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Human centric collaborative workplace: the human robot interaction system perspective

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DECLARATION

I hereby declare that, the contents and organisation of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

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"-Where should I go?

-That depends on where you want to end up."

Lewis Carroll, Alice Adventures in Wonderland

Abstract

The implementation of smart technologies and physical collaboration with robots in manufacturing can provide competitive advantages in production, performance and quality, as well as improve working conditions for operators. Due to the rapid advancement of smart technologies and robot capabilities, operators face complex task processes, decline in competences due to robots overtaking tasks, and reduced learning opportunities, as the range of tasks that they are asked to perform is narrower. The Industry 5.0 framework introduced, among others, the human-centric workplace, promoting operators wellbeing and use of smart technologies and robots to support them. This new human centric framework enables operators to learn new skills and improve their competencies. However, the need to understand the effects of the workplace changes remain, especially in the case of human robot collaboration, due to the dynamic nature of human robot interaction.

A literature review was performed, initially, to map the effects of workplace changes on operators and their capabilities. Operators need to perform tasks in a complex environment in collaboration with robots, receive information from sensors or other means (e.g. through augmented reality glasses) and decide whether to act upon them. Meanwhile, operators need to maintain their productivity and performance. This affects cognitive load and fatigue, which increases safety risks and probability of human-system error. A model for error probability was formulated and tested in collaborative scenarios, which regards the operators as natural systems in the workplace environment, taking into account their condition based on four macro states; behavioural, mental, physical and psychosocial. A scoping review was then performed to investigate the robot design features effects on operators in the human robot interaction system. Here, the outcomes of robot design features effects on operators were mapped and potential guidelines for design purposes were identified. The results of the scoping review showed that, apart from cognitive load, operators perception on robots reliability and their safety, along with comfort can influence team cohesion and quality in the human robot interaction system.

From the findings of the reviews, an experimental study was designed with the support of the industrial partner. The main hypothesis was that cognitive load, due to collaboration, is correlated with quality of product, process and human work. In this experimental study, participants had to perform two tasks; a collaborative assembly and a secondary manual assembly. Perceived task complexity and cognitive load were measured through questionnaires, and quality was measured through errors participants made during the experiment. Evaluation results showed that while collaboration had positive influence in performing the tasks, cognitive load increased and the temporal factor was the main reason behind the issues participants faced, as it slowed task management and decision making of participants. Potential solutions were identified that can be applied to industrial settings, such as involving participants/operators in the task and workplace design phase, sufficient training with their robot co-worker to learn the task procedures and implement direct communication methods between operator and robot for efficient collaboration.

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Contents

List of Abbreviations

Abbreviation	Description
AI	Artificial Intelligence
AR/VR	Augmented Reality / Virtual Reality
CL	Cognitive Load
Cobot	Collaborative Robot
CPS	Cyber Physical System
EEG	Electroencephalogram
EU-OSHA	European Union – Occupational Safety and Health Administration
HRC	Human Robot Collaboration
HRI	Human Robot Interaction
HF	Human Factors and Ergonomics
IEA	International Ergonomics Association
I5.0	Industry 5.0
I4.0	Industry 4.0
KPI	Key performance indicator
NASA-TLX	NASA – Task Load Index
PE	Probability of error
PERCLOS	Percentage of Eyelid Closure over time
STS	Sociotechnical systems

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1. INTRODUCTION

1.1 Defining the operators issue

The Fourth Industrial Revolution, or Industry 4.0 (I4.0), encompasses smart technologies and promotes rapid technology advancements, fast paced systems and processes with increased interconnectivity, and rapid automation and digitalization (Bai et al., 2020). Artificial Intelligence (AI), Augmented and Virtual reality (AR/VR) along with collaborative robots (cobots) and cyber systems (such as cloud computing), are some of the smart technologies and tools deployed in the workplace of I4.0 (Frank et al., 2019). Physical barriers between human and robots are removed, allowing for more close human-robot and human-machine interaction (De Santis et al., 2008). With the breakthroughs in machine learning and data analysis, big data analytics can provide (near-) real time data processing, which in turns presents numerous opportunities for management, including better informed decision making and faster reactions to events (Gokalp et al., 2016).

In that evolving, dynamic and complex environment, humans need to be able to work alongside robots, interact with smart technologies in their tasks (e.g. AR tools in maintenance or assembly), and act as safeguard entities (Reason, 2000). Moreover, operators need to be able to receive real-time information from their robotic co-workers and other “tools”, such as cyber physical systems (CPS) or AR glasses. As such, operators need to decide whether to act upon the information on not, in order to fulfil the goals set by management and logistics (Panagou et al., 2021b). With the capabilities offered in the I4.0 framework and the new HRI, customers are able to choose from a wide range of industries and their products, and are also able to follow along the production and delivery due to the interconnection provided by Internet of Things (IoT). To stay competitive in this fast-paced and changing market, companies are pushed to develop mass-customizable products by altering assembly lines, in order to be able to provide, through market demand or forecasting, their customers the product they need (Brettel et al., 2014). This adds complexity to an already complex environment while adding more pressure to human workers; in addition to working with robots and new advanced tools, they need to be able to learn and get accustomed to new product requirements, which could be in short periods of time (Panagou et al., 2021a).

An additional change in the workplace is also the gradual eclipse of distinct roles of operators and robots in the workplace (Scholtz, 2003). With the advancement of AI, programming of robots allows them to perform task and roles autonomously without the need for human supervision. In cases, robots take the supervisory roles in HRI situations (Gonzalez et al., 2017). As technology advances, and robots get upgraded functionalities and capabilities, they can replace human workers in certain tasks. Automation technology and robots replacing manual human work, creates new challenges for the workforce. Forbes in a published study, predict over 73 million jobs lost to automation by 2030 in USA, 17 million in Germany, and over 200 million jobs lost in China alone.

While I4.0 smart technologies introduction to the workplace environment create a highly dynamic and complex workplace with increased uncertainty, they can support human workers and improve the workplace conditions as can be seen by the Operators 4.0 (Romero et al. 2020) concept. Existing human operators can become highly skilled in their assigned tasks, while automation and new technologies create new opportunities; World Economic Forum, in a published report (2020), states that while automation and digitalization will result in the loss of 85 million jobs by 2025, it will create 97 new million jobs; although creation of new jobs may slow down due to the COVID-19 pandemic. However, despite the expected support and positive effects, and although human operators are considered an integral part in engineering projects and workplaces, they are not considered in research and engineering projects (Neumann et al., 2021).

