Heliyon 10 (2024) e30162

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

A comprehensive STPA-PSO framework for quantifying smart glasses risks in manufacturing

Ali Karevan, Sylvie Nadeau *

École de technologie supérieure, Mechanical Engineering Department, Montréal, Quebec H3C 1K3, Canada

ARTICLE INFO

Keywords:
Risk management
Systems-theoretic process analysis (STPA)
Particle swarm optimization (PSO)
Industry 5.0
Smart glasses
Manufacturing

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.

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 [1]. The concept of risk is rooted in the uncertainty of outcomes rather than their certainty [2].

In the realm of system design and improvement, engineers aim to anticipate potential patterns of system operation under various circumstances or uncertain situation [1]. The concept of risk, deeply rooted in the uncertainty of outcomes rather than their certainty, underscores the dynamic nature of engineering endeavors [2]. Moreover, emerging risks, characterized by their novelty, limited data, and absence of verifiable information, pose unique obstacles in decision-making processes [3]. 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

* Corresponding author.
E-mail addresses: ali.karevan.1@ens.etsmtl.ca (A. Karevan), sylvie.nadeau@etsmtl.ca (S. Nadeau).

https://doi.org/10.1016/j.heliyon.2024.e30162
Received 5 September 2023; Received in revised form 18 April 2024; Accepted 21 April 2024
Available online 23 April 2024

internal operations [3].

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 [4]. Factors such as insufficient operator qualifications, inaccuracies during work, and misunderstandings of instructions contribute to this risk landscape [5]. To mitigate the occurrence of accidents, a deeper understanding of human error and its causes is imperative [4]. An interesting observation is that a significant proportion, ranging from 50 % to 90 %, of reported incidents in industry can be attributed to human errors [6]. Given the preceding, extensive research has therefore been carried out on improving human reliability and reducing human errors [7,8].

In product manufacturing, human behavior is influenced by situations involving machines, systems, and organizations [9]. Human variability makes errors inevitable and cannot be eliminated entirely [10]. 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 [11].

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 [12]; 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 [13]. 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 [14]. 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 [15]. 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 [16]. Through the use of IoTs, humans can optimize their efficiency in performing critical tasks and responsibilities, resulting in enhanced safety, productivity, and overall performance [17].

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 [18], 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 [14]. Thus, the risks associated with their integration into complex systems must be considered [11,19]. 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 [11].

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 [20]) in a complex system with the STPA-PSO 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 the 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.

2. State of the art

2.1. Complex systems

There are two main types of systems: simple and complex [21]. A complex system consists of numerous interconnected components whose behavior cannot be simply inferred from the behavior of the individual components [22]. In understanding complexity, the number of units is not the most important factor. While complex systems may consist of only two units, their intricate nature arises from relationships that are not apparent from the unit level alone [23]. Complex systems are more than the sum of their components [24]. It is impossible to predict the behavior of a system as a whole, despite knowing the functions of its individual components [21]. 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 [25].

In sociotechnical systems, social and technical elements are integrated into a defined objective [26]. 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 [21]. 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. [27]. Simulation and modeling can reduce unintended consequences and unforeseen, negative interactions in sociotechnical systems [26]. 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 [27]. 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.

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 [28]. Multiple methodologies have been developed that enable the estimation of human error probability [29,30]. Human Reliability Analysis (HRA) focuses on identifying errors, identifying reasons for faults, and reducing the likelihood of human error [31]. It aims to optimize safety, reliability, and productivity by predicting and mitigating errors [10].

The HRA process involves identifying essential functions, analyzing relevant tasks, and quantifying the risk of human error [32]. Table 1 presents a variety of main methods that have been introduced in this regard [33]. 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. [34]. 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 [35].

PRA is a traditional risk assessment method used by engineers to quantify failure probabilities and severity [36]. Failure Modes and Effects Analysis (FMEA) [37], Fault Tree Analysis (FTA) [38], and Event Tree Analysis (ETA) [39] 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) [30] and the Technique for Human Error Rate Prediction (THERP) [40]. 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 [41]. 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 [35].

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 [42]. It was also previously found that these two methods can be used in identifying risks, specially human error risks of using wearables in complex systems [11]. 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 [60]. 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 [43]. 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 [44]. The STAMP-STPA approach can play an important role in improving systemic safety [45]. However, the application of STAMP can be intricate and demanding, particularly for individuals

Table 1
Main HRA and risk management methods.

Method	Reference	School of thought	Model (Qualitative/Quantitative)
Functional Resonance Analysis Method (FRAM)	[46]	Resilience Engineering	Qualitative
Systems Theoretic Accident Model and Processes (STAMP)	[47]	System Theory	
Failure Modes and Effects Analysis (FMEA)	[48]	Safety Engineering	
Fault Tree Analysis (FTA)	[49]		
Technique for Human Error Rate Prediction (THERP)	[50,51]	Reliability Engineering	Quantitative
Human Error Assessment and Reduction Technique (HEART)	[52]		
Systematic Human Error Reduction and Prediction Approach (SHERPA)	[53]		
Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H)	[54]		
Cognitive Reliability and Error Analysis Method (CREAM)	[55]	Cognitive Engineering	
A Technique for Human Error Analysis (ATHEANA)	[56]		
Successive Likelihood Index Method (SLIM)	[57]	Safety Engineering	
Bayesian Network (BN)	[58]	Artificial Intelligence	

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 can necessitate a thorough understanding of system theory [43]. By combining qualitative and quantitative methods, researchers are attempting to assess human error risks in a way that is more reliable and effective [11].

2.3. STAMP-STPA

Based on the concept of system theory, STAMP was developed in 2004 by Nancy Leveson to deal with complex systems [47,59]. 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 [60]. STAMP allows to detect 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 [61], and can describe how inadequate control actions can violate safety constraints [62]. STAMP examines the safety control structure in order to determine the cause of its failure to maintain safe behavior limits [47]. 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 [45]. 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 [60].

In the context of hazard analysis, STAMP is known as STPA , while in accident and incident analysis, it is known as CAST (Causal Analysis based on Stamp) [63]. To address the systemic focus offered by STAMP, the STPA method was developed, and included control types and factors not addressed by traditional techniques [64]. 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 [65]. 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 [59]. In order to avoid or control hazards during development, STPA analyzes the potential causes of accidents [60].

