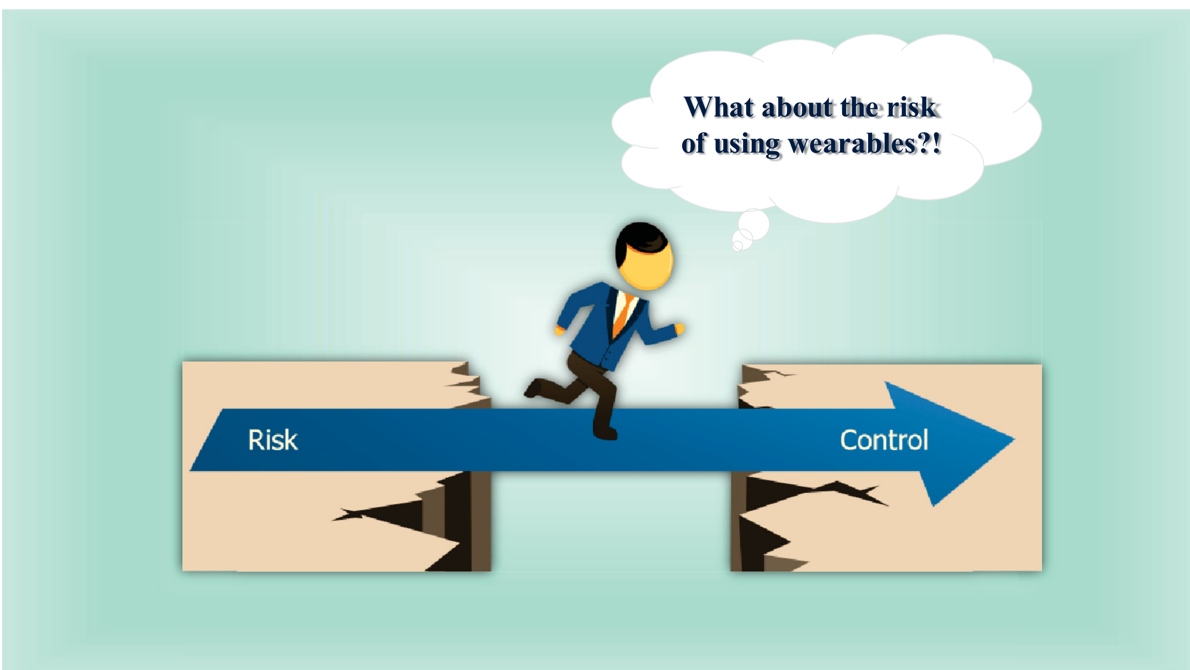
ANNEX VI

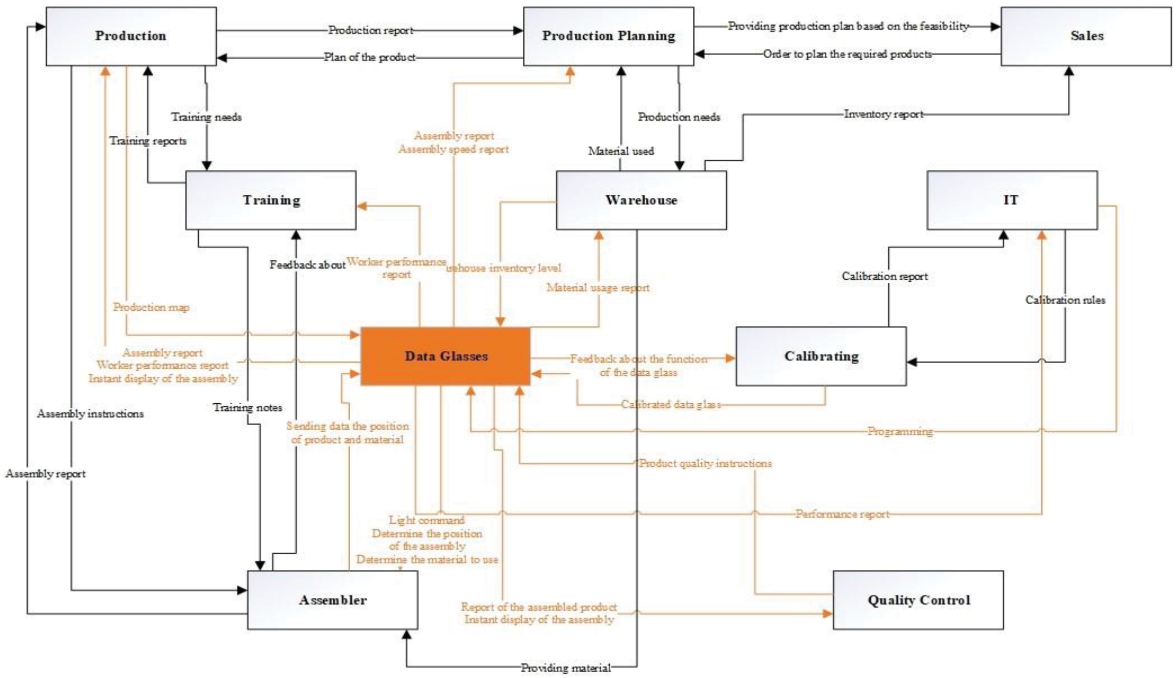
CAÉC 2024 PRESENTATION

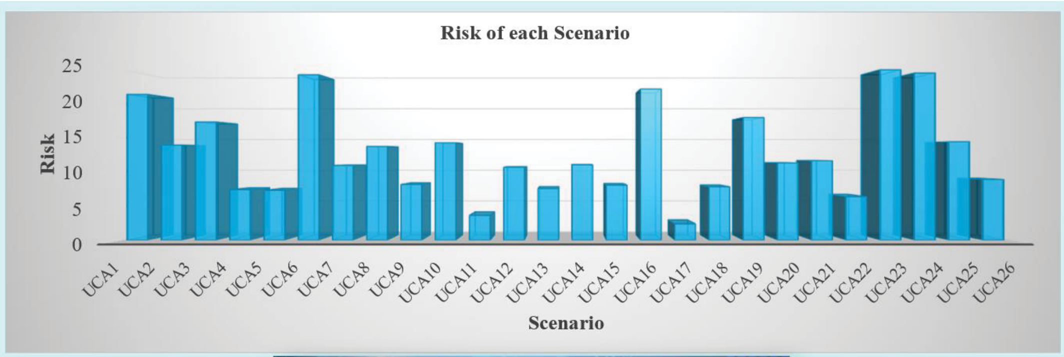





Wearables can make a huge
impact in employee training.


What about the risk
of using wearables?!
Risk
Control


Production
Production report
Plan of the product
Production Planning
Providing production plan based on the feasibility
Order to plan the required products
Sales
Training needs
Training reports
Assembly report
Assembly speed report
Production needs
Material used
Inventory report
Training
Warehouse
IT
Feedback about
Worker performance report
Material usage report
Calibration report
Calibration rules
Production map
Data Glasses
Assembly report
Worker performance report
Instant display of the assembly
Feedback about the function of the data glass
Calibrating
Calibrated data glass
Assembly instructions
Training notes
Sending data the position of product and material
Programming
Product quality instructions
Assembly report
Performance report
Light command
Determine the position of the assembly
Determine the material to use
Assembler
Report of the assembled product
Instant display of the assembly
Quality Control
Providing material


Risk of each Scenario
Risk
25
20
15
10
5
0
UCA1
UCA2
UCA3
UCA4
UCA5
UCA6
UCA7
UCA8
UCA9
UCA10
UCA11
UCA12
UCA13
UCA14
UCA15
UCA16
UCA17
UCA18
UCA19
UCA20
UCA21
UCA22
UCA23
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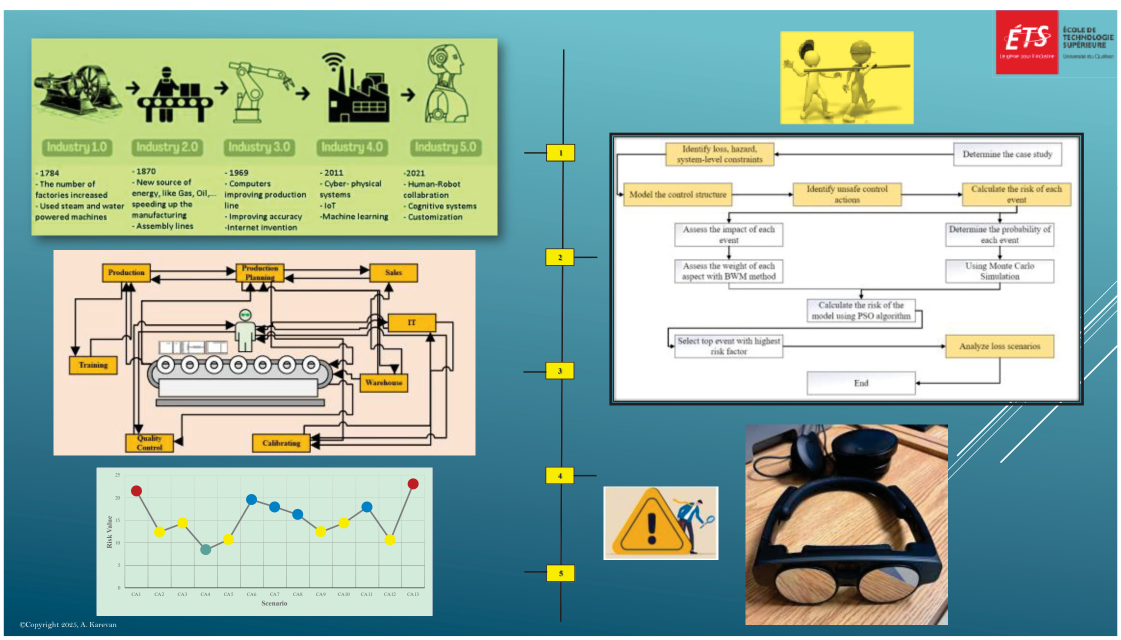
UCA26
Scenario


RISK
LOW
MEDIUM
HIGH

ANNEX VII

CAÉC 2025 PRESENTATION



ANNEX VIII

3-MINUTE THESIS 2025 PRESENTATION

ANNEX IX

MAKING MANUFACTURING SMARTER, SAFER AND MORE SUSTAINABLE

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Article published in: Substance ÉTS, September 2025

Abstract

Walk into a modern factory and you'll see the future of work in action: operators wearing smart glasses and gloves that guide their hands, and sensors connecting equipment/tools/humans on an assembly line. This is the promise of Industry 5.0, a world of greater precision, faster results, and fewer errors.

But behind this promise lies a critical challenge. With every new device, we introduce a new layer of complexity. How do we ensure these technologies support and empower workers, instead of quietly creating new risks (including occupational health and safety)?

This is the question driving our research. We found that the traditional risk assessment tools wouldn't be enough. So we improved qualitative risk assessment approaches to emerging complex systems, and proposed a new class of hybrid and quantitative tools to manage risk in these complex environments, especially where people and smart technologies interact. We developed prototypes and tested STPA-PSO and FRAM-PSO across three realistic case studies in industrial assembly and disassembly.

What we've discovered is that it's possible to design a safe system from the ground up—and that smarter risk management goes hand-in-hand with sustainability.

Hybrid Tools for Hybrid Workplaces!

Smart wearables, like data glasses or sensor gloves, are becoming increasingly common in manufacturing. They guide workers, gather data and facilitate the manufacturing process. But they also add complexity. If a device delays, distracts, or confuses, the consequences can ripple through the entire production system and have negative impacts on workers.