Human Factors and Ergonomics (HFE) can provide directions and tools for human consideration, as its focus is the interactions of humans with entities in a system, however HFE and human workers are systematically left out of research concerning human robot interaction and Industry 4.0 (Neumann et al. 2021). This absence of consideration, comes in contrast with the Socio-Technical System Theory (STS), which pushes towards joint optimization for technical and social parts of a system in order to increase effectiveness. An added factor to the issue, is the ageing population and ageing workforce, a trend widely recognized by governments. The European Union in a report published in 2019, shows that worker aged 55 and more will rise from 21% in 2014 to 26% in 2019, to an estimated 55% of the overall labour force in 2030. New guidelines, training, support tools and safety guidelines should be introduced to accommodate the ageing workforce, due to the change in human capabilities as they age (Di Pasquale et al. 2020; Panagou et al. 2021). Towards the goal of providing human support in the era of smart manufacturing and advanced robots, Industry 5.0 (I5.0) was introduced by the European Union. I5.0 concept aims in the use of the I4.0 framework and smart technologies towards a human-centric workplace (Xu et al. 2021). However, despite this new development, research into how to support humans and the move towards human-centric workplace requires several issues to be addressed for successful implementation.

1.2 Industrial Revolutions and Human operators

Before moving forward to the research purpose and research questions, briefly describing the changes brought to human workers by the industrial revolutions (figure 1) can provide information and indications on the context of those changes, which in turn can assist in forming the hypothesis and research questions. The term industrial revolution usually refers to a time period where there is discovery or advancement of manufacturing techniques or methodologies, and/or significant changes in production methods. Those changes affect the design of manufacturing plants, which in turn increases productivity, performance and also allows for manufacturing of new products or services. However, each time a new industrial revolution happened, the changes also affected other sectors of society and its surroundings. From positive or negative changes to the human workers, to a single household way of life, to large society changes and effects on the environment and land.

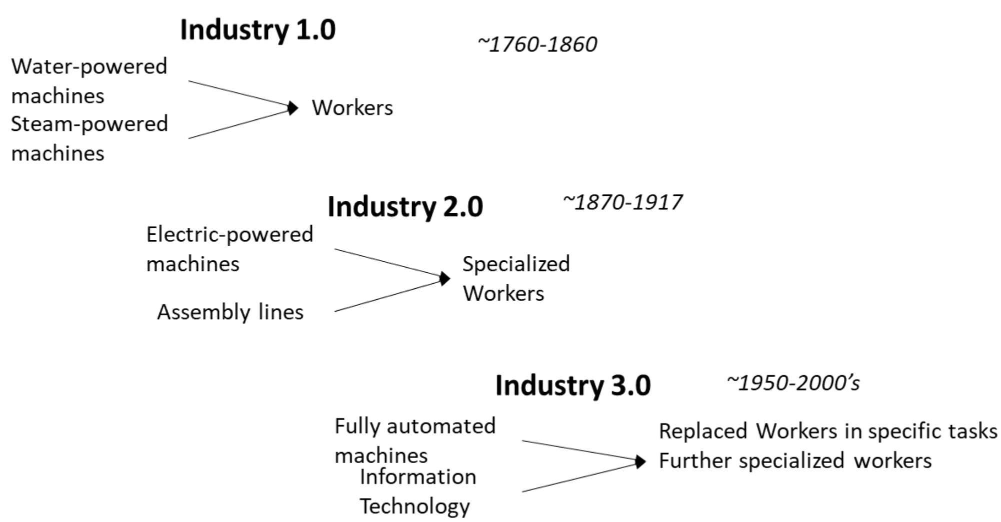


Figure 1. Industrial Revolutions Timeline, changes and impact to workers.

1.2.1 First Industrial Revolution

The first industrial revolution started sometime in 1760 and lasted until sometime between 1840 and 1860 (Council of Europe, 2021). The main factor that propelled this era was the development of steam engines; hand operated methods gave way to steam and water operated machines, which also introduced chemical methodologies in manufacturing and iron production. The rise of machine-led factory systems paved the way for the introduction of structured organizations, from owner to manager to worker to customer, which replaced the “cottage” style industry. While the new machines had a positive influence on human workers and led to population increase the transition to full mechanized factories was finished after a large period of time, while having to overcome numerous issues regarding time shifts and healthy and safe working conditions in the factories (Bain, 2020).

1.2.2 Second Industrial Revolution

The second industrial revolution was prompted by the stagnation of new innovations during the latter part of the first industrial revolution. From a historical point of view, the time period of this revolution is between 1870 and 1917, which signalled the beginning of the first World War (Mokyr and Strotz, 1998). This revolution was propelled by the use of coal, steel and iron and the use of electricity. With electricity, new machines and the telegraph were invented that speed up production and communication. One of the most significant advancements in manufacturing was the introduction of fully powered assembly lines in 1913 by Ford. In this era, each worker specialized in one manual operation, instead of multiple ones, which further sped up production. These led to a specialized and professional workforce that could produce mass quantities in short time (Hounsell, 1984). Furthermore, it led to development of inter- and across- continent transportation through air, sea and land; leading to the fast and rapid expansion of railroad, which culminated in a new rise of globalization. Although this revolution led to the development of a professional workforce and the advancement of the middle class, the first and second world war and the period in between, did not allow much consideration on the human factors and issues that workers faced in their tasks.

1.2.3 Third Industrial Revolution

The third industrial revolution, also known as Digital Revolution, starting point is the second half of the 20th century (Dreyer et al., 2006). In this era, digital electronics and electrical engineering replaced the mechanical and analogue electronic technology. Digital communication and computing technologies brought rapid changes in industrial manufacturing. Computers, microprocessors, smartphones and the internet are some of the most influential technologies that helped transformed business techniques and industries. Fully automated machines supplemented workers or in cases replaced them, while being surrounded by physical barriers for safety reasons.

Enterprise resources planning tools influenced logistics and supply chain planning. The mentality of mass production from the previous revolution, was updated through the addition of low-cost mentality; manufacturing plants were moved to low-cost countries and through the use of software planning systems, supply chain management in a global scale flourished. Although, automated machines supported human workers in difficult tasks, and further supported specialization, it raised concerns on information overload and privacy issues (Hodson, 2018). Moreover, this era is considered as one of the least sustainable as the transformations required mass amount of electronics and the processes used create a lot of waste. Lean management, focusing on sustainability and reduce of waste, was an answering transformation, however it focuses only on the business side of the equation and not the environmental one. In this revolution as in the previous one, further specialization in human work was required in many cases and led to the creation of new professions. Human manufacturing jobs, requiring little skill and prior knowledge, declined in the period between 1970 to 2000 by 3%, and steadily declined after 2000, while production grew by almost 20% (Business Insider).