Despite a component functioning correctly, STPA assumes that failure can occur due to unsafe interactions among components [60]. In addition to accident analysis, STPA can successfully be used to lead a safety assessment process as well [62]. STPA assumes that system components may have failed but that accidents can still occur due to unsafe interactions within them [60]. 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 [64]. 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 [59]. Several studies have shown that this method is effective in complex operating environments with multiple controllers controlling the same process [66].

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 [44]. 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 [67]. The reader is invited to consult the Methodology section, for more details.

2.4. PSO

Metaheuristics algorithms help determine what to do when faced with a problem [68]. Metaheuristics are employed in the fields of science and engineering to effectively tackle intricate and complex problems within a reasonable timeframe [69]. 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 [69].

Metaheuristic algorithms are instrumental in addressing complex optimization problems by enhancing calculation accuracy, reducing the computational burden, and generating high-quality optimal solutions [70]. 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 [68].

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 [71]. 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 [72].

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 [73]. It is one of the well-known swarm-based optimization methods [74]. 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 [75].

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 [76]. 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 [73].

As a tool for solving complex optimization problems, PSO has demonstrated excellent flexibility and practicality [77]. Numerous optimization domains have successfully used PSO because of its ease of implementation [78]. 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 [74]. Also, it can be used with other methods to quantify the risk probability [73]. The reader is invited to consult the methodology section for more details.

2.5. Wearables in manufacturing

IoT finds applications in various fields and products, and wearables are just one example of its implementation [79]. 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 [80].

Wearable computers should be mobile and provide context-sensitive information [81]. Using wearables equipped with IoT sensors in manufacturing or healthcare can trigger automated alerts in the event of hazardous conditions [12]. With wearables, users can now perform tasks such as aircraft maintenance, navigation, and vehicle inspection much more efficiently [81]. 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 [82].

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 [82]. 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

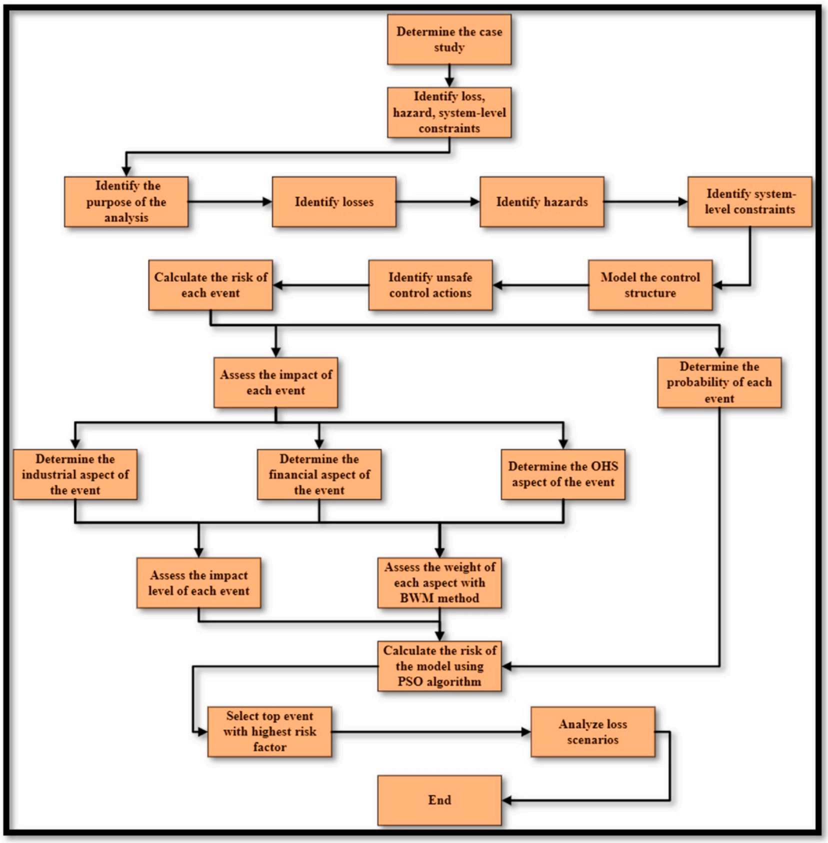

Fig. 1. STPA-PSO methodology.

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 [83]. 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 % [20,82].

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 [84]. 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 [20,85].

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 [80]. These devices can pose new risks, which need to be analyzed and reduced [86], such as user interface challenges, interactions challenges, calibration challenges, social acceptance challenges, eye fatigue challenges, and data security challenges [87,88].

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 [59]. The STPA analysis has four main steps [89]. Fig. 1 shows the proposed methodology of this study. Based on its algorithm, the steps of this methodology are structured as follows.

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 [60]. 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" [60].

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" [60].

System-level constraints: "A system-level constraint specifies system conditions or behaviors that need to be satisfied to prevent hazards (and ultimately prevent losses)" [60].

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 [59]. Hierarchical control structures typically encompass five essential components: controllers, control actions, feedback, other inputs and outputs from components, and processes controlled by the controllers [60].

In this step, there are several points of misunderstanding [60].

- 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. 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" [60].

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 [59]. The following four scenarios can make control actions unsafe [60].

- 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 [60].

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.1 shows the standard formula for calculating the risk [90]:

$$\text{Risk (i)} = \text{Imapct (i)} * \text{Probability (i)} \tag{1}$$

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) [90]. Researchers have used various methods to determine the impact of an event, and almost all of them are based on the judgement of experts in each field. For example [91], 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 [92].

- 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 which analyzes different categories, such as health and safety, environmental impact, financial loss and reputation [93]. La fata et al. (2023) used five-level incidents: no incidence, low incidence, medium incidence, high incidence, and very high incidence [94]. [95] used a seven point-scale method: very low, low, moderately low, average, moderately high, high, very high [96]. used a five point-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 [97], and thus, a five point-scale is used in this study. Using the results of [93], 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 [91]. To address this relationship and its impact on risk assessment, we have proposed several scenarios in Table 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, 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 [98].

Table 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 the realm of decision-making theory, MCDM plays a pivotal role, offering a range of methodologies tailored to different decision contexts [99]. 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 [99]. 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 [98]. 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 [98, 99].

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 Ref. [99]. 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 it demonstrated in Eq.2:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{2}$$

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)):

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T \tag{3}$$

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

- Calculate the optimal weights ($w^*_1, w^*_2, \ldots, w^*_n$) by using Eq. (4) to Eq. (6):

$$\min \ \max j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \tag{4}$$

$$s.t.$$

$$\sum_j w_j = 1 \tag{5}$$

$$w_j \geq 0, for\ all\ j \tag{6}$$

3.4.2. Probability

To proceed, it is crucial to determine the probability of each event occurring. Table 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

Table 3
Range of occurrence.