The problem is, traditional risk assessment tools were never built for this. They excel at analyzing mechanical failures or isolated events, not in the complex, dynamic interactions between people, machines, tools, software, instructions and the environment.

This is where our hybrid and quantitative prototype tools come in. We created our risk assessment prototype tools by blending human insight with the analytical power of AI to give us a much deeper understanding of workplace risks. Two of the key prototype tools we've developed are STPA-PSO and FRAM-PSO. Our prototype tools combine two parts:

1. **Emergent systemic qualitative risks assessment approaches (STPA, FRAM):** in other words, how workers, machines, tools, software, instructions and the environment all interact.
2. **AI optimization (PSO):** specifically, to quantify and prioritize risks, and to help decision-makers focus on what matters most.

While these terms might sound technical, the idea behind them is simple:

First, we use systemic approaches (STPA and FRAM) to map out the entire work process. This isn't just a simple flowchart; it's a dynamic map that shows how workers' actions, the technology they use, the instructions they receive, and the factory environment influence each other. It helps us see hidden connections and understand how one issue can trigger a chain reaction.

Then, we bring in AI. An algorithm called Particle Swarm Optimization (PSO) analyzes this complex map. It breaks down the data to quantify and prioritizes the biggest risks, so we can focus our attention where it really matters.

These hybrid and quantitive prototype tools allow us to move towards real, preventative solutions. Our prototype tools aren't black boxes; we designed them to support decision-makers, engineers and managers, with visual, understandable and actually useful results during the design phase, when it's easier and more efficient to shape outcomes. We tested this approach across three distinct realistic industrial settings: an assembly shop, a complex disassembly line and an assembly line.

But identifying risks was only the first step. It led us to a deeper question: What kind of workplace are we trying to build?

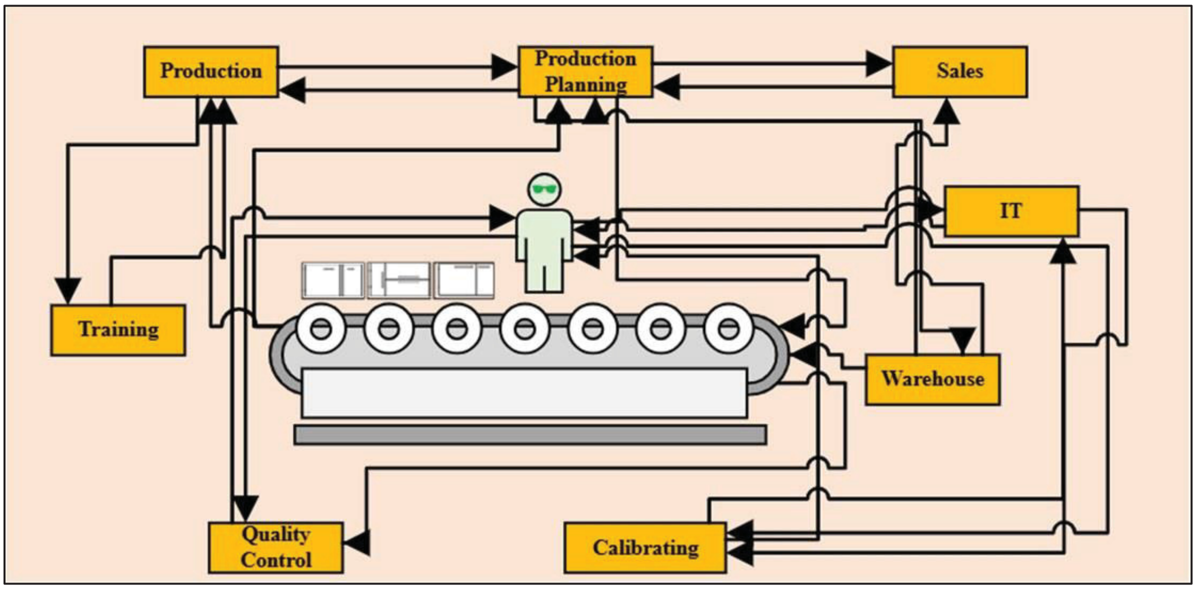

Figure-AX-1 Assmebly workstation

Beyond Occupational Health and Safety: Designing for Sustainability

For us, a truly advanced workplace is a sustainable workplace, and that means looking after people and the planet, as well as profits! Our prototype tools are designed to embed sustainability into every decision. When a risk is identified, we don't just ask, "How do we fix this?" We ask, "How do we fix this in a way that’s good for our workers, our business and our environment?"

- **Social sustainability**: It's all about the worker. Are the smart glasses causing eye strain? Is the workflow creating stress? Our prototype tools help pinpoint and reduce these OHS risks, leading to a healthier and more productive workforce. It’s about supporting and empowering people with technology, not overwhelming them.
- **Environmental sustainability**: It's all about our planet. The solutions weren’t just about OHS risks, but also about designing environmentally sound processes, promoting recycling and minimizing waste.

- **Economic sustainability**: By preventing errors, reducing material waste, and streamlining task flows, our prototype tools improve both OHS and productivity. The result? Smarter planning, lower costs and a more resilient operation.

Ultimately, our work is about fostering true collaboration between people and technology. Industry 5.0 is not about replacing humans, but about putting them back at the center, supported and empowered by intelligent tools. With approaches and new prototype tools like STPA-PSO and FRAM-PSO, we can design systems that are not only efficient but also safe, resilient and sustainable, right from the start.

This is our fundamental belief: Health, safety and sustainability aren't costs to be managed; they are outcomes to be designed. And with the right tools, we can build a future that’s not only smarter, but more human-centric.

Figure-AX-2 Smart wearables

REFERENCES

Ab Rahim, M. S., Reniers, G., Yang, M., & Bajpai, S. (2024). Risk assessment methods for process safety, process security and resilience in the chemical process industry: A thorough literature review. *Journal of Loss Prevention in the Process Industries*, 105274.

Abbassinia, M., Kalatpour, O., Motamedzade, M., Soltanian, A., & Mohammadfam, I. (2020). Dynamic human error assessment in emergency using fuzzy Bayesian CREAM. *Journal of Research in Health Sciences, 20*(1), e00468.

Adel, A. (2022). A conceptual framework to improve cyber forensic Administration in Industry 5.0: qualitative study approach. *Forensic Sciences, 2*(1), 111-129.

Adem, A., Çakit, E., & Dağdeviren, M. (2020). Occupational health and safety risk assessment in the domain of Industry 4.0. *SN Applied Sciences, 2*, 1-6.

Adriaensen, A., Decré, W., & Pintelon, L. (2019). Can complexity-thinking methods contribute to improving occupational safety in industry 4.0? A review of safety analysis methods and their concepts. *Safety, 5*(4), 65.

Afenyo, M., Khan, F., Veitch, B., & Yang, M. (2017). Arctic shipping accident scenario analysis using Bayesian Network approach. *Ocean Engineering, 133*, 224-230.

Afnor. (2024). *Qualité en expertise - Prescriptions générales de compétence pour une expertise*.

Aghabegloo, M., Rezaie, K., Torabi, S. A., & Yazdani, M. (2023). A metaheuristic-driven physical asset risk management framework for manufacturing system considering continuity measures. *Engineering Applications of Artificial Intelligence, 126*, 106789.

Aivaliotis, S., Papavasileiou, A., Konstantinou, C., Anastasiou, T., Gkournelos, C., Koukas, S., & Makris, S. (2024). An interactive Augmented Reality based framework assisting operators in human-robot collaborative assembly operations. *Procedia CIRP, 126*, 170-175.

Alenjareghi, M. J., Sekkay, F., Dadouchi, C., & Keivanpour, S. (2025). Wearable sensors in Industry 4.0: Preventing work-related musculoskeletal disorders. *Sensors International*, 100343.

Aliabadi, M. M. (2021). Human error analysis in furnace start-up operation using HEART under intuitionistic fuzzy environment. *Journal of Loss Prevention in the Process Industries, 69*, 104372.

Allison, C. K., Revell, K. M., Sears, R., & Stanton, N. A. (2017). Systems Theoretic Accident Model and Process (STAMP) safety modelling applied to an aircraft rapid decompression event. *Safety science, 98*, 159-166.

Alogla, A. A., & Alruqi, M. (2021). Aircraft assembly snags: human errors or lack of production design? *Aerospace, 8*(12), 391.

Alvarenga, M., e Melo, P. F., & Fonseca, R. (2014). A critical review of methods and models for evaluating organizational factors in Human Reliability Analysis. *Progress in Nuclear Energy, 75*, 25-41.

Andrews, T., Moulton, A., & Madnick, S. (2018). An Examination of Software Tool Features Needed to Help Secure Energy Delivery Industrial Control Systems. *MIT Sloan Research Paper, 18*, 5722. doi: 10.2139/ssrn.3370547

Angelopoulou, A., Mykoniatis, K., & Boyapati, N. R. (2020). Industry 4.0: The use of simulation for human reliability assessment. *Procedia Manufacturing, 42*, 296-301.

Aniceski, T. A., Miranda, L. T. P., Junior, O. C., & Benitez, G. B. (2024). The Four Smarts of Industry 4.0 and barriers for technology deployment: a TOE perspective. *Computers & Industrial Engineering, 193*, 110345.

Arana-Landín, G., Laskurain-Iturbe, I., Iturrate, M., & Landeta-Manzano, B. (2023). Assessing the influence of industry 4.0 technologies on occupational health and safety. *Heliyon, 9*(3). doi: 10.1016/j.heliyon.2023.e13720.

Badri, A., Boudreau-Trudel, B., & Souissi, A. S. (2018). Occupational health and safety in the industry 4.0 era: A cause for major concern? *Safety science, 109*, 403-411.

Badri, A., Nadeau, S., & Gbodossou, A. (2011). Integration of OHS into risk management in an open-pit mining project in Quebec (Canada). *Minerals, 1*(1), 3-29.

Baglietto, E., Consilvio, A., Di Febbraro, A., Papa, F., & Sacco, N. (2018). A Bayesian Network approach for the reliability analysis of complex railway systems. Dans *2018 international conference on intelligent rail transportation (ICIRT)* (pp. 1-6). IEEE.

Bahoo Toroody, A., Bahoo Toroody, F., & De Carlo, F. (2017). Development of a risk based methodology to consider influence of human failure in industrial plants operation. *Summer School "Francesco Turco*.

Bahoo Toroody, A., Talaee, A., Abaei, M. M., & Gholamnia, R. (2016). Applicability of integrating BN and resilience engineering on qualitative to quantitative description of human error. *J. Offshore Struct. Technol, 3*, 6-16.

Baig, M. M. H. A., & Prasanthi, S. G. (2013). Failure Modes and Effect Analysis of a Mechanical Assembly by Using Mil-Std 1629a Method. *the moon, 13*(13).

Baranoff, E., Brockett, P. L., & Kahane, Y. (2009). Risk Management for Enterprises and Individuals, Flat World Knowledge: Inc.

Barata, J., & da Cunha, P. R. (2019). *Safety Is the New Black: The Increasing Role of Wearables in Occupational Health and Safety in Construction* Conference Paper présentée à 22nd International Conference on Business Information Systems, BIS 2019. doi: 10.1007/978-3-030-20485-3_41.

Bavaresco, R., Arruda, H., Rocha, E., Barbosa, J., & Li, G. P. (2021). Internet of Things and occupational well-being in industry 4.0: A systematic mapping study and taxonomy. *Computers and Industrial Engineering, 161*. doi: 10.1016/j.cie.2021.107670.