Mass digitalization and the shift to a digital age at the late 1990's to early 2000's, led to increased connectivity and technological use in all aspects of society. This change in society, the advances in technology and robot development, and the need for better productive and mass-customization created the need to introduce those new tools and robots in manufacturing, which led to new forms of interactions between humans and robots without physical barriers, as the robots were flexible; in contrast to the machines introduced in the third industrial revolution, which were bulky and posed serious safety concerns towards the humans workers in the same workplace.

1.2.4 Fourth Industrial Revolution

Although a more detailed analysis of Industry 4.0 will be shown in Chapter 3, a brief description is given here. Industry 4.0 represents the shift to an era of interconnectivity and increased technological use of society. It conceptualises rapid change of technology, industry, processes and society for increased efficiency and economic growth. Especially in industries, it pushes for joining of technologies, artificial intelligence, gene editing, advanced robotics and virtual reality. As such, it results in automation of traditional manufacturing and practices, physical collaboration between human and robots, and the internet of things. The interconnectivity and advanced machine-to-machine communication, along automation, improved communication and self-monitoring, allows for smart machines to analyse information and data received to diagnose issues without direct human intervention. However, it creates issues that need to be investigated and solved for smooth integration, such as privacy concerns, safety issues at work, loss of jobs and the need for operators to re-skill or up-skill. And although automation can increase production and effectiveness, it raises issues of quality and reliability, as the value of self-made and human-made products increase (Norton et al., 2011).

1.3 Human Robot Interaction

Human and robot interaction is a topic that gathers interest and focus in both scientific and fictional world. Mentions of robots can be found in the ancient Greek literature, which performed tasks that could bring them in contact with humans. The robot Talos, for example, was created to guard the island of Crete against intruders. Hephaestus the god of metallurgy, had numerous robots that helped him in his work and creations. Ancient Chinese texts (4^{th} century BC), discuss the implications of automatons with human features. There are also texts describing automata that could be powered by hydraulics or steam, from the Alexandrian engineers (285-222 BC). Mentions of constructed automata can be found in Byzantine and Arabian literature. Leonardo da Vinci drew the first verifiable automated humanoid in 1495 (Moran, 2006). In the 1770s, Pierre Jaquet-Droz created automata with human-like features that could move. Hisashige Tanaka, a Japanese craftsman, created complex mechanical automata that could perform from simple to complex tasks (Hornyak, 2006). Nicola Tesla in 1898, presented a remote controlled submarine, that could act by itself as if possessing human reason (Nocks, 2007). One of the most prominent works is the fictional novel I, Robot, by Isaac Asimov an academic and writer, in 1941. In his work, human robot interaction was first stated as a discrete issue, and moreover, the Three Laws of Robotics were stated, which provide a foundation for the safety aspect of HRI:

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

Human and robot, or machine, task and roles allocation changed as a result of the programming capabilities and design opportunities that smart technologies and I4.0 framework brought (Frank et al., 2019). As the older machines were large in bulk and presented serious danger for human workers, physical proximity or direct interaction was not possible, and so physical barriers were designed between them. As such the safest form of interaction that could be achieved was coexistence; both present in the workspace but with no contact or any form of assistance during a task. New design of robots and machines makes them smaller while also being more flexible and with wider move capabilities. Moreover, with the assistance of AI programming strengthening their functions and capabilities, and with the aid of sensors, they can work in close proximity to their human co-workers and also provide assistance at the same tasks. This is aided by use of computer vision, giving them sensing capabilities. As such, cooperation and collaboration now are possible. Humans and robots can work on the same task with no direct interaction (cooperation) or work closely with direct and physical contact (collaboration).

With those interactions becoming the prevalent form of workplace design, robots and their design features are becoming more advanced and more elaborate. Some of the features that are being actively researched and worked on are motion planning, cognitive modelling and communication capabilities. Motion planning to avoid collisions allowing also a wider range of tasks to be performed by the robots. Cognitive modelling for robots, as a form to lower the distrust of humans, by mimicking human movement and gestures. Moreover, communication capabilities for human support and coordination during tasks. However, interaction and new capabilities are not only used in manufacturing. Robots are being used in (i) healthcare services, from surgery to rehabilitation to elder care, (ii) social robots, from home companions to museum guides and hike trail guides, (iii) automatic driving, (iv) search and rescue missions, especially in dangerous areas or difficult to reach areas, (v) space exploration, as consideration for crewed missions to Mars or elsewhere, and many more potential areas.

However, despite all the advances, benefits and support that robot can offer, due to the rapid advancement and integration of robots in the workplace, it can negatively affect humans. The International Federation of Robotics (IFR) showed that the number of industrial robots increases by close to 14% every year; in 2020 the number of industrial robots globally were 2.7 million. While increased automation boost revenues, estimated $12.6 billion in medical robot market, increase by close to 10% in annual revenue for businesses, and an estimated GDP growth of 26% and 14% in North America by 2030 (PwC), it is also predicted that close to 30% of the job market will be covered by robots, with over 20 million manufacturing jobs lost (Oxford Economics). Low-level education workers will suffer more than high-level ones; 40% will be displaced compared to 10% of high level (PwC). While 70% of the workers believe that robots will provide opportunities for better employment (IFR), education and training programs are needed in preparation of supporting and aiding those who will be replaced by automation for upskilling and reskilling purposes.

The push for automation and robot integration in the workplace creates feelings of distrust in operators towards robots and discomfort working with them. Moreover, as robots replaces operators in tasks, operators feel threatened by robots (Ford, 2016). The negative values of trust and feelings against robots can create issues in safety and productivity, in part also due to the non consideration of human workers in smart manufacturing research and projects (Neumann et al. 2021). As such, it is crucial for research to understand the issues that can be created from integrating robots into workplaces on operators. From their perception and knowledge on robots, to mental effects, and from physical to psychosocial effect. In that way, design guidelines and advice along with training and information can provide operators the necessary tools and knowledge for them to become accustomed to the needs and demands created by I4.0 and I5.0 frameworks.

The focus of this research work is to investigate (i) the issues brought upon human operators by the integration of robots and smart technologies inside the workplace, and (ii) the difficulties operators face in collaboration leading to errors or other issues. Those can lead to potential design guidelines and solutions for HRC, aiming towards a human-centric workplace where the implemented changes support operators. Thus, optimizing collaboration and task management, and improving reliability, safety and performance.

This work is structured as following. In chapter 2 the research rationale and the research questions are presented. In chapter 3 a background of Industry 4.0 and Industry 5.0 frameworks, along with the human robot collaboration basic framework and parameters, and the HFE are presented. Chapters 4 through 6 include the research activities that were developed and performed based on the research questions. The final chapter (chapter 7) include the final discussion, conclusions and possible future research directions.