Reference	Industry	Range of occurrence				
[101]	Healthcare	Low [<0.2]		Medium [0.2–0.8]		High [>0.8]
[102]	Aviation	Exceptional [1]	Unlikely [2]	Possible [3]	Likely [4]	Certain [5]
[103]	Power plant	Unlikely [1]	Low [2,3]	Moderate [4–6]	High [7,8]	Very high [9]
[104]	Aviation	Extremely improbable [1]	Extremely remote [2]	Remote [3]	Reasonably probable [4]	Frequent [5]
[105]	Power plant	Insignificant [<0.2]	Minor [0.2–0.4]	Moderate [0.4–0.6]	Major [0.6–0.8]	Catastropic [>0.8]
[106]	Mining	Rare [1]	Unlikely [2]	Possible [3]	Likely [4]	Almost certain [5]
[107]	Maintenance	Non expected [1]	Very unlikely [2]	Unlikely [3]	Possible [4]	Expected [5]
[108]	Supply Chain	Very small [1]	Small [2]	Medium [3]	High [4]	Catastrophic [5]
[109]	LPG unloading operation	Highly unlikely [0–2]	Rare [1–4]	Occasional [3–6]	Repeated [5–8]	Unavoidable [7–10]

each UCA.

For analyzing uncertain scenarios and calculating probabilities, the Monte-Carlo simulation (MCS) is an extremely helpful mathematical technique [100]. Due to its ability to achieve a closer adherence to reality, MCS represents an effective method of analyzing complex systems [1], and with it, input variables that are risky can be investigated methodically [100]. By employing 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 [1].

MCS has been used in different industries and for different purposes, including finance, reliability analysis and six sigma, mathematics and statistical physics, engineering, etc. [100]. 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 MCS procedures, occurrences of system failures and success state transitions can be simulated stochastically using models of process evolution and operator behavior [1]. MCS uses the repeated random sampling and statistical analysis method to compute the results [100].

3.4.3. *Risk calculation*

Eq. (7) will be used to assess the risk of each UCA:

$$R_i = P_i * ((W_{IND\ i} * I_{IND\ i}) + (W_{OHS\ i} * I_{OHS\ i}) + (W_{FIN\ i} * I_{FIN\ i})) \tag{7}$$

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 factor of 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 grade 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 [73].

The PSO parallel space represents a *d-dimensional* space, with each candidate solution termed a “particle” [110]. 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* [111] which are shown in Eq. (8) to Eq. (10).

$$X_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \quad for \ \ i = 1, 2, \ldots, N \tag{8}$$

$$V_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \quad for \ \ i = 1, 2, \ldots, N \tag{9}$$

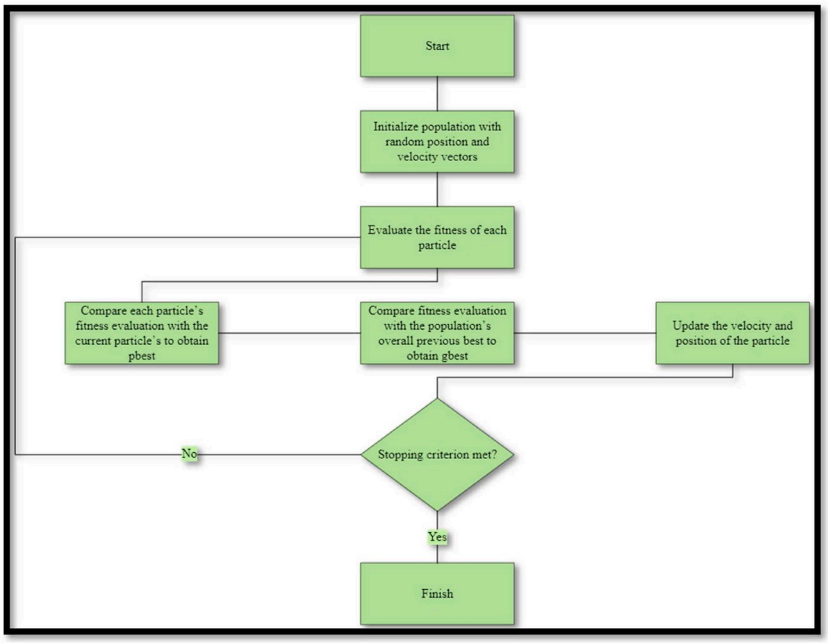

Fig. 2. PSO algorithm [111].

$$P_i = (p_{i1}, p_{i2}, \ldots, p_{id}) \quad for \;\; i = 1, 2, \ldots, N \tag{10}$$

In order to optimize the solution in the search space, this algorithm regulates the velocity of particles as a major feature. Based on Eq. (11), particle k's velocity is updated in the *(i+1)*th iteration [74]:

$$V_k(i+1) = V_k(i) + c_1 r_1 \left(P^k_{best,i} - X_k(i)\right) + c_2 r_2 \left(g_{best,i} - X_k(i)\right) \tag{11}$$

In the *(i+1)*th iteration, the velocity of the kth particle is updated based on three components [74].

1. 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.
2. Cognitive part ($c_1 r_1 (P^k_{best,i} - X_k(i))$): The particle is driven to its best position by this cognitive part, which equals the particle's distance from its best position.
3. Social part ($c_2 r_2 (g_{best,i} - X_k(i))$): 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. (12):

$$X_k(i+1) = X_k(i) + V_k(i+1) \tag{12}$$

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 [112]. The PSO flowchart is shown in Fig. 2.

Thus, 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.

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 MCS 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.

3.5. Identify loss scenarios

An unsafe control action or hazard is the result of the causal factors described in a loss scenario [60]. 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 [59].

4. 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

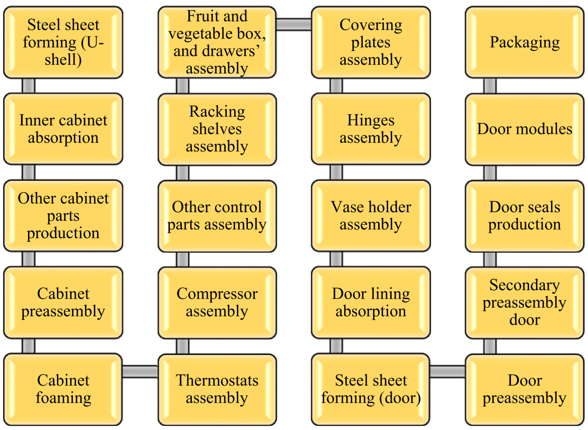

Fig. 3. Refrigerator manufacturing process [113].

assembly operations of a refrigerator manufacturing plant was examined. The refrigerator manufacturing process is demonstrated in Fig. 3.