Bavelos, A. C., Anastasiou, E., Dimitropoulos, N., Oikonomou, G., & Makris, S. (2024). Augmented reality-based method for road maintenance operators in human–robot collaborative interventions. *Computer-Aided Civil and Infrastructure Engineering, 39*(7), 1077-1095.

Beheshti, Z., & Shamsuddin, S. M. H. (2013). A review of population-based meta-heuristic algorithms. *Int. J. Adv. Soft Comput. Appl, 5*(1), 1-35.

Bell, J., & Holroyd, J. (2009). Review of human reliability assessment methods. *Health & Safety Laboratory, 78*.

Bellini, E., Coconea, L., & Nesi, P. (2019). A functional resonance analysis method driven resilience quantification for socio-technical systems. *IEEE Systems Journal, 14*(1), 1234-1244.

Berx, N., Decré, W., Morag, I., Chemweno, P., & Pintelon, L. (2022). Identification and classification of risk factors for human-robot collaboration from a system-wide perspective. *Computers & Industrial Engineering, 163*, 107827.

Billey, A., & Wuest, T. (2024). Energy digital twins in smart manufacturing systems: A case study. *Robotics and Computer-Integrated Manufacturing, 88*, 102729.

Billinghurst, M., & Starner, T. (1999). Wearable devices: new ways to manage information. *Computer, 32*(1), 57-64.

Bjerga, T., Aven, T., & Zio, E. (2016). Uncertainty treatment in risk analysis of complex systems: The cases of STAMP and FRAM. *Reliability Engineering & System Safety, 156*, 203-209.

Boring, R. L. (2012). *Fifty years of THERP and human reliability analysis* présentée à Probabilistic Safety Assessment and Management (PSAM11),Helsinki, Finland,06/24/2012,06/29/2012, United States.

Brocal, F., González, C., Komljenovic, D., Katina, P. F., & Sebastián, M. A. (2019). Emerging risk management in industry 4.0: an approach to improve organizational and human performance in the complex systems. *Complexity, 2019*.

Bubb, H. (2005). Human reliability: A key to improved quality in manufacturing. *Human Factors and Ergonomics in Manufacturing & Service Industries, 15*(4), 353-368.

Caeiro-Rodríguez, M., Otero-González, I., Mikic-Fonte, F. A., & Llamas-Nistal, M. (2021). A systematic review of commercial smart gloves: Current status and applications. *Sensors, 21*(8), 2667.

Calixto, E. (2016). *Gas and oil reliability engineering: modeling and analysis*. Gulf Professional Publishing.

Canadian Centre for Occupational Health and Safety, C. (2017). Hazard and Risk - Risk Assessment. Repéré

Cao, X., Ren, L., Wang, X., & Sun, C. (2025). Path Re-planning method of unmanned underwater vehicles based on dynamic bayesian threat assessment. *Ocean Engineering, 315*, 119819.

Carniel, A., Bezerra, J. D. M., & Hirata, C. M. (2023). An Ontology-Based Approach to Aid STPA Analysis. *IEEE Access, 11*, 12677-12697.

Castiglia, F., & Giardina, M. (2013). Analysis of operator human errors in hydrogen refuelling stations: Comparison between human rate assessment techniques. *International Journal of Hydrogen Energy, 38*(2), 1166-1176.

Castillo, E., Calviño, A., Grande, Z., Sánchez-Cambronero, S., Gallego, I., Rivas, A., & Menéndez, J. M. (2016). A Markovian–Bayesian network for risk analysis of high speed and conventional railway lines integrating human errors. *Computer-Aided Civil and Infrastructure Engineering, 31*(3), 193-218.

Ceylan, B. O., Akyuz, E., & Arslanoğlu, Y. (2022). Modified quantitative systems theoretic accident model and processes (STAMP) analysis: A catastrophic ship engine failure case. *Ocean Engineering, 253*, 111187.

Chang, P.-C. (2024). A path-based simulation approach for multistate flow network reliability estimation without using boundary points. *Reliability Engineering & System Safety, 249*, 110237.

Chari, A., Stahre, J., Bärring, M., Despeisse, M., Li, D., Friis, M., . . . Johansson, B. (2023). Analysing the antecedents to digital platform implementation for resilient and sustainable manufacturing supply chains-An IDEF0 modelling approach. *Journal of cleaner production, 429*, 139598.

Cheng, P.-F., Li, D.-P., He, J.-Q., Zhou, X.-H., Wang, J.-Q., & Zhang, H.-Y. (2020). Evaluating surgical risk using FMEA and MULTIMOORA methods under a single-valued trapezoidal neutrosophic environment. *Risk Management and Healthcare Policy, 13*, 865.

Chien, C.-F., & Peng, J.-Y. (2025). Bayesian inference for multi-label classification for root cause analysis and probe card maintenance decision support and an empirical study. *Journal of Intelligent Manufacturing, 36*(3), 1943-1958.

Ciccarelli, M., Papetti, A., & Germani, M. (2023). Exploring how new industrial paradigms affect the workforce: A literature review of Operator 4.0. *Journal of Manufacturing Systems, 70*, 464-483.

Coccia, A., Capodaglio, E. M., Amitrano, F., Gabba, V., Panigazzi, M., Pagano, G., & D'Addio, G. (2024). Biomechanical effects of using a passive exoskeleton for the upper limb in industrial manufacturing activities: A pilot study. *Sensors, 24*(5), 1445.

Cooper, S. E., Ramey-Smith, A., Wreathall, J., & Parry, G. (1996). *A technique for human error analysis (ATHEANA)*. United States: Nuclear Regulatory Commission.

Costantino, F., Di Gravio, G., & Tronci, M. (2018). Environmental Audit improvements in industrial systems through FRAM. *IFAC-PapersOnLine, 51*(11), 1155-1161.

Cox, L. (2008). What's Wrong with Risk Matrices? Risk Analyses, Vol. 28, No 2.

Cristaldi, L., Khalil, M., & Soulatintork, P. (2017). A root cause analysis and a risk evaluation of PV balance of system failures. *Acta Imeko, 6*(4), 113-120.

Das, P., Benneyan, J., Powers, L., Carmody, M., Kerwin, J., & Singer, S. (2018). Engineering safer care coordination from hospital to home: lessons from the USA. *Future healthcare journal, 5*(3), 164.

de Andrade Melani, A. H., de Carvalho Michalski, M. A., da Silva, R. F., & de Souza, G. F. M. (2021). A framework to automate fault detection and diagnosis based on moving window principal component analysis and Bayesian network. *Reliability Engineering & System Safety, 215*, 107837.

de Carvalho, E. A., Gomes, J. O., Jatobá, A., da Silva, M. F., & de Carvalho, P. V. R. (2021). Employing resilience engineering in eliciting software requirements for complex systems: experiments with the functional resonance analysis method (FRAM). *Cognition, Technology & Work, 23*(1), 65-83.

de Carvalho, P., Villarinho, L., & Haddad, A. (2016). FRAM-AHP: A systemic methodology for occupational risk assessment FRAM-AHP: A systemic methodology for occupational risk. Dans *Proceedings of the 8th WOS International Conference*.

De Linhares, T., Maia, Y., & e Melo, P. F. F. (2021). The phased application of STAMP, FRAM and RAG as a strategy to improve complex sociotechnical system safety. *Progress in Nuclear Energy, 131*, 103571.

de Paula Ferreira, W., Armellini, F., & De Santa-Eulalia, L. A. (2020). Simulation in industry 4.0: A state-of-the-art review. *Computers & Industrial Engineering, 149*, 106868.

de Paula Ferreira, W., Armellini, F., de Santa-Eulalia, L. A., & Thomasset-Laperrière, V. (2022). A framework for identifying and analysing industry 4.0 scenarios. *Journal of Manufacturing Systems, 65*, 192-207.

Demir, K. A., & Cicibaş, H. (2019). The next industrial revolution: industry 5.0 and discussions on industry 4.0. *Industry, 4*, 247-260.

Devarajan, M., Khan, M. S., Sandeep, K., Hamza, L. H., Soujanya, K., & Munirathinam, S. (2025). Smart Manufacturing Assessment on Cybersecurity Risks using Bayesian and Hybrid Fuzzy Logic Networks. Dans *2025 International Conference on Computational Innovations and Engineering Sustainability (ICCIES)* (pp. 1-6). IEEE.

Di Pasquale, V., De Simone, V., Giubileo, V., & Miranda, S. (2023). A taxonomy of factors influencing worker's performance in human–robot collaboration. *IET Collaborative Intelligent Manufacturing, 5*(1), e12069.

Di Pasquale, V., De Simone, V., Radano, M., & Miranda, S. (2022). Wearable devices for health and safety in production systems: a literature review. *IFAC-PapersOnLine, 55*(10), 341-346.

Digiesi, S., Facchini, F., Mossa, G., & Vitti, M. (2023). A model to evaluate the human error probability in inspection tasks of a production system. *Procedia Computer Science, 217*, 1775-1783.

Dipietro, L., Sabatini, A. M., & Dario, P. (2008). A survey of glove-based systems and their applications. *Ieee transactions on systems, man, and cybernetics, part c (applications and reviews), 38*(4), 461-482.

Djefour, D., Nadeau, S., & Landau, K. (2024). Mise en application d'une analyse ergonomique couplée à une étude et une mesure du travail dans JACK 7.1.

Dong, C., & Yang, Y. (2025). Dynamic risk-informed verification prioritization for Complex Product Systems: A tri-metric approach using a Multi-State Hierarchical Bayesian Network. *Reliability Engineering & System Safety*, 111146.

Du, G., Liang, X., Ouyang, X., & Wang, C. (2021). Risk prediction of hypertension complications based on the intelligent algorithm optimized Bayesian network. *Journal of Combinatorial Optimization, 42*, 966-987.

Du, T., Zhang, S., & Wang, Z. (2005). Efficient learning bayesian networks using pso. Dans *International Conference on Computational and Information Science* (pp. 151-156). Springer.

Due, B. L. (2014). *The future of smart glasses: An essay about challenges and possibilities with smart glasses* (Vol. 1). Centre of Interaction Research and Communication Design, University of ….

Dul, J., & Hak, T. (2007). *Case study methodology in business research*. Routledge.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of management review, 14*(4), 532-550.

El Helou, M., Benfriha, K., Al-Ahmari, A. M., Wardle, P., Talhi, E., Loubère, S., . . . Charrier, Q. (2022). A Modular Smart Vision System for Industrial Inspection and Control of Conformity.

Elidrisy, A. (2024). Comparative Review of ESG Reporting Standards: ESRS European Sustainability Reporting Standards "versus ISSB" International Sustainability Standards Board (Comparative Analysis of ESG Reporting Standards). *International Multilingual Journal of Science and Technology, 9*(3), 7191-7198.

Eljaoued, W., Yahia, N. B., & Saoud, N. B. B. (2020). A Qualitative-quantitative resilience assessment approach for socio-technical systems. *Procedia Computer Science, 176*, 2625-2634.

Emami-Mehrgani, B., Neumann, W. P., Nadeau, S., & Bazrafshan, M. (2016). Considering human error in optimizing production and corrective and preventive maintenance policies for manufacturing systems. *Applied mathematical modelling, 40*(3), 2056-2074.

Embrey, D. (1986). SHERPA: A systematic human error reduction and prediction approach. Dans *Proceedings of the international topical meeting on advances in human factors in nuclear power systems*.

Embrey, D., Humphreys, P., Rosa, E., Kirwan, B., & Rea, K. (1984). *SLIM-MAUD: an approach to assessing human error probabilities using structured expert judgment. Volume I. Overview of SLIM-MAUD*. United States: Brookhaven National Lab., Upton, NY (USA).