2. Research Rationale and Activities

2.1 Problem statement and Research Questions

With the introduction of Industry 4.0 framework and the use of smart technologies and cobots in the workplace, some of the expectations on the benefits it provides were in terms of productivity, performance and minimizing error in the system. However, although I4.0 was a subject of research interests its focus was more on the technological side. The lack of consideration for operators, along with the continuous advancement in technology, robot capabilities and the increased complexity and dynamic interactions, creates further issues to operators, which places more demands not only on their physical safety but also their mental and psychosocial status. Those issues are especially important in scenarios where human robot collaboration is required. Due to the new capabilities and less bulkier sides, robots can now work into the same tasks with humans, and in cases physical contact between them during a procedure is required, which brings into attention the requirement for research to investigate humans in those scenarios as to improve safety aspect and also create new design guidelines to support humans. The need for human-centric workplaces, was underlined in the Industry 5.0 framework introduced in 2021.

The importance for human-centric functionality in the workplace is highlighted by the roles that human operators need to perform in collaborative scenarios. Humans are now expected to be able to work alongside and in close physical distance with robots, handle new technologies and equipment, receive information from analysed data and decide whether to react or not, maintain performance and quality at high levels, while also act as a safeguard entity in the workplace. Those responsibilities become more difficult due to the added complexity involved and the dynamic interactions needed in their everyday tasks. All those responsibilities and expectations place increased demands in their capabilities; physical, mental and psychosocial. With increased demand, fatigue is an issue both physical and mental, with the latter being important in the decision-making process as it can lead to mistakes and errors. Although those errors or mistakes should be treated as a human-system error and and investigated as such, in most cases human operators are blamed as being the root cause, which in turn affect the investigation process and cost in both money and time. This treatment creates a discrepancy in how the human resources are managed and viewed in an organization.

The lack of human consideration creates feelings of distrust towards robots, discomfort working with them and also a negative bias towards robots, technology and management. Moreover, by not involving operators in the implementation of smart technologies and robots in their workstations, it can further influence the belief of operators that they are not valued enough which further impacts the negative perception towards change.

Based on the above, the main aim for this study was to assess the effects on operators from robots in human robot collaboration and smart manufacturing context and to assist in identifying possible design guidelines and solutions for a human-centric workplace. The aim of this study was further strengthened by the Industry 5.0 framework introduced by the European Union, proposed during the project, which promotes, among others, human-centric workplaces using the Industry 4.0 pillars and technologies. A logical sequence of research questions was formed and activities were designed to answer those questions and achieve the main aim of this study as seen in figure 2.

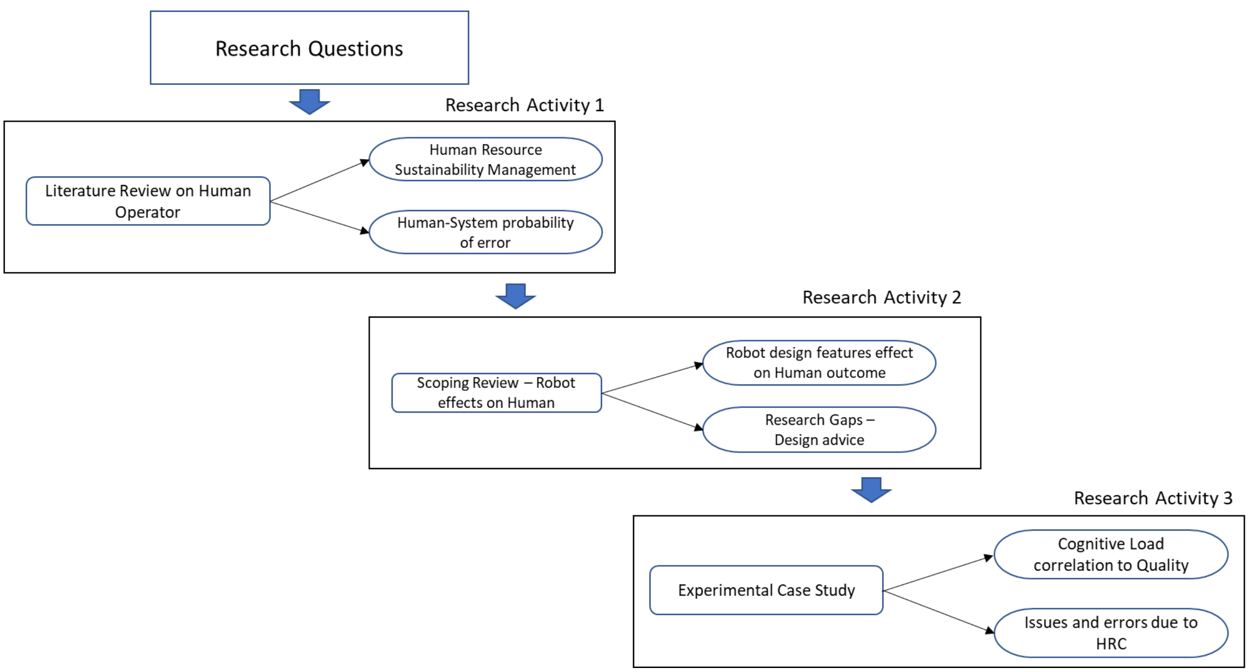


Figure 2. Research activities performed during this work and their results.

To investigate the human-robot interaction from a systems perspective, first there is a need to understand the changes in the workplace environment and how operators are affected. This can help in investigating the HRI as a system and also to design and perform the experimental study in order to focus on the factors influencing operators.

Research Activity 1. The goals of the initial activity were to understand the changes in the workplace and effects on operators, by investigating the new workplace environment. During this activity, a literature review was performed on workplace changes and workforce management which resulted in the proposal of a (i) human sustainability management model, and (ii) human-system probability of error decision-support tool. The research questions developed during this activity were the following:

- What are the changes in the workplace due to smart manufacturing and robot integration?
- How can a human-centric model be designed?
- How do the humans react to robots in their workstation? During this activity, an addition was made to the research question, due to the research literature analysis: What are the changes to capabilities of ageing human workers?
- What are the variables for human sustainability?

Research Activity 2. The results of the first activity were used to develop the focus of the second activity. The goals of this activity were to study the HRC as a system and, investigate the effects of robots on humans and study a collaborative assembly scenario, with the purpose of identifying possible design guidelines and solutions for a human-centric workplace. During this activity a scoping review on scientific literature with empirical studies on HRI was performed focusing on robot design features effects on humans. The research questions developed during this activity were the following:

- Which robot design features can be used to control and improve the human-robot interactions?
- How are HF capabilities affected by robot design features?
- What is the outcome on human operator?