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 [114]. 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. Fig. 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.
- 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 [60]. We intend to analyze the risks associated with the introduction of the IoT (smart glasses) in this assembly area.

5. Results

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

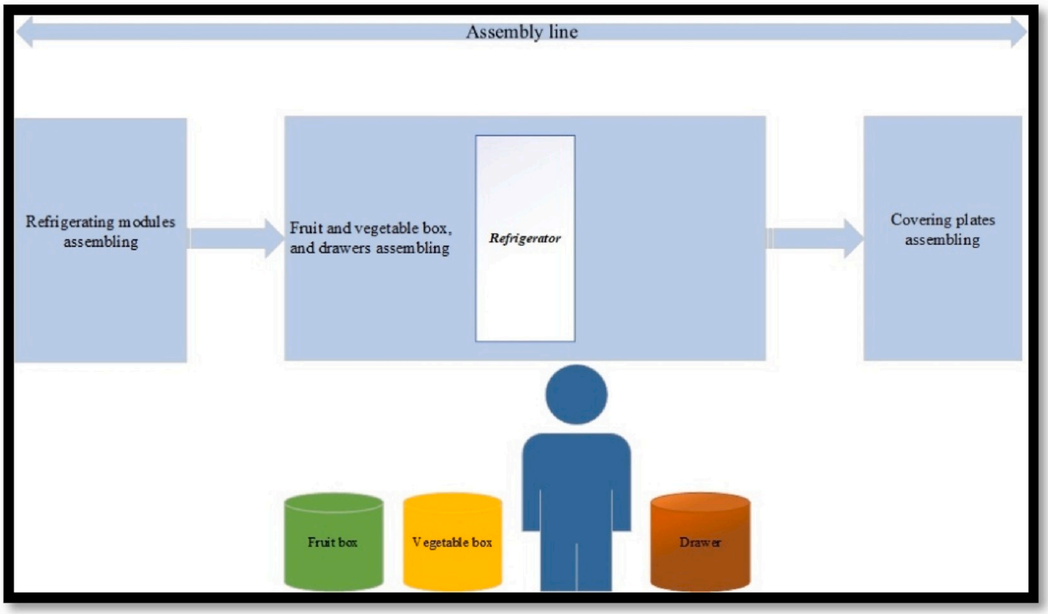

Fig. 4. Assembly of fruit box, vegetable box, and drawers.

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

5.1.1. 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.

5.1.2. Identify the 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.

5.1.3. 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.

5.1.4. Identify system-level constraints

System-level constraints are shown in Table 4.

5.2. 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 [60]. Fig. 5 shows the smart glasses control structure model. In this figure, smart glasses and all the interactions between smart glasses and other departments, are shown in orange.

5.3. Identification of hazardous (unsafe) control actions

UCAs are control actions that could lead to a hazard in particular contexts and worst-case environments [60]. By demonstrating where safety constraints may be violated or insufficiently enforced, the STPA aims to eliminate unsafe conditions [59]. 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).

Table 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

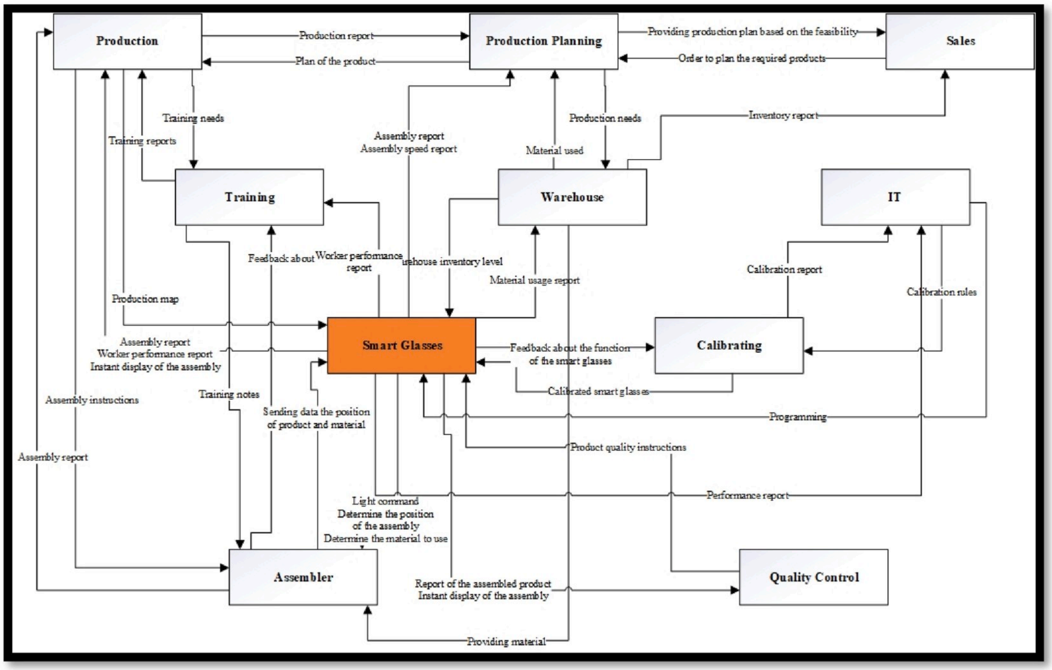

Fig. 5. Control structure model of smart glasses.

- 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 of each UCA to hazards [60].

Table 5 shows the unsafe control actions for the present case study.

Once all the 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 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 connection, 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.

Table 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 6
Consequence 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		*	*	*

5.4. Calculate the risk of the model

Initially, the BWM solver, as developed by its founder [99], was employed to ascertain the weight of each impact. Priority was given to the OHS aspect, followed by the financial and industrial aspects, resulting in respective weights of 0.65, 0.25, and 0.125. 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 and the entire model. The PSO parameters used in the study are detailed in Table 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 Fig. 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 as a medium risk factor.

5.5. 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 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 Fig. 7. Herein, we focused on the scenarios with 'high' and 'very high' risk values (higher than 15). These

Table 7
PSO parameters.