Engelbrecht, A. P. (2007). *Computational intelligence: an introduction*. John Wiley & Sons.

Érdi, P. (2008). *Complexity explained*. Springer.

Ericson, C. A. (2015). *Hazard analysis techniques for system safety*. John Wiley & Sons.

Foo, D. C., & Tan, R. R. (2016). A review on process integration techniques for carbon emissions and environmental footprint problems. *Process safety and environmental protection, 103*, 291-307.

França, J. E., Hollnagel, E., dos Santos, I. J., & Haddad, A. N. (2020). FRAM AHP approach to analyse offshore oil well drilling and construction focused on human factors. *Cognition, Technology & Work, 22*(3), 653-665.

França, J. E., Hollnagel, E., dos Santos, I. J., & Haddad, A. N. (2021). Analysing human factors and non-technical skills in offshore drilling operations using FRAM (functional resonance analysis method). *Cognition, Technology & Work, 23*(3), 553-566.

Friedmann, H. (1978). World market, state, and family farm: Social bases of household production in the era of wage labor. *Comparative studies in society and history, 20*(4), 545-586.

Gaiardelli, S., Spellini, S., Lora, M., & Fummi, F. (2021). Modeling in Industry 5.0: What Is There and What Is Missing: Special Session 1: Languages for Industry 5.0. Dans *2021 Forum on specification & Design Languages (FDL)* (pp. 01-08). IEEE.

Gertman, D., Blackman, H., Marble, J., Byers, J., & Smith, C. (2005). The SPAR-H human reliability analysis method. *US Nuclear Regulatory Commission, 230*(4), 35.

Ghasemi, F., Ghasemi, A., & Kalatpour, O. (2022). Prediction of human error probability during the hydrocarbon road tanker loading operation using a hybrid technique of fuzzy sets, Bayesian network and CREAM. *International Journal of Occupational Safety and Ergonomics, 28*(3), 1342-1352.

Glover, F., & Laguna, M. (1997). Tabu Search Kluwer. *Boston, MA*.

Gorrod, M. (2003). *Risk management systems: process, technology and trends*. Springer.

Groth, K., & Mosleh, A. (2011). Development and use of a Bayesian network to estimate human error probability. Dans *ANS PSA,(2011) International Topical Meeting on Probabilistic Safety Assessment and Analysis Wilmington. NC, Wilmington, NC*.

Gualtieri, L., Rauch, E., & Vidoni, R. (2021). Emerging research fields in safety and ergonomics in industrial collaborative robotics: A systematic literature review. *Robotics and Computer-Integrated Manufacturing, 67*, 101998.

Gualtieri, L., Rauch, E., & Vidoni, R. (2022). Development and validation of guidelines for safety in human-robot collaborative assembly systems. *Computers & Industrial Engineering, 163*, 107801.

Guo, Y., Jin, Y., Hu, S., Yang, Z., Xi, Y., & Han, B. (2022). Risk evolution analysis of ship pilotage operation by an integrated model of FRAM and DBN. *Reliability Engineering & System Safety*, 108850.

Gustafsson, J. (2017). Single case studies vs. multiple case studies: A comparative study. Halmstad University.

Haddad, A. N., & Rosa, L. V. (2015). Construction sustainability evaluation using AHP and FRAM methods. Dans *IIE Annual Conference. Proceedings* (pp. 556). Institute of Industrial and Systems Engineers (IISE).

Hao, Y., & Helo, P. (2017). The role of wearable devices in meeting the needs of cloud manufacturing: A case study. *Robotics and Computer-Integrated Manufacturing, 45*, 168-179.

Harrison, H., Birks, M., Franklin, R., & Mills, J. (2017). Case study research: Foundations and methodological orientations. Dans *Forum qualitative Sozialforschung/Forum: qualitative social research* (Vol. 18).

Hasanain, B. (2024). The role of ergonomic and human factors in sustainable manufacturing: A review. *Machines, 12*(3), 159.

Hasibuan, C. F., Daeng, P. Y., & Hasibuan, R. R. (2020). Human Reliability Assessment Analysis with Human Error Assessment and Reduction Technique (HEART) Method on Sterilizer Station at XYZ Company. Dans *IOP Conference Series: Materials Science and Engineering* (Vol. 851, pp. 012019). IOP Publishing.

Hayat, H., & Reda, G. A. (2022). An IoT and spatial Big data based architecture for monitoring Occupational Health Risks exposure. Dans *1st International Conference on Big Data, IoT, Web Intelligence and Applications, BIWA 2022* (pp. 13-18). Institute of Electrical and Electronics Engineers Inc. doi: 10.1109/BIWA57631.2022.10037804.

He, B., & Bai, K.-J. (2021). Digital twin-based sustainable intelligent manufacturing: A review. *Advances in Manufacturing, 9*(1), 1-21.

He, W., Lin, Z., Li, W., Wong, C., Kong, D., & Loh, W. E. (2025). The comprehensive safety assessment method for complex construction crane accidents based on scenario analysis–A case study of crane accidents. *Computers & Industrial Engineering, 199*, 110716.

Helbing, D. (2013). Globally networked risks and how to respond. *Nature, 497*(7447), 51-59.

Hettinger, L. J., Kirlik, A., Goh, Y. M., & Buckle, P. (2015). Modelling and simulation of complex sociotechnical systems: envisioning and analysing work environments. *Ergonomics, 58*(4), 600-614.

Hibbard, M. J., Peskin, E. R., & Sahin, F. (2013). FPGA implementation of particle swarm optimization for Bayesian network learning. *Computers & Electrical Engineering, 39*(8), 2454-2468.

Hollnagel, E. (1998). *Cognitive reliability and error analysis method (CREAM)*. Elsevier.

Hollnagel, E. (2012). *FRAM: The functional resonance analysis method: Modelling complex socio-technical systems, FRAM: The Functional Resonance Analysis Method: Modelling Complex Socio-technical Systems*. Ashgate Publishing.

Hollnagel, E., & Goteman, O. (2004). The functional resonance accident model. *Proceedings of cognitive system engineering in process plant, 2004*, 155-161.

How_It's_Made_Show. (2016). How It’s Made Fridge.

Hu, S., Li, W., Xi, Y., Li, W., Hou, Z., Wu, J., & Han, B. (2022). Evolution pathway of process risk of marine traffic with the STAMP model and a genetic algorithm: A simulation of LNG-fueled vessel in-and-out harbor. *Ocean Engineering, 253*, 111133.

Huang, K., Jia, G., Wang, Q., Cai, Y., Zhong, Z., & Jiao, Z. (2024). Spatial relationship-aware rapid entire body fuzzy assessment method for prevention of work-related musculoskeletal disorders. *Applied Ergonomics, 115*, 104176.

Huang, T., Xiahou, T., Mi, J., Chen, H., Huang, H.-Z., & Liu, Y. (2024). Merging multi-level evidential observations for dynamic reliability assessment of hierarchical multi-state systems: A dynamic Bayesian network approach. *Reliability Engineering & System Safety, 249*, 110225.

Hulme, A., McLean, S., Dallat, C., Walker, G. H., Waterson, P., Stanton, N. A., & Salmon, P. M. (2021). Systems thinking-based risk assessment methods applied to sports performance: A comparison of STPA, EAST-BL, and Net-HARMS in the context of elite women's road cycling. *Applied ergonomics, 91*, 103297.

Hulme, A., Stanton, N. A., Walker, G. H., Waterson, P., & Salmon, P. M. (2019). What do applications of systems thinking accident analysis methods tell us about accident causation? A systematic review of applications between 1990 and 2018. *Safety science, 117*, 164-183.

Hunte, J. L., Neil, M., & Fenton, N. E. (2024). A hybrid Bayesian network for medical device risk assessment and management. *Reliability Engineering & System Safety, 241*, 109630.

Ioniță, A.-R., Anghel, D.-C., & Boudouh, T. (2025). Mind, Machine, and Meaning: Cognitive Ergonomics and Adaptive Interfaces in the Age of Industry 5.0. *Applied Sciences (2076-3417), 15*(14).

Irshad, L., Hulse, D., Demirel, H. O., Tumer, I. Y., & Jensen, D. C. (2021). Quantifying the Combined Effects of Human Errors and Component Failures. *Journal of Mechanical Design, 143*(10).

ISO. (2023). *ISO/DTS31050, Risk management — Guidelines for managing emerging risk to enhance resilience*.

Jain, M., Saihjpal, V., Singh, N., & Singh, S. B. (2022). An Overview of Variants and Advancements of PSO Algorithm. *Applied Sciences, 12*(17), 8392.

Jasiulewicz-Kaczmarek, M., & Gola, A. (2019). Maintenance 4.0 technologies for sustainable manufacturing-an overview. *IFAC-PapersOnLine, 52*(10), 91-96.

Javaid, M., & Haleem, A. (2020). Critical components of Industry 5.0 towards a successful adoption in the field of manufacturing. *Journal of Industrial Integration and Management, 5*(03), 327-348.

Jensen, A., & Aven, T. (2018). A new definition of complexity in a risk analysis setting. *Reliability Engineering & System Safety, 171*, 169-173.

Jensen, M. C. (1993). The modern industrial revolution, exit, and the failure of internal control systems. *the Journal of Finance, 48*(3), 831-880.

Jovanović, B., & Filipović, J. (2016). ISO 50001 standard-based energy management maturity model–proposal and validation in industry. *Journal of cleaner production, 112*, 2744-2755.

Jwo, J.-S., Lin, C.-S., & Lee, C.-H. (2021). Smart technology–driven aspects for human-in-the-loop smart manufacturing. *The International Journal of Advanced Manufacturing Technology, 114*(5), 1741-1752.

Kane, E. A., & Higham, T. E. (2015). Complex systems are more than the sum of their parts: using integration to understand performance, biomechanics, and diversity. *Integrative and Comparative Biology, 55*(1), 146-165.

Kaneko, T., Yoshioka, N., & Sasaki, R. (2020). STAMP S&S: Safety & Security Scenario for Specification and Standard in the society of AI/IoT. Dans *2020 IEEE 20th International Conference on Software Quality, Reliability and Security Companion (QRS-C)* (pp. 168-175). IEEE.

Karevan, A., & Nadeau, S. (2023). The Role of Industry 5.0 in Reducing the Risk of Human Error in Manufacturing A Critical Literature Review. Dans *CIGI QUALITA MOSIM 2023*.

Karevan, A., & Nadeau, S. (2024a). A comprehensive STPA-PSO Framework for quantifying smart glasses risks in manufacturing. *Heliyon, 10*(9). doi: 10.1016/j.heliyon.2024.e30162

Karevan, A., & Nadeau, S. (2024b). Fostering AI-human collaboration in industry 5.0 manufacturing. Dans *Congress of the International Ergonomics Association* (pp. 457-463). Springer.

Karevan, A., & Nadeau, S. (2024d). FRAM effectiveness in the era of Industry 4.0: A dual perspective review. Dans *IISE Annual Conference. Proceedings* (pp. 1-6). Institute of Industrial and Systems Engineers (IISE). doi: 10.21872/2024IISE_6792

Karevan, A., & Nadeau, S. (2025a). FRAM-PSO: A semi-quantitative framework integrating multi-dimensional sustainability criteria. *Computers & Industrial Engineering, 210*, 111560. doi: https://doi.org/10.1016/j.cie.2025.111560

Karevan, A., & Nadeau, S. (2025b). Integrating Smart Glasses and Smart Gloves in Hybrid Assembly/Disassembly Systems: An Stpa-Driven Semi-Automated Risk Management Tool. *Robotics and Computer-Integrated Manufacturing, Manuscript under review*. doi: dx.doi.org/10.2139/ssrn.5033707

Karevan, A., Tee, K. F., & Vasili, M. (2020). A reliability-based and sustainability-informed maintenance optimization considering risk attitudes for telecommunications equipment. *International Journal of Quality & Reliability Management, 38*(4), 873-891.