Research Activity 3. An experimental study was developed with the assistance of the industrial partner and the results of the first and second activities. The experiment was designed to study the effects of HRC and correlation of cognitive load with quality of product, process and human work and the causes of errors with the aim to propose and design solutions. The main hypothesis of the experimental study is as follows; The cognitive load resulting from the changes and physical collaboration affects the quality of assembled product, assembly process and human work. The research questions formed for this experimental study were the following:

- What are the issues that operators face in HRC?
- What is the root cause of those issues?
- What are possible solutions for those issues?

2.2 Research Roadmap

Figure 3. Research output from each research activity. This figure serves as an outlook of the research performed and presented in this work.

In this section a brief presentation of the research performed and presented in this work (chapters 4 through 6) is given. The research methodology that was followed can be seen in figure 2 and a brief outline of the result of each research activity in figure 3. A literature analysis was performed at the start of the activities to gain knowledge on I4.0 framework, pillars and technologies involved (Research activity 1). From this analysis, a simulation model was designed to emulate the changes in the workplace and the change in model, from a “physical” model to “cyber” model. Following the simulations, a literature review was performed to understand the human management in this new environment and changes when workers age, due to the ageing workforce trend. This work resulted in the proposal of two approaches; one aimed at sustainability management for operators and the other focused on probability of human-system error. Both of the methodologies were based on the concept of entropy derived from non-extensive statistical mechanics. While the sustainability concept is not a new concept, the novelty of the proposal was the addition of the behavioural category, complimenting the existing mental, physical and psychosocial ones. The probability of human-system error can be used as a management support tool as it can provide insights on HRC and the areas that need to be improved; either through training and/or re-skilling/up-skilling for human operators, or tasks and areas of work where they need to be supported.

From the output of the first activity new research questions emerged and the proposed human-centric workplace of I5.0 framework, the second research activity aimed in understanding how robots affect humans in HRC. A scoping review was performed to investigate the literature about robot design features effects on humans and potential research gaps. In this work, the HRI and HRC was investigated as a system and not as individual parts, following the SocioTechnical Systems Theory (STS). From the results, possible design guidelines aiming at improving collaboration and human support were identified. With the knowledge from the first activity and the scoping review, the next step was to investigate HRC and the issues that human operators face in collaborative assembly. An experimental case study was designed with an actual assembly line as guidance, with the help of the industrial partner, aiming at investigating the correlation between cognitive load and quality. Non-invasive methodologies were selected, to emulate a real assembly workstation, and qualitative and quantitative tools were used for data collection. The experimental case study results provided insights on the aspects affecting and increasing cognitive load, and also the human-system error causes affecting decision making and work processes. Furthermore, it allowed to investigate potential solutions, and a smaller in size validation case study was designed and executed in how controlling assembly by humans through communication can improve performance and quality, and also perceived reliability and safety in the workplace.

3. Background

In this chapter the terms used in this work are introduced. As this work investigates HRC the frameworks of Industry 4.0 and 5.0 are introduced. Their implementation brought changes into the workplace, introducing smart technologies and allowed for physical collaboration between human and robot. In this work Human Factors and Ergonomics (HF) were utilised during the research activities as to investigate HRC. As such a brief description of HF and their domains (cognitive, physical, organisational) is presented. Lastly, as the focus of this work and of the experimental study is HRC, an introduction to HRI, HRC and cobots is also presented.

3.1 General Introduction

With the introduction of I4.0, smart technologies and robots, that are less bulkier than previous machines and lighter in weight, were implemented in the workplace and shopfloor of assembly lines. Those implementations enables human robot interaction to be the normal working scenario for young and old workers. This partnership, free of the physical barriers of pre-I4.0 era between humans and machines/robots, enables close physical interaction, which apart from the safety concerns it also raises issues on what other effects it brings to the human side of the interaction. Furthermore, I4.0 pushes for increased automation and link of all productive units through an information-based network. This creates a highly complex and dynamic environment, where humans should be able to receive information relevant to their task and position, while also interact with their robot/cobot co-workers. From a design perspective, several considerations need to be taken into account, such as quality, technical, economic and ergonomic factors (Gualtieri et al., 2021). However, HF are not given serious consideration into research and design as shown in literature (Neumann and Dul, 2010, Grosse et al., 2017, and Neumann et al. 2021), which with the advancement of technology and robot capabilities, it creates an uneven workplace for human operators. STS theory can be used to even the interaction and improve human quality of work issues, as it aims is joint optimization of social and technical side in a system. Moving towards a more human-centric solution can improve safety and reliability of the human robot collaboration and quality, which is the agenda brought forward also by I5.0. As such a description of those terms is given below.

3.2 Industry 4.0 and 5.0

3.2.1 Industry 4.0

Industry 4.0 aims in digitalization, interconnectivity and smart automation in industries, systems and processes and is a by-product of diminishing production in the early 2000s and the increased technological use by humans, changing the culture and the rapid sharing of knowledge and information through the world wide web (Lee, M. et al., 2018). The term is widely used in the literature (Colombo et al., 2014) and promotes the use and combination of advanced technologies such as artificial intelligence, advanced robotic capabilities, IoT and CPS amongst others, to promote automation and interconnectivity in the workplace. Interconnection between the agents and entities of an organization, transparency of practices and processes, use of information to assist and support in decision making, and decentralization through use of CPS to enable autonomous decision-making are four of the principles used as part of I4.0 to increase operational efficiency (Hermann et al., 2016).

The I4.0 promotes the use of certain principles to achieve efficiency (Hermann et al., 2016). *Interoperability*, which refers to the interconnection between operators, humans and robots, CPS and smart devices through use of IoT. *Decentralization* of an organization, enabling work-cells and smaller systems to decide autonomously on matters of day-to-day matters, while delegating conflicting matters and exceptions to the higher levels of the organization. *Real-time capability* of the organization, referring to data and information collection and analysis to be communicated to all agents of the organization for insights and probable needed action to be taken through use of IoT and other technological tools. *Modularity*, referring to the ability to adapt to circumstances and information and change the modules requirements. *Virtualization*, referring to the use of sensors, collected real-time data and simulation models to create a virtual copy of the physical workplace to run simulations and collect data for potential issues, e.g. used for predictive maintenance to avoid extended downtime of production. Last one is *service orientation*, through use of IoT and Internet of people to connect with the market and allow the organization and its productive assets to offer their services in direct communication with other industries or customers.