Parameters	Value
Number of particles	50
Number of iterations	1000
Inertia weight	0.5
Cognitive weight	0.9
Social weight	1.5
Number of links	3

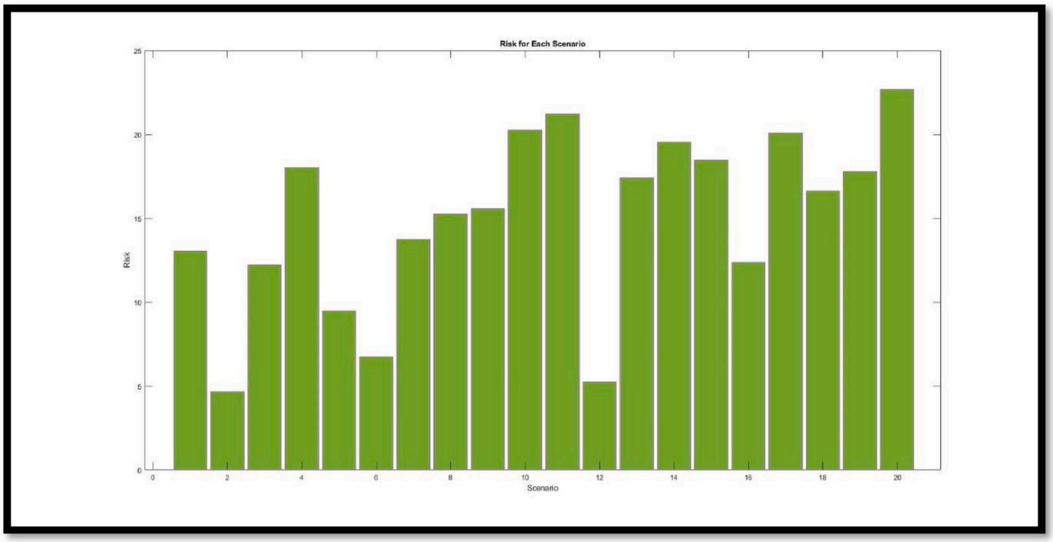

Fig. 6. Risk of each scenario.

scenarios are shown in Table 9.

6. 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 [60]. Several studies have shown that this method is effective in complex operating environments with multiple controllers controlling the same process [66]. STPA, based on the STAMP technology that attributes accidents to inadequate control, exhibits the following characteristics [59].

- 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 [66]. As compared to traditional risk analysis techniques, STPA has the following advantages [60].

- 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 [60]. By considering all aspects of the system, including humans, technology, and organizations, STPA enables the identification of hazards [59]. 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 [66]. The STAMP-STPA approach plays a crucial role in enhancing systemic safety [45].

However, a major drawback of STPA is its qualitative nature [11]. 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 [11]. The methodology presented in this study is straightforward and applicable to real cases, as demonstrated above. 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 MCS due to the absence of real data.

Table 8
Risk matrix.

Risk Impact		Probability			
	Very Low (1)	Low (2)	Medium (3)	High (4)	Very High (5)
Very Low (1)	1	2	3	4	5
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

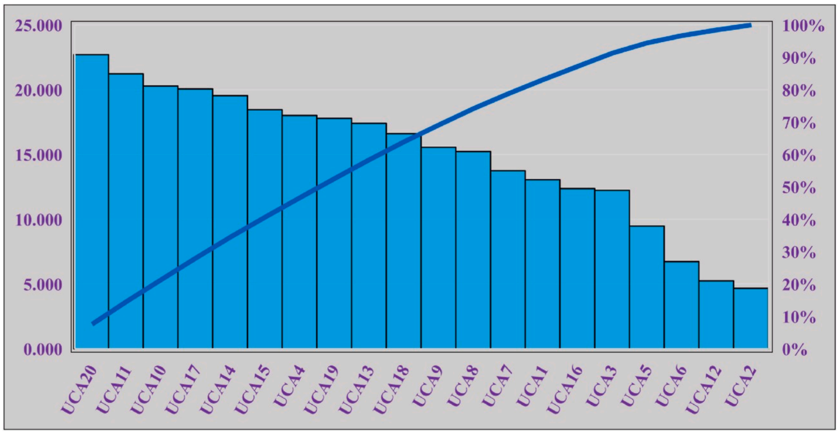

Fig. 7. UCA Pareto chart.

Table 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

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 [115]. On the other hand, as BWM is based on the decision-makers and their judgement, in order to avoid motivational and cognitive biases, it is recommended to use debiasing techniques which is provided by Ref. [116].

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.

7. 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. 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.

Data availability statement

The data associated with our work has not been deposited into a publicly available repository. The data will be available on request.

CRediT authorship contribution statement

Ali Karevan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis. **Sylvie Nadeau:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflict of interest.

Acknowledgments

The authors acknowledge the funding and support of École de technologie supérieure (ÉTS) as well as the Natural Sciences and Engineering Research Council of Canada (NSERC).

