# 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 technologydriven 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 personalization (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: <u>Section 2</u> describes the methodology of the literature review. <u>Section 3</u> presents the results, while the discussion is conducted in <u>Section 4</u>. Finally, the conclusion is given in <u>Section 5</u>.

# 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 1. Keywords			
human acodents		RISK	H C Ch
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.

Significant term	Search term		
	["human error" OR "human reliability"		
Human error	OR "Occupational Health and Safety"		
	OR "OHS"]		
	AND		
	["manufacturing" OR "complex system"		
Manufacturing	OR "industry" OR "production" OR		
	"assembly" OR "disassembly"].		
	AND		
Dielz	["Risk" OR "risk analysis" OR "risk		
KISK	management"]		
	AND		
	["Industry 5.0" OR "I5.0" OR "Industry		
Industry 5.0	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 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 4. Eligibility criteria		
	Manufacturing	
Scope	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 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 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 5. Journal title			
Journal Title	Frequency		
Computers and Industrial Engineering	2		
Robotics and Computer-Integrated	2		
Manufacturing			
Safety Science	2		
Advanced Intelligent Systems	1		
Process Safety and Environmental Protection	1		
CIRP Journal of Manufacturing Science and	1		
Technology			
Complexity	1		
Heliyon	1		
International Journal of Environmental Research	1		
and Public Health			
Safety	1		
Smart and Sustainable Manufacturing Systems	1		
SN Applied Sciences	1		



**Figure 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 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 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 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.

Reference	Main objectives		
(Arana- Landín et al., 2023)	An examination of the impact of Industry 4.0 technologies on OHS risks, with particular focus on new emerging risks.		
(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 et al., 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 et al., 2022)	A smart sole solution that collects workers' postural data and alerts them, when necessary, ultimately supporting their wellbeing		
(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 et al., 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.		
(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 et al., 2022) As part of this work, guidelines for develop safe human-robot collaborative assemblies developed, focusing specifically on the system's features. In this work, a set of structured guidelines is presented to simpl the design process for the features definin CAS from the perspective of preventing mechanical hazards. The digital twin mod and laboratory case study are used to valid these results.			

(Di Pasquale et al., 2022) (Bavaresco et al., 2021)	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. The study outlines the impact of IoT on occupational well-being for the period 2009 to	Based on the table above, most use of IoTs on OHS. Occupatio be reduced through Industry Internet of Things, Robotics, Reality (Arana-Landín et al., 20 papers analyzed the risk of using	
ot ul., 2021)	2019.	Ta	ble 7. Included pa
(Silve et al	support human activities in confined spaces in this work, which examines technologies used	Reference	IoT used
(Shva et al., 2021)	in the industry. The purpose of this project is to analyze and develop augmented reality devices for these environments under these perspectives. In addition to identifying positive effects, the	(Hayat & Reda, 2022)	A system that measures occupational health risk exposure to
	research was aimed at identifying negative effects in human–cobot interactions (HCI) while meeting the requirements for health and		follow digital workplace transformation
(Pauliková et al., 2021)	safety at work as well as ensuring the production process meets quality standards. We conducted this research to determine	(Naeini & Nadeau, 2023)	Data glove
	which negative effects may be caused by HCI, and then propose preventive and corrective	(Bavaresco et al., 2021)	Various
	Through the use of a multi-criteria approach, occupational risk is assessed. It is indeed	da Cunha, 2019)	Structured sensors
(Lolli et al.,	possible to assess the dynamic, individual, and integrated risk that a worker is subjected to	(Teixeira et al., 2022)	Smart soles
/	over time by using a TOPSIS approach after pre-processing the time series using a segmentation algorithm.	(Arana- Landín et al., 2023)	N/A
(Adem et al., 2020)	In this study, they are investigating three objectives: investigating OHS risks that may arise with Industry 4.0 integration in	(Naeini & Nadeau, 2022c)	Data glove
(Polak-	categorizing these risks; and prioritizing them. List some recommendations regarding the	(Adriaensen et al., 2019)	N/A
Sopinska et al., 2020)	integration of OHS into manufacturing in the context of Industry 4.0 and its effects.	(Silva et al., 2021)	AR glasses
	Robot Interactions are examples of complex systems that are linked to emerging rick	(Zorzenon et al., 2022)	N/A
(Brocal et al., 2019)	management. The objective of this paper is to propose an organizational and human	(Badri et al., 2018)	N/A Data-driven
	performance approach to improve risk management associated with such complex	$\frac{2023)}{(Patel et al.,}$	models
(Barata & da Cunha, 2019)	Provide a comprehensive solution for their adoption in OHS	. <u>2022)</u> (Naeini & Nadeau, 2022a)	Data glove
(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	(Di Pasquale et al., 2022)	Various
	derived from complexity thinking and theories derived from complex adaptive systems. In	(Brocal et al., 2019)	N/A
(Badri et al.,	spite of this, this review demonstrates that no single solution-fits-all approach exists. In this article, the authors aim to provoke reflection regarding OHS integration into Industry 4.0 by raising related questions. They	(El Helou et al., 2022)	Smart vision system embedded in industrial robot
2018)	integrating OHS into Industry 4.0 and how this can create new risks and opportunities.	(Polak- Sopinska et	N/A

papers aimed to investigate the nal health and safety risks can 4.0 applications such as the and Virtual and Augmented 023). However, just 13% of the g IoTs in manufacturing.

# per'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		N/A
(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
(Naeini & Nadeau, 2022c)	Data glove		STPA
(Adriaensen et al., 2019)	N/A	Qualitative	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
(Naeini & Nadeau, 2022a)	Data glove		FRAM
(Di Pasquale et al., 2022)	Various		N/A
(Brocal et al., 2019)	N/A		N/A
(El Helou et al., 2022)	Smart vision system embedded in industrial robot		N/A
(Polak- Sopinska et al., 2020)	N/A		N/A

(Pauliková et al., 2021)	Cobots		N/A
(Gualtieri et al., 2022)	Digital twin	Quantitative	N/A
(Lolli et al., 2021)	N/A		Fuzyy TOPSIS
(Adem et al., 2020)	N/A		Hesitant Fuzzy AHP

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. 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 humanmachine 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, to the best of our knowledge, there is not a significant number of 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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