Smart manufacturing, or smart automation, relies on advanced technologies and system designs forming the pillars for successful implementation in the workplace/organization. Internet of Things (IoT) enables the digitization and interconnectivity of productive units, systems, sensors and higher levels of organization. It allows communication and information/data transfer to all levels and agents, and with the market, enabling real time capabilities of an organization. Big data analytics, is used to collect and make sense of the data and information gathered. It uses pattern recognition and forecasting methodologies for feedback on related processes and systems, which can increase effectiveness and competitiveness of the organization. Cloud computing and storage to support decision making and information gathering and sharing. It is used in data analytics, supply chain and logistics operational management, allowing employers and employees to access information and perform the required actions such as data analytics and information update. It also allows use from customers to obtain information in real time on product and/or their order status update. Augmented and virtual reality (AR/VR) tools can support processes and tasks by providing information on maintenance or through providing assistance during tasks. Schedule on maintenance and processes, virtual assistance to perform a task or assist in training, or support in performing tasks in non-safe areas through the use of virtual interface to connect with robotics or sensors, increasing safety.

Along with AR/VR, IoT and cloud computing providing real-world data, simulation methodologies can be used to create digital twins; those represents a virtual copy of the physical world where running multiple simulations can provide_safe conclusion and information by recreating procedures, investigate improved or new processes or tasks, and testing for maintenance purposes. Additive manufacturing or 3D printing allows for the creation of products from a digital 3D model under computer control, by depositing the chosen material layer by layer. Although the procedure was first introduced in literature in the 1940s and refined through research, with the introduction of I4.0 the procedure matured and can contribute to sustainable development by reducing waste in production. Moreover, it simplified product design process, reduce warehousing costs, and supported the mass customization business strategy. Through technology advancement, advanced robots were researched and developed, smaller in size and more flexible, while with the programming capabilities of today, they can be programmed to perform advanced procedures and processes. Furthermore, with those capabilities, close physical interactions with humans are available, providing more flexibility and support to their human co-workers. The link between top to bottom and vice versa of the organization layers is achieved through horizontal and vertical integration, providing the necessary transparency and use of the principles needed for smooth I4.0 implementation. Vertical communication in the organization providing the necessary input and information on the strategy or what is needed to achieve the goals, and horizontal communication inside each aspect of operations management. However, despite the benefits that those principles and methodologies bring to an organisation, they increase complexity in the workplace and the dynamic nature of interactions between the agents, thus, impacting operators.

Despite the promises for effectiveness and increased production, implementation of I4.0 was not smooth as it requires a lot of financial investment, business adaptation and acceptance for increased automation and digitization. Introduction of robots in the workplace, resulted in confusion and in many cases replacement of human operators by robots/cobots, increasing social isolation and feelings of distrusts towards them (Birkel and Hartmann, 2019). Moreover, lack of regulations for human robot interactions in terms of safety and human involvement, as well as lack of training and instructions for humans, can result in distrust towards robots and technology, increased safety concerns and lack of stability for human workers (Longo et al., 2020). Adding the lack of consideration for human factors and the human resource in this highly complex and dynamic collaborative environment, and the need for clear directions and workplace design guidelines led to the introduction of the Industry 5.0 concept by the European Union, Research and Innovation Commission in 2020 and 2021. This new concept aims at a human-centric workplace, where the I4.0 smart technologies and principles support the human operators.

3.2.2 Industry 5.0

Industry 5.0 (I5.0) paradigm was introduced by Research and Innovation Committee of the European Union in 2020 and finalized the paradigm in 2021. It is not regarded as a replacement for I4.0, but it is considered "… an evolution and logical continuation of the existing Industry 4.0 paradigm.", as stated in the Enabling Technologies for Industry 5.0 report of the same committed in 2020. I5.0 aims in merging human and technological skills and capabilities to benefit both the industries and SME's but also human workers. Moreover, its aim is not in replacing human workers with technologies, but using those technologies to empower and complement human workers; enhance existing skill and assist in learning new skills, support their flexibility and creativity for problem-solving and decision-making and improving working environments. I5.0 enhances the human-centric goal through its turn to sustainable development and circular economy, by including the social and environmental aspects of sustainability.

I5.0 uses several smart technologies to support its goals. Human centric mentality in business solutions for SME's and human robot/machine interactions. It maintains interconnectivity as a key concept, while combining the strengths and capabilities of both humans and machines, and maintains the need for real time capabilities in its designed systems. Recyclable and/or remanufactured smart materials for sensors in order to improve their features and capabilities. Artificial Intelligence is a key concept in the drive of I5.0 for human centric purposes. With the use of AI, robots and machines can be programmed to detect abnormalities in their environment and support humans navigate and perform in their highly complex and dynamic collaborative workplaces and assignments. Interoperability in the system is enhanced with cybersecurity to protect transmission through IoT and cloud systems, to enable data gathering and analysis. Renewable technologies to improve energy efficiency and reduce ecological footprint required from smart technologies, strengthening connection with human resources and society.

For human robot collaboration I5.0 aims in combining the capabilities of robots with the flexibility and creativity of humans. Artificial intelligence can provide solutions and methods to improve human robot teamwork. Gesture and speech recognition for efficient communication or input through natural language processing. Moreover, it can provide support and solutions in decision making and work tasks through its processing speed capabilities. Research can focus on programming sensors to sense human fatigue, both physical and mental, as a way to improve injury avoidance and human-system errors. AR/VR tools can be utilized in training and during tasks by providing information to the user, while also improving inclusiveness. Digital Twins can also aid in improving working environments and safety, through extensive testing and simulation of production and processes.

3.3 Human Factors and Ergonomics

Human Factors and Ergonomics (HF) is a discipline that concentrates on humans at work. As per the International Ergonomics Association (IEA), HF is "… concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimize human well-being and overall system performance". HF draws from multiple scientific disciplines, such as psychology, sociology, and engineering among others, different methodologies and tools to assess human capabilities and weaknesses to ensure the suitability and usability of the tasks and the workplace environment for the human.

HF has three main domains of research: physical, cognitive and organizational. Physical ergonomics is concerned with the physical wellbeing of the human, and relies on anthropometric, physiological and bio mechanical characteristics. Cognitive ergonomics is concerned with the mental aspects and processes of humans at work. Cognitive load and mental fatigue are important for humans at work, as they are important for cognitive processes and decision making, and affect work stress and performance. Organizational ergonomics are concerned with the socio-technical system and their organization and optimization. It aims in improving the processes, structure and policies to improve both social and technical sides of the system it is applied to.