Karevan, A., & Vasili, M. (2018). Sustainable reliability centered maintenance optimization considering risk attitude. *Journal of applied research on industrial engineering, 5*(3), 205-222.

Karwowski, W., Salvendy, G., Endsley, M., Rouse, W., Salmon, P., Stanney, K., . . . Ayaz, H. (2025). Grand challenges for human factors and ergonomics. *Theoretical Issues in Ergonomics Science*, 1-96.

Kaya, G. K., & Hocaoglu, M. F. (2020). Semi-quantitative application to the Functional Resonance Analysis Method for supporting safety management in a complex health-care process. *Reliability Engineering & System Safety, 202*, 106970.

Kaya, G. K., Ozturk, F., & Sariguzel, E. E. (2021). System-based risk analysis in a tram operating system: Integrating Monte Carlo simulation with the functional resonance analysis method. *Reliability Engineering & System Safety, 215*, 107835.

Kazaras, K., Kirytopoulos, K., & Rentizelas, A. (2012). Introducing the STAMP method in road tunnel safety assessment. *Safety science, 50*(9), 1806-1817.

Khanzode, K. C. A., & Sarode, R. D. (2020). Advantages and disadvantages of artificial intelligence and machine learning: A literature review. *International Journal of Library & Information Science (IJLIS), 9*(1), 3.

Khodammohammadi, N., Ngô, V. T. M., & Nadeau, S. (2023). *Integrating Smart Glasses in a Hybrid Manufacturing System: Towards a Better Understanding of Impacts on Productivity, Quality and Ergonomics/Human Factors* présentée à CIGI QUALITA MOSIM 2023, Trois-Rivières, Canada.

Khoddammohammadi, N. (2023). *Modeling and Qualification of Future Digitalized Assembly Work* (École de technologie supérieure).

Kim, D., & Choi, Y. (2021). Applications of smart glasses in applied sciences: A systematic review. *Applied Sciences, 11*(11), 4956.

Kim, Y. C., & Yoon, W. C. (2021). Quantitative representation of the functional resonance analysis method for risk assessment. *Reliability Engineering & System Safety, 214*, 107745.

Kirwan, B. (1983). Technique for human error rate prediction (THERP). *Swain and Guttman*.

Kirwan, B. (1992). Human error identification in human reliability assessment. Part 1: Overview of approaches. *Applied ergonomics, 23*(5), 299-318.

Knight, J. F., & Baber, C. (2007). Assessing the physical loading of wearable computers. *Applied ergonomics, 38*(2), 237-247.

Köpke, C., Schäfer-Frey, J., Engler, E., Wrede, C. P., & Mielniczek, J. (2020). A joint approach to safety, security and resilience using the functional resonance analysis method. Dans *8th REA Symposium on Resilience Engineering: Scaling up and Speeding up*.

Kraidi, L., Shah, R., Matipa, W., & Borthwick, F. (2021). An investigation of mitigating the safety and security risks allied with oil and gas pipeline projects. *Journal of Pipeline Science and Engineering, 1*(3), 349-359.

Krivogorsky, V. (2024). Sustainability reporting with two different voices: the European Union and the international sustainability standards board. *Journal of International Accounting, Auditing and Taxation, 56*, 100635.

Krzywdzinski, M., Pfeiffer, S., Evers, M., & Gerber, C. (2022). *Measuring work and workers: Wearables and digital assistance systems in manufacturing and logistics* (Vol. SP III 2022-301). Wissenschaftszentrum Berlin für Sozialforschung gGmbH.

Kumar, A., Upadhyay, R., Samanta, B., & Bhattacherjee, A. (2024). Improving safety in complex systems: A review of integration of functional resonance analysis method with semi-quantitative and quantitative approaches. *Human Factors and Ergonomics in Manufacturing & Service Industries, 34*(6), 572-588.

Kumar, A. M., Rajakarunakaran, S., & Prabhu, V. A. (2017). Application of Fuzzy HEART and expert elicitation for quantifying human error probabilities in LPG refuelling station. *Journal of Loss Prevention in the Process Industries, 48*, 186-198.

Kumar, D., Soni, G., Jabeen, F., Tiwari, N. K., Sariyer, G., & Ramtiyal, B. (2024). A hybrid Bayesian approach for assessment of industry 4.0 technologies towards achieving decarbonization in manufacturing industry. *Computers & Industrial Engineering, 190*, 110057.

Kumar, N. M., Singh, N. K., & Peddiny, V. (2018). Wearable smart glass: features, applications, current progress and challenges. Dans *2018 second international conference on green computing and internet of things (ICGCIoT)* (pp. 577-582). IEEE.

Kutz, J., Neuhüttler, J., Spilski, J., & Lachmann, T. (2022). *Implementation of AI Technologies in Manufacturing–Success Factors and Challenges* présentée à AHFE (2022) International Conference, USA. doi: 10.54941/ahfe1002565.

La Fata, C., Adelfio, L., Micale, R., & La Scalia, G. (2023). Human error contribution to accidents in the manufacturing sector: A structured approach to evaluate the interdependence among performance shaping factors. *Safety science, 161*, 106067.

Lalwani, S., Singhal, S., Kumar, R., & Gupta, N. (2013). A comprehensive survey: Applications of multi-objective particle swarm optimization (MOPSO) algorithm. *Transactions on combinatorics, 2*(1), 39-101.

Lee, J., & Chung, H. (2018). A new methodology for accident analysis with human and system interaction based on FRAM: Case studies in maritime domain. *Safety science, 109*, 57-66.

Lee, L.-H., & Hui, P. (2018). Interaction methods for smart glasses: A survey. *Ieee Access, 6*, 28712-28732.

Lehre, P. K., & Witt, C. (2013). Finite first hitting time versus stochastic convergence in particle swarm optimisation. Dans *Advances in metaheuristics* (pp. 1-20). Springer.

Leveson, N. (2004). A new accident model for engineering safer systems. *Safety science, 42*(4), 237-270.

Leveson, N., & Thomas, J. P. (2018). STPA handbook. *Cambridge, MA, USA*.

Li, D., Xiong, G., Zeng, H., Zhou, Q., Jiang, J., & Guo, X. (2021). Machine learning-aided risk stratification system for the prediction of coronary artery disease. *International Journal of Cardiology, 326*, 30-34.

Li, G., Xing, L., & Chen, Y. (2015). A new BN structure learning mechanism based on decomposability of scoring functions. Dans *Bio-Inspired Computing-Theories and Applications* (pp. 212-224). Springer.

Li, H., Ren, X., & Yang, Z. (2023). Data-driven Bayesian network for risk analysis of global maritime accidents. *Reliability Engineering & System Safety, 230*, 108938.

Liu, X., Liu, Z., Lin, K.-C., Huang, Z.-L., Ling, M.-Y., Chen, P.-Q., . . . Zhai, Y.-J. (2021). Evaluation of the Operation Process of Medical Equipment to Enhance Ergonomic Reliability Based on FRAM–Moran's I and CREAM. *Applied Sciences, 12*(1), 200.

Lolli, F., Coruzzolo, A. M., Alessandro, G., Balugani, E., Butturi, M. A., Marinello, S., & Marinelli, S. (2021). The Dynamic, Individual and Integrated Risk Assessment: A Multi-criteria Approach Using Big Data. Dans *Advances in Safety Management and Human Performance: Proceedings of the AHFE 2021 Virtual Conferences on Safety Management and Human Factors, and Human Error, Reliability, Resilience, and Performance, July 25-29, 2021, USA* (pp. 207-215). Springer.

Lopez de Obeso, L., Mock, R. G., & Zipper, C. (2016). Operationalization of an ISO 31000-compliant resilience engineering method, applied to the temperature control in a smart building. Dans *6th International Disaster and Risk Conference (IDRC Davos 2016), Davos, 28 August-1 September 2016* (pp. 393-397). Global Risk Forum.

Lu, X., Zeng, S., Guo, J., Deng, W., He, M., & Che, H. (2025). An integrated method of extended STPA and BN for safety assessment of man-machine phased-mission system. *Reliability Engineering & System Safety, 253*, 110569.

Luke, S. (2013). *Essentials of metaheuristics* (Vol. 2). Lulu Raleigh.

Lundblad, K., Speziali, J., Woltjer, R., & Lundberg, J. (2008). FRAM as a risk assessment method for nuclear fuel transportation. Dans *Proceedings of the 4th International Conference Working on Safety* (Vol. 1, pp. 223-221).

Ma, S., Ding, W., Liu, Y., Zhang, Y., Ren, S., Kong, X., & Leng, J. (2024). Industry 4.0 and cleaner production: A comprehensive review of sustainable and intelligent manufacturing for energy-intensive manufacturing industries. *Journal of cleaner production*, 142879.

MacAllister, A., Kohl, A., & Winer, E. (2020). Using high-fidelity meta-models to improve performance of small dataset trained Bayesian Networks. *Expert Systems with Applications, 139*, 112830.

Machado, C. G., Winroth, M. P., & Ribeiro da Silva, E. H. D. (2020). Sustainable manufacturing in Industry 4.0: an emerging research agenda. *International Journal of Production Research, 58*(5), 1462-1484.

Maddikunta, P. K. R., Pham, Q.-V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., . . . Liyanage, M. (2022). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration, 26*, 100257.

Makris, S., Michalos, G., Dimitropoulos, N., Krueger, J., & Haninger, K. (2024). Seamless human–robot collaboration in industrial applications. Dans *CIRP Novel Topics in Production Engineering: Volume 1* (pp. 39-73). Springer.

Mannan, S. (2013). *Lees' Process Safety Essentials: Hazard Identification, Assessment and Control*. Butterworth-Heinemann.

Marini, F., & Walczak, B. (2015). Particle swarm optimization (PSO). A tutorial. *Chemometrics and Intelligent Laboratory Systems, 149*, 153-165.

Marino, E., Barbieri, L., Bruno, F., & Muzzupappa, M. (2024). Assessing user performance in augmented reality assembly guidance for industry 4.0 operators. *Computers in Industry, 157*, 104085.

Martín-Gómez, A. M., Agote-Garrido, A., & Lama-Ruiz, J. R. (2024). A framework for sustainable manufacturing: Integrating industry 4.0 technologies with industry 5.0 values. *Sustainability, 16*(4), 1364.

Melanson, A., & Nadeau, S. (2019). Resilience engineering for sustainable prevention in the manufacturing sector: A comparative study of two methods of risk analysis. *American Journal of Industrial and Business Management, 9*(1), 267-281.

Meng, H., Hu, M., Kong, Z., Niu, Y., Liang, J., Nie, Z., & Xing, J. (2024). Risk analysis of lithium-ion battery accidents based on physics-informed data-driven Bayesian networks. *Reliability Engineering & System Safety, 251*, 110294.

Micu, E. A., Asgari, F., Khouadjia, M., Connolly, L., & Zavitsas, K. (2024). A probabilistic digital twin model for inland waterway transportation systems using Bayesian networks. Dans *CSuM 2024-Climate Crisis and Resilient Transportation Systems*.

Military, U. (1949). Procedures for Performing a Failure Mode, Effects and Criticality Analysis, . *United States military procedure MIL-P-1629*.