References

[1] E. Zio, Monte Carlo Simulation: the Method, Springer, 2013.
[2] M. Gorrod, Risk Management Systems: Process, Technology and Trends, Springer, 2003.
[3] ISO, ISO/DTS31050, Risk Management — Guidelines for Managing Emerging Risk to Enhance Resilience, 2023.
[4] D.A. Wiegmann, S.A. Shappell, Human Error Analysis of Commercial Aviation Accidents Using the Human Factors Analysis and Classification System (HFACS), Office of Aviation Medicine, United States, 2001.
[5] E. Stojiljkovic, B. Bijelic, M. Cvetkovic, *Application of HEART technique for human reliability assessment–a Serbian experience.* Facta Universitatis, Series: Working and Living Environmental Protection (2018) 187–196.
[6] F. Castiglia, M. Giardina, Analysis of operator human errors in hydrogen refuelling stations: comparison between human rate assessment techniques, Int. J. Hydrogen Energy 38 (2) (2013) 1166–1176.
[7] E. Calixto, Gas and Oil Reliability Engineering: Modeling and Analysis, Gulf Professional Publishing, 2016.
[8] B. Emami-Mehrgani, W.P. Neumann, S. Nadeau, M. Bazrafshan, Considering human error in optimizing production and corrective and preventive maintenance policies for manufacturing systems, Appl. Math. Model. 40 (3) (2016) 2056–2074.
[9] H. Bubb, Human reliability: a key to improved quality in manufacturing, Human Factors and Ergonomics in Manufacturing & Service Industries 15 (4) (2005) 353–368.
[10] Y. Torres, S. Nadeau, K. Landau, Classification and quantification of human error in manufacturing: a case study in complex manual assembly, Appl. Sci. 11 (2) (2021) 749.
[11] A. Karevan, 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.
[12] S. Riso, Digitisation in the Workplace, Publications Office of the European Union: Eurofound, Luxembourg, 2021.
[13] S. Nahavandi, Industry 5.0—a human-centric solution, Sustainability 11 (16) (2019) 4371.
[14] A. Reiman, et al., Human factors and ergonomics in manufacturing in the industry 4.0 context–A scoping review, Technol. Soc. 65 (2021) 101572.
[15] M. Raya, Implantation et technologies de conception en contexte d'industrie 5.0 : le cas du secteur aéronautique, in: ÉCOLE DE TECHNOLOGIE SUPÉRIEURE: ÉCOLE DE TECHNOLOGIE SUPÉRIEURE, 2022, p. 134. Mechanical Engineering.
[16] I. Sharma, I. Garg, D. Kiran, Industry 5.0 and smart cities: a futuristic approach, European Journal of Molecular & Clinical Medicine 7 (8) (2020) 2515–8260.
[17] S. Gaiardelli, S. Spellini, M. Lora, F. Fummi, Modeling in industry 5.0: what is there and what is missing: special session 1: languages for industry 5.0, in: 2021 Forum on Specification & Design Languages (FDL), IEEE, 2021.
[18] F. Brocal, et al., Emerging risk management in industry 4.0: an approach to improve organizational and human performance in the complex systems, Complexity (2019) 2019.
[19] A. Mofidi Naeini, S. Nadeau, Proposed integrated FRAM/STPA risk analysis of data gloves in assembly 4.0 system, Robot. Comput. Integrated Manuf. 81 (2023) 102523.
[20] S. Nadeau, R. Bruder, L. Hof, Using smart glasses in assembly/disassembly: current state of the art, Travail et Santé 37 (2) (2021) 2–6.