Below that, information on the domains of HF and its applications on HRI are provided, along with detailed information on specific topics. Moreover, a brief description on fatigue and stress is given after the domains. Fatigue and stress are factors that were investigated in this work and are related to HF due to the risks and safety concerns when operators are fatigued or stressed; especially in the investigated HRC scenario.

3.3.1 Physical HF

Physical HF concerns itself with the safety and physical wellbeing of the human body (IEA). It considers the anthropometric, biomechanical and physiological human characteristics to provide guidelines for workplace and task designs, while taking into account the movements needed, the amount of repetitions and the required body posture. The DIN 33402-2, 2020 standard provides average body characteristics that can be used as physical HF considerations for workplace, system, processes and task design to prevent or treat work-related disorders. In general the advantages of using physical HF are: improved physical safety, reduced injuries related to non ideal physical activity, improved productivity and performance leading to improved product and work life quality and competitiveness in market.

With the introduction of robots in the workplace, physical HF are important to protect humans and prevent safety concerns in physical collaboration. In this complex workplace, general HF measurements can be considered for a supportive and human-centric environment, such as body posture, physical workplace layout, collaboration procedures, repetition and health and safety amongst others (Rücker et al., 2019). However, it is important to take into account the robot design features and capabilities when implementing HF in HRI. Although smaller in size, robots can pose a physical threat to humans with their dynamic capabilities such as their speed, acceleration and force of contact they can impose. Moreover, there are several other factors that should be considered in the interaction, such as functions, reliability, behaviour and appearance amongst others, as they can affect human workers during work.

To evaluate if a workplace, or system, design is supporting the physical wellbeing of the operators, methods, such as anthropometric measurements and simulating body posture and movements, are used to assess the workplace convenience, comfortability and usability for the user which also allows for better productivity. Anthropometric measurements are essential in workstations design and assigning tasks, as to not place workers in workstations that are not fitting avoiding accidents and chronic injuries. Body posture and movements needed to perform a task or a process is important to be part of the design; adhering to conventional designs and not taking into account the anthropometric characteristics of workers, leads to lack of flexibility and body issues (e.g. musculoskeletal issues).

3.3.2 Mental and Cognitive HF

Mental and cognitive ergonomics is a scientific discipline concerned with *"... mental processes, such as perception, memory reasoning and motor response, as they affect interactions among humans and other elements of a system"*, as defined by the International Ergonomics Association. It studies how mental processes are done during tasks, jobs, environments and systems to assess the quality of work depending on the individual and the goals and constraints imposed. It aims to understand the effects of mental workload in decision making, performance, human interaction with other elements in the system (e.g. robots, machines), stress and human reliability, as related to human-system design. By studying those effects, the goal of mental ergonomics is to improve performance in several areas, such as human-centered interaction design, training programs and accessible systems by everyone.

Mental ergonomics are important due to the effects of mental workload to the mental health of humans. Stress, physical and mental, due to excess workload impacts the cognitive processes and cognitive load. Cognitive load indicates the amount of working memory used, or manipulations needed during a task. It is divided into three types:

i. Intrinsic load, which is a function of task complexity and depends on the difficulty of the task or process and affects mental fatigue,

ii. Extraneous load, which is depended on the amount of information that the operator need to process or is present during a task; the more irrelevant information present, the more the load. Information on task processes, safety guidelines and during interactions that the operator need to process can affect his performance and lead to redundancy and overload,
iii. Germane load, which is generated by the creation of mental schemas in the mind of an operator, creating knowledge on interactions, processes, tasks and system design.

Evaluation of cognitive load is complex as it is depended on the individual and their personal bias, thus making it harder to create a unified approach. Questionnaires have been developed to observe effects and trends. The NASA Task Load Index (Hart, 2006), NASA-TLX, questionnaire is commonly used to measure cognitive load during a task by assessing the mental, physical and temporal demand needed and frustration, effort and performance (Fridman et al., 2018, Paas et al., 2003). Cognitive load can also be measured by using key performance indicators (KPI), such as overall task performance, error-rate and response time, however they are dependent on the task. Physiological trends and effects can also be used. Some of the physiological indicators are:

i. Heart rate, can indicate physical and mental workload, neurochemical effects,
ii. Brain activity, through electroencephalogram (EEG) measurements showing theta waves activity increase during mental tasks (Gevins et al., 1998),
iii. Eye movement and blinking, e.g. in case of increased load blinking rate decreases (Reilly et al., 2018),
iv. Skin conductance, galvanic skin conductance increases as cognitive load increase (Shu et al., 2007).

3.3.3 Organizational HF

Organizational ergonomics, or macro-ergonomics, as per the definition of International Ergonomics Association, "… concerns the optimization of socio-technological systems, including organizational structures rules and processes". The focus is in the subjective aspects of institutions and workplaces, such as communication, crew and quality management, teamwork and new work paradigms. It aims in optimized and harmonized systems, as to ensure satisfactory work quality for operators, utilizing study of consequences of technological advancements on processes, systems, institutions and human interactions. It aims at (i) participatory ergonomics, where workers are included in identifying issues and provide feedback for solutions, (ii) improve managerial processes and value streams, and (iii) promoting safety guidelines and solutions in organizational culture.

Organization ergonomics aims towards balance and joint optimization; if an aspect of a system changes then it impacts the other aspects and thus needs to be changed. If there is no joint optimization and the agents and elements of the system are not designed to work fluently together, then the safety, productivity, performance and quality will suffer. Moreover, through joint optimization organizations can balance finances as it saves costs and avoids losses that can incur if they do not balance the system from the beginning. Factors that alter the balance can be individual based or organization-wide: (i) Environmental issues, (ii) workplace issues from outside factors, (iii) need of operator retraining to improve or acquire skill to improve their efficiency, and (iv) disharmony between management and workforce. Organizational ergonomics are useful in the introduction and integration of new technologies and systems into the workplace, such as collaborative robotics and the I4.0 and I5.0 frameworks. For smooth and successful implementation, it takes into account the following factors of a workplace or organization: (i) functions, (ii) capabilities, operators and organization, (iii) user-friendliness of the implemented technology, (iv) integrated workplaces, and (v) capacity for improvement. The most commonly used tool for organizational ergonomics is the Work Design Questionnaire by Morgeson and Humphrey (2006). It assesses the design of tasks, knowledge, social factors and work factors, in order to evaluate job satisfaction as a means to improve work design.