Mirabel, M. E., Yuliana, O. Y., & Yahya, B. N. (2022). Conceptual Framework for Efficient Inbound Supply Chain Analytics. Dans *2022 6th International Conference on Business and Information Management (ICBIM)* (pp. 196-201). IEEE.

Mkrtchyan, L., Podofillini, L., & Dang, V. N. (2015). Bayesian belief networks for human reliability analysis: A review of applications and gaps. *Reliability Engineering & System Safety, 139*, 1-16.

Mofidi Naeini, A. (2022). *Development of a risk management approach for data gloves used in assembly* (École de technologie supérieure).

Mofidi Naeini, A., & Nadeau, S. (2022a). Application of FRAM to perform Risk Analysis of the Introduction of a Data Glove to Assembly Tasks. *Robotics and Computer-Integrated Manufacturing, 74*, 102285.

Mofidi Naeini, A., & Nadeau, S. (2022b). Comparing FRAM and STAMP for occupational health and safety (OHS) and operational risks analysis: The case of data gloves in assembly 4.0 production. *Safety and Health at Work, 13*, S89.

Mofidi Naeini, A., & Nadeau, S. (2022c). STPA systemic approach for OHS and operational risk analysis of data glove use in 4.0 assembly. *CIRP Journal of Manufacturing Science and Technology, 39*, 317-331.

Mofidi Naeini, A., & Nadeau, S. (2023). Proposed integrated FRAM/STPA risk analysis of data gloves in assembly 4.0 system. *Robotics and Computer-Integrated Manufacturing, 81*, 102523.

Mokhtarzadeh, M., Rodríguez-Echeverría, J., Semanjski, I., & Gautama, S. (2025). Hybrid intelligence failure analysis for industry 4.0: a literature review and future prospective. *Journal of Intelligent Manufacturing, 36*(4), 2309-2334.

Montibeller, G., & Von Winterfeldt, D. (2015). Cognitive and motivational biases in decision and risk analysis. *Risk Analysis, 35*(7), 1230-1251.

Morais, C., Moura, R., Beer, M., & Patelli, E. (2020). Analysis and estimation of human errors from major accident investigation reports. *ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg, 6*(1).

Moslem, S., Gholamizadehc, K., Zarei, E., Pasman, H. J., Martinez-Pastor, B., & Pilla, F. (2025). A Comparative Assessment of Domino Accident Analysis Methods in Process Industries Using LMAW and DNMA Techniques. *Reliability Engineering & System Safety*, 110981.

Mostafa, M. F., Aleem, S. H. A., & Zobaa, A. F. (2016). Risk assessment and possible mitigation solutions for using solar photovoltaic at airports. Dans *2016 eighteenth international middle east power systems conference (MEPCON)* (pp. 81-88). IEEE.

Mousavi, M., Shen, X., & Li, B. (2023). Online safety risk management for underground mining and construction based on IoT and Bayesian networks. Dans *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction* (Vol. 40, pp. 498-505). IAARC Publications.

Mukherjee, P., Patra, S. S., Samantaray, S., Barik, L., & Barik, R. K. (2022). SCSF: supply chain sustainability framework by Bayesian theory and Markov model for risk analysis. Dans *Evolution in Computational Intelligence: Proceedings of the 9th International Conference on Frontiers in Intelligent Computing: Theory and Applications (FICTA 2021)* (pp. 301-308). Springer.

Mutual, L. (2017). Tailor made to reduce risk: wearable technology in the workplace.

Nadeau, S. (2005). Can ergonomics (and investments in health and safety) be useful in sustaining a competitive advantage? Dans *Contemporary Ergonomics 2005: Proceedings of the International Conference on Contemporary Ergonomics (CE2005), 5-7 April 2005, Hatfield, UK* (pp. 313). CRC Press.

Nadeau, S., Bruder, R., & Hof, L. (2021). Using smart glasses in assembly/disassembly: current state of the art. *Travail et Santé, 37*(2), 2-6.

Nadeau, S., & Landeau, K. (2018). Utility, advantages and challenges of digital technologies in the manufacturing sector. *Ergonomics International Journal, 2*(12).

Nahavandi, S. (2019). Industry 5.0—A human-centric solution. *Sustainability, 11*(16), 4371.

Nakajima, K. (2017). Blood transfusion with health information technology in emergency settings from a Safety-II perspective. Dans *Resilient Health Care, Volume 2* (pp. 129-144). CRC Press.

Neapolitan, R. E., & Naimipour, K. (2004). *Foundations of algorithms using Java pseudocode*. Jones & Bartlett Learning.

Nesmachnow, S. (2014). An overview of metaheuristics: accurate and efficient methods for optimisation. *International Journal of Metaheuristics, 3*(4), 320-347.

Ngô, V. T. M., Nadeau, S., & Hallé, S. (2020). Validation of ergonomic criteria of a cooling vest for deep and ultra-deep mining. *International Journal of Industrial Ergonomics, 78*, 102980.

Noman, M. A., Alqahtani, F. M., Alharkan, I., Alabdulkarim, S. A., & Alasim, F. (2023). A new integrated risk-assessment model for minimizing human-machine error consequences in a preventive maintenance system. *Ieee Access*.

Norman, D. (2013). *The design of everyday things: Revised and expanded edition*. Basic books.

O'Hagan, A., Buck, C. E., Daneshkhah, A., Eiser, J. R., Garthwaite, P. H., Jenkinson, D. J., . . . Rakow, T. (2006). Uncertain judgements: eliciting experts' probabilities.

Pasi, B. N., Dongare, P. V., Rawat, S. J., Oza, A. D., Padheriya, H., Gupta, M., . . . Kumar, M. (2024). Design and modeling to identify a defective workpiece in manufacturing process: an industry 4.0 perspective. *International Journal on Interactive Design and Manufacturing (IJIDeM), 18*(8), 6123-6139.

Pasi, B. N., Mahajan, S. K., & Rane, S. B. (2023). Strategies for risk management in adopting Industry 4.0 concept in manufacturing industries. *Journal of Science and Technology Policy Management, 14*(3), 563-591.

Patel, V., Chesmore, A., Legner, C. M., & Pandey, S. (2022). Trends in workplace wearable technologies and connected-worker solutions for next-generation occupational safety, health, and productivity. *Advanced Intelligent Systems, 4*(1), 2100099.

Patriarca, R., Chatzimichailidou, M., Karanikas, N., & Di Gravio, G. (2022). The past and present of System-Theoretic Accident Model And Processes (STAMP) and its associated techniques: A scoping review. *Safety science, 146*, 105566.

Patriarca, R., Di Gravio, G., & Costantino, F. (2017). A Monte Carlo evolution of the Functional Resonance Analysis Method (FRAM) to assess performance variability in complex systems. *Safety science, 91*, 49-60.

Patriarca, R., Di Gravio, G., Costantino, F., & Tronci, M. (2017). The Functional Resonance Analysis Method for a systemic risk based environmental auditing in a sinter plant: A semi-quantitative approach. *Environmental Impact Assessment Review, 63*, 72-86.

Patriarca, R., Di Gravio, G., Woltjer, R., Costantino, F., Praetorius, G., Ferreira, P., & Hollnagel, E. (2020). Framing the FRAM: A literature review on the functional resonance analysis method. *Safety science, 129*, 104827.

Patriarca, R., Lovaglio, L., & Simone, F. (2025). Functional resonance analysis via a genetic algorithm to ensure cost-effective maintenance planning. *International Journal of Production Economics*, 109516.

Pauliková, A., Gyurák Babeľová, Z., & Ubárová, M. (2021). Analysis of the impact of human–cobot collaborative manufacturing implementation on the occupational health and safety and the quality requirements. *International Journal of Environmental Research and Public Health, 18*(4), 1927.

Pavón, I., Sigcha, L., Arezes, P., Costa, N., Arcas, G., & López, J. (2018). Wearable technology for occupational risk assessment: Potential avenues for applications. Dans *Occupational safety and hygiene VI* (pp. 447-452). CRC Press.

Pearl, J. (1985). Bayesian netwcrks: A model cf self-activated memory for evidential reasoning. Dans *Proceedings of the 7th conference of the Cognitive Science Society, University of California, Irvine, CA, USA* (pp. 15-17).

Peng, C., Zhen, X., & Huang, Y. (2022). A multi-layer FRAM based approach to short-term human-automation resilience assessment: A case study on dynamic positioning system in offshore tandem offloading process. *Ocean Engineering, 266*, 112728.

Polak-Sopinska, A., Wisniewski, Z., Walaszczyk, A., Maczewska, A., & Sopinski, P. (2020). Impact of industry 4.0 on occupational health and safety. Dans *Advances in Manufacturing, Production Management and Process Control: Proceedings of the AHFE 2019 International Conference on Human Aspects of Advanced Manufacturing, and the AHFE International Conference on Advanced Production Management and Process Control, July 24-28, 2019, Washington DC, USA 10* (pp. 40-52). Springer.

Popkova, E. G., Ragulina, Y. V., & Bogoviz, A. V. (2019). Fundamental differences of transition to industry 4.0 from previous industrial revolutions. Dans *Industry 4.0: Industrial Revolution of the 21st Century* (pp. 21-29). Springer.

Pozdnyakova, U. A., Golikov, V. V., Peters, I. A., & Morozova, I. A. (2019). Genesis of the revolutionary transition to industry 4.0 in the 21st century and overview of previous industrial revolutions. Dans *Industry 4.0: Industrial Revolution of the 21st Century* (pp. 11-19). Springer.

Praetorius, G., Graziano, A., Schröder-Hinrichs, J.-U., & Baldauf, M. (2017). FRAM in FSA—Introducing a function-based approach to the Formal Safety Assessment framework. Dans *Advances in Human Aspects of Transportation* (pp. 399-411). Springer.

Pricop, E., Fattahi, J., Dutta, N., & Ibrahim, M. (2020). *Recent Developments on Industrial Control Systems Resilience*. Springer.

Qiao, L., Li, X., Wang, X., & Peng, K. (2024). Root cause diagnosis and fault propagation path identification for complex industrial processes based on data space. *Measurement, 226*, 114219.

Qiao, W., Li, X., & Liu, Q. (2019). Systemic approaches to incident analysis in coal mines: Comparison of the STAMP, FRAM and “2–4” models. *Resources Policy, 63*, 101453.

Qiao, W., Ma, X., Liu, Y., & Deng, W. (2022). Resilience evaluation of maritime liquid cargo emergency response by integrating FRAM and a BN: A case study of a propylene leakage emergency scenario. *Ocean Engineering, 247*, 110584.

Qureshi, M. M. R. (2023). Building proactive organizational resilience against the risk of major process safety incidents. *Process Safety Progress, 42*(1), 48-55.

Rao, S. S. (2019). *Engineering optimization: theory and practice*. John Wiley & Sons.

Rashid, Y., Rashid, A., Warraich, M. A., Sabir, S. S., & Waseem, A. (2019). Case study method: A step-by-step guide for business researchers. *International journal of qualitative methods, 18*, 1609406919862424.

Rathnakumar, R., Huang, J., Yan, H., & Liu, Y. (2025). Bayesian Entropy Neural Networks for physics-aware prediction. *Reliability Engineering & System Safety*, 111575.

Raya, M. (2022). *Implantation et technologies de conception en contexte d’industrie 5.0 : le cas du secteur aéronautique* (ÉCOLE DE TECHNOLOGIE SUPÉRIEURE, ÉCOLE DE TECHNOLOGIE SUPÉRIEURE).

Raychaudhuri, S. (2008). Introduction to monte carlo simulation. Dans *2008 Winter simulation conference* (pp. 91-100). IEEE.