[21] H. Slim, A proposal of a mixed fuzzy logic/rough sets FRAM model for complex systemic analyses of sociotechnical systems, in: École de technologie supérieure: École de technologie supérieure, 2020. Mechanical Engineering.
[22] J.B. Smith, Complex Systems, 2003 arXiv preprint cs/0303020.
[23] A. Jensen, T. Aven, A new definition of complexity in a risk analysis setting, Reliab. Eng. Syst. Saf. 171 (2018) 169–173.
[24] E.A. Kane, T.E. Higham, Complex systems are more than the sum of their parts: using integration to understand performance, biomechanics, and diversity, Integr. Comp. Biol. 55 (1) (2015) 146–165.
[25] D. Helbing, Globally networked risks and how to respond, Nature 497 (7447) (2013) 51–59.
[26] L.J. Hettinger, A. Kirlik, Y.M. Goh, P. Buckle, Modelling and simulation of complex sociotechnical systems: envisioning and analysing work environments, Ergonomics 58 (4) (2015) 600–614.
[27] A. Mofidi Naeini, Development of a Risk Management Approach for Data Gloves Used in Assembly, École de technologie supérieure, 2022.
[28] J. Bell, J. Holroyd, Review of Human Reliability Assessment Methods, Health & Safety Laboratory, 2009, p. 78.
[29] B. Kirwan, Human error identification in human reliability assessment. Part 1: overview of approaches, Appl. Ergon. 23 (5) (1992) 299–318.
[30] Y. Torres, S. Nadeau, K. Landau, Application of SHERPA (Systematic Human Error Reduction and Prediction Approach) as an alternative to predict and prevent human error in manual assembly, in: Congress of the International Ergonomics Association, Springer, 2021.
[31] A.M. Kumar, S. Rajakarunakaran, V.A. Prabhu, Application of Fuzzy HEART and expert elicitation for quantifying human error probabilities in LPG refuelling station, J. Loss Prev. Process. Ind. 48 (2017) 186–198.
[32] M.M. Aliabadi, Human error analysis in furnace start-up operation using HEART under intuitionistic fuzzy environment, J. Loss Prev. Process. Ind. 69 (2021) 104372.
[33] L. Mkrtchyan, L. Podofillini, V.N. Dang, Bayesian belief networks for human reliability analysis: a review of applications and gaps, Reliab. Eng. Syst. Saf. 139 (2015) 1–16.
[34] E. Castillo, et al., A Markovian–Bayesian network for risk analysis of high speed and conventional railway lines integrating human errors, Comput. Aided Civ. Infrastruct. Eng. 31 (3) (2016) 193–218.
[35] L. Irshad, et al., Quantifying the combined effects of human errors and component failures, J. Mech. Des. 143 (10) (2021).
[36] M. Stamatelatos, et al., Probabilistic Risk Assessment Procedures Guide for NASA Managers and Practitioners, NASA: NASA, 2011.
[37] M.M.H.A. Baig, S.G. Prasanthi, Failure modes and effect analysis of a mechanical assembly by using mil-std 1629a method, Moon 13 (13) (2013).
[38] W.E. Vesely, F.F. Goldberg, N.H. Roberts, D.F. Haasl, Fault Tree Handbook, Nuclear Regulatory Commission, Washington DC, 1981.
[39] C.A. Ericson, Hazard Analysis Techniques for System Safety, John Wiley & Sons, 2015.
[40] R.L. Boring, Fifty years of THERP and human reliability analysis, in: Probabilistic Safety Assessment and Management (PSAM11),Helsinki, Finland,06/24/2012,06/29/2012, Idaho National Lab.(INL), Idaho Falls, ID (United States): **United States**, 2012.
[41] Y. Guo, et al., Risk evolution analysis of ship pilotage operation by an integrated model of FRAM and DBN, Reliab. Eng. Syst. Saf. (2022) 108850.
[42] P. Underwood, P. Waterson, A critical review of the STAMP, FRAM and Accimap systemic accident analysis models. Advances in Human Aspects of Road and Rail Transportation, 2012(January 2016, pp. 385–394.
[43] P. Underwood, P. Waterson, G. Braithwaite, 'Accident investigation in the wild'–A small-scale, field-based evaluation of the STAMP method for accident analysis, Saf. Sci. 82 (2016) 129–143.
[44] B.O. Ceylan, E. Akyuz, Y. Arslanoğlu, Modified quantitative systems theoretic accident model and processes (STAMP) analysis: a catastrophic ship engine failure case, Ocean Eng. 253 (2022) 111187.
[45] C.K. Allison, K.M. Revell, R. Sears, N.A. Stanton, Systems Theoretic Accident Model and Process (STAMP) safety modelling applied to an aircraft rapid decompression event, Saf. Sci. 98 (2017) 159–166.
[46] E. Hollnagel, O. Goteman, The functional resonance accident model. Proceedings of Cognitive System Engineering in Process Plant, 2004, pp. 155–161, 2004.
[47] N. Leveson, A new accident model for engineering safer systems, Saf. Sci. 42 (4) (2004) 237–270.
[48] U. Military, Procedures for performing a failure mode, effects and criticality analysis. United States Military Procedure MIL-P-1629, 1949.
[49] H.A. Watson, Launch Control Safety Study, Bell labs, 1961.
[50] A.D. Swain, Therp. Sandia Corp, 1964. Albuquerque, N. Mex.
[51] B. Kirwan, The validation of three human reliability quantification techniques—THERP, HEART and JHEDI: Part 1—technique descriptions and validation issues, Applied ergonomics 27 (6) (1996) 359–373.
[52] J.C. Williams. A proposed method for assessing and reducing human error, Univ. of Bradford, Chicago, 1986.
[53] D. Embrey, SHERPA: a systematic human error reduction and prediction approach, in: Proceedings of the International Topical Meeting on Advances in Human Factors in Nuclear Power Systems, 1986.
[54] D. Gertman, et al., The SPAR-H human reliability analysis method, US Nuclear Regulatory Commission 230 (4) (2005) 35.
[55] E. Hollnagel, Cognitive Reliability and Error Analysis Method (CREAM), Elsevier, 1998.
[56] Cooper, S.E., A. Ramey-Smith, J. Wreathall, and G. Parry, *A Technique for Human Error Analysis (ATHEANA)*. 1996, Nuclear Regulatory Commission: United States..
[57] Embrey, D., et al., SLIM-MAUD: an Approach to Assessing Human Error Probabilities Using Structured Expert Judgment. Volume I. Overview of SLIM-MAUD. 1984, Brookhaven National Lab., Upton, NY (USA): United States..
[58] J. Pearl, Bayesian netwcrks: a model cf self-activated memory for evidential reasoning, in: Proceedings of the 7th Conference of the Cognitive Science Society, University of California, Irvine, CA, USA, 1985.
[59] A. Mofidi Naeini, S. Nadeau, 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 (2022) 317–331.
[60] N. Leveson, J.P. Thomas, STPA Handbook, 2018. Cambridge, MA, USA.
[61] P.M. Salmon, M. Cornelissen, M.J. Trotter, Systems-based accident analysis methods: a comparison of Accimap, HFACS, and STAMP, Saf. Sci. 50 (4) (2012) 1158–1170.
[62] K. Kazaras, K. Kirytopoulos, A. Rentizelas, Introducing the STAMP method in road tunnel safety assessment, Saf. Sci. 50 (9) (2012) 1806–1817.
[63] E. Pricop, J. Fattahi, N. Dutta, M. Ibrahim, Recent Developments on Industrial Control Systems Resilience, Springer, 2020.
[64] A. Hulme, et al., 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, Appl. Ergon. 91 (2021) 103297.
[65] T. Andrews, A. Moulton, S. Madnick, An examination of software tool features needed to help secure energy delivery industrial control systems, MIT Sloan Research Paper 18 (2018) 5722.
[66] J.M. Rising, N.G. Leveson, Systems-Theoretic Process Analysis of space launch vehicles, Journal of Space Safety Engineering 5 (3–4) (2018) 153–183.
[67] A. Bahoo Toroody, F. Bahoo Toroody, F. De Carlo, Development of a risk based methodology to consider influence of human failure in industrial plants operation, Summer School "Francesco, Turco, Proceedings (2017) 215–221.
[68] S. Luke, Essentials of Metaheuristics, vol. 2, 2013. Lulu Raleigh.
[69] E.-G. Talbi, Metaheuristics: from Design to Implementation, John Wiley & Sons, 2009.
[70] S. Nesmachnow, An overview of metaheuristics: accurate and efficient methods for optimisation, Int. J. Metaheuristics (IJMHeur) 3 (4) (2014) 320–347.
[71] C. Zhu, M. Qi, J. Jiang, Quantifying human error probability in independent protection layers for a batch reactor system using dynamic simulations, Process Saf. Environ. Protect. 133 (2020) 243–258.
[72] K.C.A. Khanzode, R.D. Sarode, Advantages and disadvantages of artificial intelligence and machine learning: a literature review, Int. J. Libr. Inf. Sci. 9 (1) (2020) 3.
[73] A. Karevan, M. Vasili, Sustainable reliability centered maintenance optimization considering risk attitude, Journal of applied research on industrial engineering 5 (3) (2018) 205–222.