Read, G. J., Shorrock, S., Walker, G. H., & Salmon, P. M. (2021). State of science: Evolving perspectives on ‘human error’. *Ergonomics, 64*(9), 1091-1114.

Reiman, A., Kaivo-oja, J., Parviainen, E., Takala, E.-P., & Lauraeus, T. (2021). Human factors and ergonomics in manufacturing in the industry 4.0 context–A scoping review. *Technology in Society, 65*, 101572.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega, 53*, 49-57.

Riccardi, L., Compare, M., Mascherona, R., & Zio, E. (2025). Structural causal modeling and STPA for the risk analysis of a rail system powered by H2 fuel. *Reliability Engineering & System Safety, 256*, 110758.

Riccardo, P., Gianluca, D. P., Giulio, D. G., & Francesco, C. (2018). FRAM for systemic accident analysis: a matrix representation of functional resonance. *International Journal of Reliability, Quality and Safety Engineering, 25*(01), 1850001.

Richert, M., & Dudek, M. (2023). Risk Mapping: Ranking and Analysis of Selected, Key Risk in Supply Chains. *Journal of Risk and Financial Management, 16*(2), 71.

Rick, V. B., Stebner, M., Dräger, L., Franken, A., Mertens, A., & Nitsch, V. (2024). Effects of AI-based technologies on employees’ work engagement: Implications for the human-centered design of digital work. *Zeitschrift für Arbeitswissenschaft*, 1-12.

Rising, J. M., & Leveson, N. G. (2018). Systems-Theoretic Process Analysis of space launch vehicles. *Journal of Space Safety Engineering, 5*(3-4), 153-183.

Riso, S. (2021). *Digitisation in the workplace*. Eurofound, Luxembourg: Publications Office of the European Union. doi: 20.500.12592/pknh4k

Rohmert, W. (1973). Problems in determining rest allowances: Part 1: Use of modern methods to evaluate stress and strain in static muscular work. *Applied ergonomics, 4*(2), 91-95.

Romero, D., Mattsson, S., Fast-Berglund, Å., Wuest, T., Gorecky, D., & Stahre, J. (2018). Digitalizing occupational health, safety and productivity for the operator 4.0. Dans *Advances in Production Management Systems. Smart Manufacturing for Industry 4.0: IFIP WG 5.7 International Conference, APMS 2018, Seoul, Korea, August 26-30, 2018, Proceedings, Part II* (pp. 473-481). Springer.

Rosa, L. V., Carvalho, P. V., & Haddad, A. N. (2020). FRAM-AHP: A Resilience Engineering Approach for Sustainable Prevention. *Occupational and Environmental Safety and Health II*, 123-131.

Rosa, L. V., França, J. E., Haddad, A. N., & Carvalho, P. V. (2017). A resilience engineering approach for sustainable safety in green construction. *Journal of Sustainable Development of Energy, Water and Environment Systems, 5*(4), 480-495.

Rosa, L. V., Haddad, A. N., & de Carvalho, P. V. R. (2015). Assessing risk in sustainable construction using the Functional Resonance Analysis Method (FRAM). *Cognition, Technology & Work, 17*, 559-573.

Sadeghi, R., & Goerlandt, F. (2023). A proposed validation framework for the system theoretic process analysis (STPA) technique. *Safety science, 162*, 106080.

Salehi, V., Tran, T., Veitch, B., & Smith, D. (2022). A reinforcement learning development of the FRAM for functional reward-based assessments of complex systems performance. *International Journal of Industrial Ergonomics, 88*, 103271.

Salihoglu, E., & Beşikçi, E. B. (2021). The use of Functional Resonance Analysis Method (FRAM) in a maritime accident: A case study of Prestige. *Ocean Engineering, 219*, 108223.

Salmon, P. M., Cornelissen, M., & Trotter, M. J. (2012). Systems-based accident analysis methods: A comparison of Accimap, HFACS, and STAMP. *Safety science, 50*(4), 1158-1170.

Schneider, D., & Weber, K. (2024). AI for decision support: What are possible futures, social impacts, regulatory options, ethical conundrums and agency constellations? *TATuP-Journal for Technology Assessment in Theory and Practice, 33*(1), 8-54.

Schweizer, H. (2014). Smart glasses: technology and applications. *Student report*.

Sedighi, A., Rashedi, E., & Nussbaum, M. A. (2020). A head-worn display ("smart glasses") has adverse impacts on the dynamics of lateral position control during gait. *Gait & posture, 81*, 126-130.

Selvaraj, A. (2019). Role of humans in Industry 5.0. *Columbus.[Online] October, 10*.

Seňová, A., Pavolová, H., & Škvareková, E. (2023). Assessment of the Impact of Working Risks in the Exploitation of Raw Materials. *Management Systems in Production Engineering, 31*(1), 86-94. doi: doi:10.2478/mspe-2023-0011.

Setayesh, A., Di Pasquale, V., & Neumann, W. P. (2022). An inter-method comparison of four human reliability assessment models. *Applied Ergonomics, 102*, 103750.

Sezer, S. I., Akyuz, E., & Gardoni, P. (2023). Prediction of human error probability under Evidential Reasoning extended SLIM approach: The case of tank cleaning in chemical tanker. *Reliability Engineering & System Safety, 238*, 109414.

Sharma, H., Sohani, N., & Yadav, A. (2022). Comparative analysis of ranking the lean supply chain enablers: An AHP, BWM and fuzzy SWARA based approach. *International Journal of Quality & Reliability Management, 39*(9), 2252-2271.

Sharma, I., Garg, I., & Kiran, D. (2020). Industry 5.0 and smart cities: A futuristic approach. *European Journal of Molecular & Clinical Medicine, 7*(08), 2515-8260.

Silva, T. R., Coelho, B. N., & Delabrida, S. E. (2021). Promising Technologies and Solutions for Supporting Human Activities in Confined Spaces in Industry. Dans *ICEIS (2)* (pp. 573-580).

Singh, M., & Pant, M. (2021). A review of selected weighing methods in MCDM with a case study. *International Journal of System Assurance Engineering and Management, 12*, 126-144.

Singh, S., & Kumar, R. (2015). Evaluation of human error probability of disc brake unit assembly and wheel set maintenance of railway bogie. *Procedia Manufacturing, 3*, 3041-3048.

Slim, H. (2020). *A proposal of a mixed fuzzy logic/rough sets FRAM model for complex systemic analyses of sociotechnical systems* (École de technologie supérieure, École de technologie supérieure).

Slim, H., & Nadeau, S. (2019). A proposal for a predictive performance assessment model in complex sociotechnical systems combining fuzzy logic and the Functional Resonance Analysis Method (FRAM). *American Journal of Industrial and Business Management, 9*(6), 1345-1375.

Slim, H., & Nadeau, S. (2020). A proposition for combining rough sets, fuzzy logic and FRAM to address methodological challenges in safety management: A discussion paper. *Safety, 6*(4), 50.

Smith, D., Veitch, B., Khan, F., & Taylor, R. (2017). Understanding industrial safety: Comparing Fault tree, Bayesian network, and FRAM approaches. *Journal of Loss Prevention in the Process Industries, 45*, 88-101.

Smith, J. B. (2003). Complex systems. *arXiv preprint cs/0303020*.

Song, C., Zhang, Y., & Xu, Z. (2019). An improved structure learning algorithm of Bayesian Network based on the hesitant fuzzy information flow. *Applied Soft Computing, 82*, 105549.

Sreenath, S., Sudhakar, K., & Yusop, A. (2020). Solar photovoltaics in airport: Risk assessment and mitigation strategies. *Environmental Impact Assessment Review, 84*, 106418.

Stake, R. (1995). *Case study research*. Springer.

Stamatelatos, M., Dezfuli, H., Apostolakis, G., Everline, C., Guarro, S., Mathias, D., . . . Smith, C. (2011). *Probabilistic risk assessment procedures guide for NASA managers and practitioners*. NASA: NASA.

Stojiljkovic, E., Bijelic, B., & Cvetkovic, M. (2018). Application of HEART technique for human reliability assessment–a Serbian experience. *Facta Universitatis. Series: Working and Living Environmental Protection*, 187-196.

Sui, Z., Yuan, X., Cai, B., Ye, F., Duan, Q., Zhao, Z., . . . Hu, Z. (2025). Integrated Bayesian and Particle Swarm Approaches for Enhanced Gas Leak Detection in Complex Commercial Structures. *Sensors, 25*(5), 1481.

Sujan, M., Slater, D., & Crumpton, E. (2025). How can large language models assist with a FRAM analysis? *Safety science, 181*, 106695.

Sun, B., Zhou, Y., Wang, J., & Zhang, W. (2021). A new PC-PSO algorithm for Bayesian network structure learning with structure priors. *Expert Systems with Applications, 184*, 115237.

Sun, H., Wang, H., Yang, M., & Reniers, G. (2022). A STAMP-based approach to quantitative resilience assessment of chemical process systems. *Reliability Engineering & System Safety, 222*, 108397.

Sun, H., Wang, H., Yang, M., & Reniers, G. (2024). Dynamic risk assessment of chemical process systems using the System-Theoretic accident model and process approach (STAMP) in combination with cascading failure propagation model (CFPM). *Safety science, 171*, 106375.

Sun, J., Fang, H., Wu, J., Sun, T., & Liu, X. (2019). Application of Bayesian belief networks for smart city fire risk assessment using history statistics and sensor data. Dans *International Conference on Data Service* (pp. 3-11). Springer.

Sun, L., Li, Y.-F., & Zio, E. (2022). Comparison of the HAZOP, FMEA, FRAM, and STPA methods for the hazard analysis of automatic emergency brake systems. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering, 8*(3), 031104.

Sun, X., Hu, Y., Qin, Y., & Zhang, Y. (2024). Risk assessment of unmanned aerial vehicle accidents based on data-driven Bayesian networks. *Reliability Engineering & System Safety, 248*, 110185.

Swain, A. D. (1964). *THERP*. Sandia Corp., Albuquerque, N. Mex.

Swain, A. D., & Guttmann, H. E. (1983). *Handbook of human-reliability analysis with emphasis on nuclear power plant applications. Final report*. Sandia National Labs., Albuquerque, NM (USA).

Syberfeldt, A., Danielsson, O., & Gustavsson, P. (2017). Augmented reality smart glasses in the smart factory: Product evaluation guidelines and review of available products. *Ieee Access, 5*, 9118-9130.

Talbi, E.-G. (2009). *Metaheuristics: from design to implementation*. John Wiley & Sons.

Tao, X. (2005). *Wearable electronics and photonics*. Elsevier.

Teixeira, D., Ferreira, J., & Gonçalves, R. (2022). Monitoring of shop-floor workers postural stability through the use of smart soles. Dans A. Bernard, A. Dolgui, H. H. Benderbal, D. Ivanov, D. Lemoine & F. Sgarbossa (Éds.), *10th IFAC Conference on Manufacturing Modelling, Management and Control, MIM 2022* (10 éd., Vol. 55, pp. 2234-2239). Elsevier B.V. doi: 10.1016/j.ifacol.2022.10.040.

Tenholt, J., Adam, S., Laun, M., Schiefer, C., Terschüren, C., Harth, V., . . . Friemert, D. (2023). Influences of smart glasses on postural control under single-and dual-task conditions for ergonomic risk assessment. *Biomedical Engineering/Biomedizinische Technik,* (0).

Thekke Kanapram, D., Marcenaro, L., Martin Gomez, D., & Regazzoni, C. (2022). Graph-Powered Interpretable Machine Learning Models for Abnormality Detection in Ego-Things Network. *Sensors, 22*(6), 2260.

Torres, Y., Nadeau, S., & Landau, K. (2021a). Application of SHERPA (Systematic Human Error Reduction and Prediction Approach) as an alternative to predict and prevent human error in manual assembly. Dans *Congress of the International Ergonomics Association* (pp. 445-453). Springer.

Torres, Y., Nadeau, S., & Landau, K. (2021b). Classification and quantification of human error in manufacturing: a case study in complex manual assembly. *Applied Sciences, 11*(2), 749.

Torres, Y., Nadeau, S., & Landau, K. (2022). Applying AcciMap and STAMP to the analysis of human error in complex manual assembly. *Human Factors and Ergonomics in Manufacturing & Service Industries, 32*(6), 462-481.

Ulmer, J., Braun, S., Cheng, C.-T., Dowey, S., & Wollert, J. (2023). A human factors-aware assistance system in manufacturing based on gamification and hardware modularisation. *International Journal of Production Research, 61*(22), 7760-7775.

Underwood, P., & Waterson, P. (2012). A critical review of the STAMP, FRAM and Accimap systemic accident analysis models. *Advances in human aspects of road and rail transportation,* (January 2016), 385-394.

Underwood, P., Waterson, P., & Braithwaite, G. (2016). 'Accident investigation in the wild'– A small-scale, field-based evaluation of the STAMP method for accident analysis. *Safety science, 82*, 129-143.

Valdesse Eko'olaa, R., & Nadeau, S. (2025). Systematic Selection of Visual and Cognitive Assistance Equipment: Case of Gas Turbine Assembly in Narrow Spaces. *Intelligent control and automation, Accepted manuscript*.

Valette, E., El-Haouzi, H. B., & Demesure, G. (2023). Industry 5.0 and its technologies: A systematic literature review upon the human place into IoT-and CPS-based industrial systems. *Computers & Industrial Engineering, 184*, 109426.

Vaughan, E. J., & Vaughan, T. (2007). *Fundamentals of risk and insurance*. John Wiley & Sons.

Veiga, E. F., Kudo, T. N., & Bulcão-Neto, R. F. (2024). Linking Agile Planning and Safety and Security Analysis in Critical IoT Systems: An Approach based on ISO/IEC/IEEE 15288. Dans *Proceedings of the XXIII Brazilian Symposium on Software Quality* (pp. 81-91).

Vesely, W. E., Goldberg, F. F., Roberts, N. H., & Haasl, D. F. (1981). *Fault tree handbook*. Nuclear Regulatory Commission Washington DC.

Vidal, G. H., Coronado-Hernández, J. R., & Minnaard, C. (2023). Measuring manufacturing system complexity: a literature review. *Journal of Intelligent Manufacturing, 34*(7), 2865-2888.

Virdi, P. S., & Pamnani, G. (2023). Human error identification and risk prioritization in LPG unloading operations. *International Journal of Occupational Safety and Ergonomics, 29*(1), 392-406.

Voß, S. (2000). Meta-heuristics: The state of the art. Dans *Workshop on Local Search for Planning and Scheduling* (pp. 1-23). Springer.

Wang, B., Zhou, H., Li, X., Yang, G., Zheng, P., Song, C., . . . Wang, L. (2024). Human Digital Twin in the context of Industry 5.0. *Robotics and Computer-Integrated Manufacturing, 85*, 102626.

Wang, Q., Jiang, X., Park, H., & Wang, M. (2023). HGV fire risk assessment method in highway tunnel based on a Bayesian network. *Tunnelling and Underground Space Technology, 140*, 105247.

Wang, T., Liu, Z., Wang, L., Li, M., & Wang, X. V. (2024). Data-efficient multimodal human action recognition for proactive human–robot collaborative assembly: A cross-domain few-shot learning approach. *Robotics and Computer-Integrated Manufacturing, 89*, 102785.

Wang, X. V., Xu, P., Cui, M., Yu, X., & Wang, L. (2024). A literature survey of smart manufacturing systems for medical applications. *Journal of Manufacturing Systems, 76*, 502-519.

Wang, Z., & Chiang, L. (2019). Monitoring chemical processes using judicious fusion of multi-rate sensor data. *Sensors, 19*(10), 2240.

Watson, H. A. (1961). Launch control safety study. *Bell labs*.

Wiegmann, D. A., & Shappell, S. A. (2001). *Human error analysis of commercial aviation accidents using the human factors analysis and classification system (HFACS)*. United States. Office of Aviation Medicine.

Williams, J. (1986). HEART—A Proposed Method for Assessing and Reducing Human Error in Ninth Advances in Reliability T echnology Symposium. *NEC, Birmingham, June, AEA, T echnology, Culcheth, Warrington*.

Wilson, P., & Mantooth, H. A. (2013). *Model-based engineering for complex electronic systems*. Newnes.

Wirawan, J. B., & Garniwa, I. (2018). Risk analysis development of solar floating power plant in the sea with Monte Carlo method. Dans *2018 3rd International Conference on Information Technology, Information System and Electrical Engineering (ICITISEE)* (pp. 396-401). IEEE.

Wong, K. V., & Chan, R. (2014). Smart glass and its potential in energy savings. *Journal of Energy Resources Technology, 136*(1).

Wrzesińska, N. (2015). The use of smart glasses in healthcare–review. *MEDtube Sci, 31*.

Wu, M., & Jiang, W. (2025). Multi-objective optimization in high-dimensional patent layout using deep Bayesian network and hybrid algorithm. *Discover Computing, 28*(1), 34.

Xia, Y., Li, W., Duan, S., Lei, W., & Wu, J. (2022). Low-cost, Light-weight Scalable Soft Data Glove for VR Applications. Dans *2022 5th International Conference on Circuits, Systems and Simulation (ICCSS)* (pp. 202-205). IEEE.

Xiao, Q., Li, Y., Luo, F., & Liu, H. (2023). Analysis and assessment of risks to public safety from unmanned aerial vehicles using fault tree analysis and Bayesian network. *Technology in Society, 73*, 102229.

Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. *Journal of Manufacturing Systems, 61*, 530-535.

Xue, S. (2021). Construction of reliability evaluation model of power Internet of Things based on Bayesian network. Dans *International Conference on Green Communication, Network, and Internet of Things (GCNIoT 2021)* (Vol. 12085, pp. 117-125). SPIE.

Yang, B., Wang, J., Zhang, X., Yu, T., Yao, W., Shu, H., . . . Sun, L. (2020). Comprehensive overview of meta-heuristic algorithm applications on PV cell parameter identification. *Energy Conversion and Management, 208*, 112595.

Yazdi, M., & Kabir, S. (2017). A fuzzy Bayesian network approach for risk analysis in process industries. *Process safety and environmental protection, 111*, 507-519.

Yazdi, M., Nedjati, A., Zarei, E., & Abbassi, R. (2020). A novel extension of DEMATEL approach for probabilistic safety analysis in process systems. *Safety science, 121*, 119-136.

Yin, R. K. (2018). *Case study research and applications*. Sage.

Yousefi, A., Rodriguez Hernandez, M., & Lopez Peña, V. (2019). Systemic accident analysis models: A comparison study between AcciMap, FRAM, and STAMP. *Process Safety Progress, 38*(2), e12002.

Yu, J., Zeng, Q., Yu, Y., Zhang, B., Ma, W., Wu, S., . . . Li, Z. (2025). Resilience assessment of FPSO leakage emergency response based on quantitative FRAM. *Reliability Engineering & System Safety, 253*, 110526.

Yuan, S., Yang, M., & Reniers, G. (2024). Integrated process safety and process security risk assessment of industrial cyber-physical systems in chemical plants. *Computers in Industry, 155*, 104056.

Yuen, J. S., Choy, K. L., Lam, H. Y., & Tsang, Y. P. (2019). An intelligent risk management model for achieving smart manufacturing on internet of things. Dans *2019 Portland International Conference on Management of Engineering and Technology (PICMET)* (pp. 1-8). IEEE.

Zarei, E., Khan, F., & Abbassi, R. (2023). How to account artificial intelligence in human factor analysis of complex systems? *Process safety and environmental protection*.

Zeng, Y., Zhang, Z., Liang, W., & Zhang, Y. (2023). Balancing optimization for disassembly line of mixed homogeneous products with hybrid disassembly mode. *Computers & Industrial Engineering, 185*, 109646.

Zerouali, B., Sahraoui, Y., Nahal, M., & Chateauneuf, A. (2024). Reliability-based maintenance optimization of long-distance oil and gas transmission pipeline networks. *Reliability Engineering & System Safety, 249*, 110236.

Zhang, G., & Thai, V. V. (2016). Expert elicitation and Bayesian Network modeling for shipping accidents: A literature review. *Safety science, 87*, 53-62.

Zhang, S., Zhou, J., Zhao, Y., Hu, G., Fu, F., Wang, L., & Xu, Y. (2024). A sustainable machining method with high efficiency, high quality and low wear-electric arc electrochemical composite machining. *Journal of cleaner production, 485*, 144376.

Zhang, W., Gu, F., & Guo, J. (2019). Can smart factories bring environmental benefits to their products?: A case study of household refrigerators. *Journal of Industrial Ecology, 23*(6), 1381-1395.

Zhang, X., Chen, G., Yang, D., He, R., Zhu, J., Jiang, S., & Huang, J. (2022). A novel resilience modeling method for community system considering natural gas leakage evolution. *Process safety and environmental protection, 168*, 846-857.

Zhang, X., Schall Jr, M. C., Chen, H., Gallagher, S., Davis, G. A., & Sesek, R. (2022). Manufacturing worker perceptions of using wearable inertial sensors for multiple work shifts. *Applied ergonomics, 98*, 103579.

Zhang, Y., Ding, K., Hui, J., Liu, S., Guo, W., & Wang, L. (2024). Skeleton-RGB integrated highly similar human action prediction in human–robot collaborative assembly. *Robotics and Computer-Integrated Manufacturing, 86*, 102659.

Zhao, W., & Xu, M. (2025). A Passenger Flow Congestion Propagation Bayesian Network Model for Urban Rail Transit Hubs. *Reliability Engineering & System Safety*, 111655.

Zheng, Q., & Liu, X. (2025). A consensus-based multi-criteria decision making method integrating GLDS method and quantum probability theory for risk analysis of human errors. *Computers & Industrial Engineering, 200*, 110847.

Zheng, Q., Liu, X., Yang, M., Wang, W., & Adriaensen, A. (2024). Enhancing emergency response planning for natech accidents in process operations using functional resonance analysis method (FRAM): A case of fuel storage tank farm. *Process safety and environmental protection, 188*, 514-527.

Zhou, Z., Matsubara, Y., & Takada, H. (2023). Developing Reliable Digital Healthcare Service Using Semi-Quantitative Functional Resonance Analysis. *Computer Systems Science & Engineering, 45*(1).

Zhu, C., Qi, M., & Jiang, J. (2020). Quantifying human error probability in independent protection layers for a batch reactor system using dynamic simulations. *Process safety and environmental protection, 133*, 243-258.

Zinetullina, A., Yang, M., Khakzad, N., Golman, B., & Li, X. (2021). Quantitative resilience assessment of chemical process systems using functional resonance analysis method and Dynamic Bayesian network. *Reliability Engineering & System Safety, 205*, 107232.

Zio, E. (2013). *Monte carlo simulation: The method*. Springer.

Zorzenon, R., Lizarelli, F. L., & Daniel, B. d. A. (2022). What is the potential impact of industry 4.0 on health and safety at work? *Safety science, 153*, 105802.