[74] M. Jain, V. Saihjpal, N. Singh, S.B. Singh, An overview of variants and advancements of PSO algorithm, Appl. Sci. 12 (17) (2022) 8392.
[75] A. Karevan, K.F. Tee, M. Vasili, A reliability-based and sustainability-informed maintenance optimization considering risk attitudes for telecommunications equipment, Int. J. Qual. Reliab. Manag. 38 (4) (2021) 873–891.
[76] P. Wilson, H.A. Mantooth, Model-based Engineering for Complex Electronic Systems, Newnes, 2013.
[77] B. Yang, et al., Comprehensive overview of meta-heuristic algorithm applications on PV cell parameter identification, Energy Convers. Manag. 208 (2020) 112595.
[78] P.K. Lehre, C. Witt, Finite first hitting time versus stochastic convergence in particle swarm optimisation, in: Advances in Metaheuristics, Springer, 2013, pp. 1–20.
[79] A. Mofidi Naeini, S. Nadeau, Application of FRAM to perform risk analysis of the introduction of a data glove to assembly tasks, Robot. Comput. Integrated Manuf. 74 (2022) 102285.
[80] D. Kim, Y. Choi, Applications of smart glasses in applied sciences: a systematic review, Appl. Sci. 11 (11) (2021) 4956.
[81] M. Billinghurst, T. Starner, Wearable devices: new ways to manage information, Computer 32 (1) (1999) 57–64.
[82] Y. Hao, P. Helo, The role of wearable devices in meeting the needs of cloud manufacturing: a case study, Robot. Comput. Integrated Manuf. 45 (2017) 168–179.
[83] M. Krzywdzinski, S. Pfeiffer, M. Evers, C. Gerber, Measuring Work and Workers: Wearables and Digital Assistance Systems in Manufacturing and Logistics, SP, Wissenschaftszentrum Berlin für Sozialforschung gGmbH, 2022, pp. III 2022–I 2301.
[84] N.M. Kumar, N.K. Singh, V. Peddiny, Wearable smart glass: features, applications, current progress and challenges, in: 2018 Second International Conference on Green Computing and Internet of Things (ICGCIoT), IEEE, 2018.
[85] N. Khodammohammadi, V.T.M. Ngô, S. Nadeau, Integrating smart glasses in a hybrid manufacturing system: towards a better understanding of impacts on productivity, quality and ergonomics/human factors, in: CIGI QUALITA MOSIM 2023, Trois-Rivières, Canada, 2023.
[86] N. Khoddammohammadi, Modeling and qualification of future digitalized assembly work, in: Mechanical Engineering, École de technologie supérieure, 2023.
[87] L.-H. Lee, P. Hui, Interaction methods for smart glasses: a survey, IEEE Access 6 (2018) 28712–28732.
[88] B.L. Due, The future of smart glasses: an essay about challenges and possibilities with smart glasses, in: Centre of Interaction Research and Communication Design, vol. 1, University of, 2014.
[89] T. Bjerga, T. Aven, E. Zio, Uncertainty treatment in risk analysis of complex systems: the cases of STAMP and FRAM, Reliab. Eng. Syst. Saf. 156 (2016) 203–209.
[90] E. Baranoff, P.L. Brockett, Y. Kahane, Risk Management for Enterprises and Individuals, Flat World Knowledge, Inc, 2009.
[91] A. Badri, S. Nadeau, A. Gbodossou, Integration of OHS into risk management in an open-pit mining project in Quebec (Canada), Minerals 1 (1) (2011) 3–29.
[92] Canadian Centre for Occupational Health, C. Safety, Hazard and Risk - Risk Assessment, 2017.
[93] M.M.R. Qureshi, Building proactive organizational resilience against the risk of major process safety incidents, Process Saf. Prog. 42 (1) (2023) 48–55.
[94] C. La Fata, L. Adelfio, R. Micale, G. La Scalia, Human error contribution to accidents in the manufacturing sector: a structured approach to evaluate the interdependence among performance shaping factors, Saf. Sci. 161 (2023) 106067.
[95] M. Yazdi, A. Nedjati, E. Zarei, R. Abbassi, A novel extension of DEMATEL approach for probabilistic safety analysis in process systems, Saf. Sci. 121 (2020) 119–136.
[96] L. Kraidi, R. Shah, W. Matipa, F. Borthwick, An investigation of mitigating the safety and security risks allied with oil and gas pipeline projects, Journal of Pipeline Science and Engineering 1 (3) (2021) 349–359.
[97] V.T.M. Ngô, S. Nadeau, S. Hallé, Validation of ergonomic criteria of a cooling vest for deep and ultra-deep mining, Int. J. Ind. Ergon. 78 (2020) 102980.
[98] M. Singh, M. Pant, A review of selected weighing methods in MCDM with a case study, International Journal of System Assurance Engineering and Management 12 (2021) 126–144.
[99] J. Rezaei, Best-worst multi-criteria decision-making method, Omega 53 (2015) 49–57.
[100] S. Raychaudhuri, Introduction to Monte Carlo simulation, in: 2008 Winter Simulation Conference, IEEE, 2008.
[101] D. Li, et al., Machine learning-aided risk stratification system for the prediction of coronary artery disease, Int. J. Cardiol. 326 (2021) 30–34.
[102] S. Sreenath, K. Sudhakar, A. Yusop, Solar photovoltaics in airport: risk assessment and mitigation strategies, Environ. Impact Assess. Rev. 84 (2020) 106418.
[103] L. Cristaldi, M. Khalil, P. Soulatintork, A root cause analysis and a risk evaluation of PV balance of system failures, Acta Imeko 6 (4) (2017) 113–120.
[104] M.F. Mostafa, S.H.A. Aleem, A.F. Zobaa, Risk assessment and possible mitigation solutions for using solar photovoltaic at airports, in: 2016 Eighteenth International Middle East Power Systems Conference (MEPCON), IEEE, 2016.
[105] J.B. Wirawan, I. Garniwa, Risk analysis development of solar floating power plant in the sea with Monte Carlo method, in: 2018 3rd International Conference on Information Technology, Information System and Electrical Engineering (ICITISEE), IEEE, 2018.
[106] A. Seňová, H. Pavolová, E. Škvareková, Assessment of the impact of working risks in the exploitation of raw materials, Manag. Syst. Prod. Eng. 31 (1) (2023) 86–94.
[107] M.A. Noman, et al., A new integrated risk-assessment model for minimizing human-machine error consequences in a preventive maintenance system, IEEE Access 11 (2023) 25253–25265.
[108] M. Richert, M. Dudek, Risk mapping: ranking and analysis of selected, key risk in supply chains, J. Risk Financ. Manag. 16 (2) (2023) 71.
[109] P.S. Virdi, G. Pamnani, Human error identification and risk prioritization in LPG unloading operations, Int. J. Occup. Saf. Ergon. 29 (1) (2023) 392–406.
[110] F. Marini, B. Walczak, Particle swarm optimization (PSO). A tutorial, Chemometr. Intell. Lab. Syst. 149 (2015) 153–165.
[111] S. Lalwani, S. Singhal, R. Kumar, N. Gupta, A comprehensive survey: applications of multi-objective particle swarm optimization (MOPSO) algorithm, Transactions on combinatorics 2 (1) (2013) 39–101.
[112] A.P. Engelbrecht, Computational Intelligence: an Introduction, John Wiley & Sons, 2007.
[113] W. Zhang, F. Gu, J. Guo, Can smart factories bring environmental benefits to their products?: a case study of household refrigerators, J. Ind. Ecol. 23 (6) (2019) 1381–1395.
[114] How_It's_Made_Show. *How It's Made Fridge*, 2016. Available from: https://www.youtube.com/watch?v=sVIECPxqSZ4.
[115] L. Cox, What's wrong with risk matrices? Risk analyses 28 (No 2) (2008).
[116] G. Montibeller, D. Von Winterfeldt, Cognitive and motivational biases in decision and risk analysis, Risk Anal. 35 (7) (2015) 1230–1251.