In this work, the STS theory was used in the second research activity to investigate the HRI as a system. The STS refers to the interrelatedness of social and technical aspects of a system and joint optimisation of those aspects, aiming at successful system performance and smooth working interaction between them (Cooper and Foster, 1971). STS aims at sustainable system development and innovations and proper investigation on the changes brought by new technology before implementation (Bednar and Welch, 2020). Moreover, it aims in joint optimisation in process improvement, task analysis and job design to ensure successful system performance. One methodology used for creating better work systems and equitable workplaces is ETHICs, developed by Mumford (1987), which includes consultative participation. This enables employees to get involved in design process and in resolving conflicts, which while not a straightforward approach for changes, it promotes ethical and supportive system design (Bednar and Welch, 2016)

3.3.4 Fatigue and Stress

Generally, fatigue describes the decline in physical and mental capabilities due to prolonged activities, loss of sleep and/or other disruptions. It is synonymous to exhaustion or tiredness and can be a symptom of muscle fatigue, due to working tasks and physical load, or from prolonged cognitive activity resulting in cognitive load and mental fatigue. In industrial settings, there are multiple causes that accumulate fatigue in a human worker; intensity and duration of activities (mental and physical), mental causes (responsibilities, conflicts, stress), disease and pain from injuries, environmental causes (noise and light levels, temperature), circadian rhythm and nutrition (Grandjean, 1979). Physical fatigue, or muscle fatigue, due to working conditions, or tasks that requires the worker to deal with heavy physical activity and load, can lead to musculoskeletal injuries or chronic neuromuscular disease. This leads to chronic pains and inability of workers to perform and lowers both their quality of work and of life. Mental fatigue is a result of extended periods of cognitive activity or overload from new information and unexpected activities. It is mostly subjective and depends on the cognitive abilities of the individual human worker.

Fatigue leads to psychophysiological responses from the human. Heart-rate variations and disruption of eye-hand coordination, some of the physical responses to the body, affects performance and response to events, either normal or unexpected to the flow of work. Fatigue affects the psychological side of the human as well. It leads to stress which in turn has several effects. High fatigue and stress, leads humans to lower attention levels and to narrow their concentration towards immediate tasks or actions needed to be taken while ignoring their surroundings. This leads them to respond quickly with lower precision, just to be able to reach their goal, lowering performance and quality. Furthermore, increased fatigue and cognitive load leads to working memory overload, and humans relying on their long-term memory to continue their work; in the event of an unexpected issue or of an event needed immediate action, humans will be slow to react and act increasing safety risks and potential injuries.

The effects of fatigue, mental and physical, can be objective or subjective depending on the individuals' capabilities: stress, weariness and distaste for work, slow and sluggish thinking, reduced perception capabilities, decline in physical and mental capabilities and reduced state of alertness. In the collaborative workplace of I4.0 and I5.0 paradigms and with the new robot and machine capabilities, heavy physical tasks are assigned to robots, alleviating humans from this tasks in an effort to reduce injuries and accidents. Although, physical activity, and in consequence fatigue, is not entirely eliminated, this thesis concentrates mostly in mental fatigue as it affects the cognitive capabilities of humans and in turn decision making capabilities and reactions, which can lead to accidents in the workplace and human-system errors.

3.4 Human Robot Interaction

Human Robot Interaction, as stated by Goodrich and Schultz (2007), is a scientific field dedicated to design, understand and evaluate robotic systems and technologies for use by or with humans. Interaction can be divided into two general categories, depending on physical proximity:

1. Remote interaction, human and robot are separated and not in the same location either spatially or temporally; e.g. Unmanned Aerial Vehicles, space missions, search and rescue robots,
2. Near-proximity interaction, human and robot are working on the same location or on the same task; e.g. social robots, industrial robots, cobots.

In the case of near-proximity, HRI can be further classified depending on task allocation, need of contact during the task, team structure and process reliability (De Luca and Flacco, 2012, Bauer et al., 2016):

a. Coexistence; human and robot share the workplace but without task assistance or need to perform the same task,
b. Cooperation; human and robot work on the same task or process, although with no direct interaction or contact between them,
c. Collaboration; human and cobot work together on the same task in a shared space with direct and/or physical interaction (Flacco et al., 2015, Fast-Berglund and Romero, 2019),
d. Synchronization; humans and robots/cobots operate on the same task sequentially (Orlandini et al., 2020).

3.4.1 Human Robot Collaboration & Cobots

With the I4.0 framework, system design and advanced robotics allow for a closer physical and safer collaboration between human and robots. In HRC, human and robot communicate in order to perform their shared plans, norms and tasks. For efficient collaboration, robots need to understand human intention and communication in a similar level as in the human-human interaction and thus, they need to perceive and understand their environment and have the ability of autonomous decision-making and cognition. As AI and machine learning are advancing, robots are able to fulfil those conditions at a large extent.

Due to the complex nature of HRC and the dynamic interactions during the tasks the uncertainty of the collaboration increases, which can lead to human-system error due to the physical and mental challenges that humans need to overcome. For that reason, one potential solution could be for human and robot to communicate their intention. Communication between human and robot can be achieved through several means: (i) Gesture, (ii) Speech, (iii) Haptic signals, (iv) Action, and (v) Physiological signals (Bauer et al., 2008). In that regard, methodologies are developed to assist in that direction through the use of simple forms of communication, e.g. use of predetermined gestures from the operator (Panagou et al., 2022).

For HRC, collaborative robots were developed with lower speed and force than robots to fulfill the safety requirements set by DIN ISO/TS 15066 (2016). Cobots are flexible in their potential use and can be easily reconfigured (Makris, 2021). Cobots' programming adds sensitivity to forces and unexpected contact, which allows them to stop immediately for collision avoidance or use of excessive force on humans. Although cobots are mostly stationary, research and industry are looking for ways to provide them with more mobility and flexibility in their actions, such as by mounting them on mobile platforms. Apart from their industrial use, cobots are being used in social events or in healthcare, equipped with human-like features or a screen with a face to increase user experience, likeability and the acceptability of humans towards cobots and robotics in general.

With the research rationale (chapter 2) explained and research activities planned, and the I4.0 and I5.0 frameworks and terms explained, the next chapter starts with the investigation on the changes brought in the workplaces by I4.0 and smart technologies. This is the initial step on understanding this new complex and dynamic workplace environments before investigating the HRI and HRC, due to limited representation of operators in research (as stated in previous chapters). This lack of consideration is against the STS theory of joint optimisation resulting and can result in issues. Thus, the rest of this work contains the research activities performed aiming in understanding the issues operators face and following a system approach try to identify potential design guidelines and solutions for successful HRC.

4. Research Activity I: Workplace changes and operators

In this chapter, the first research activity performed during the thesis is presented (figure 4). The goal was to understand the changes in the workplace brought by I4.0 and its enabling technologies and how it affects the operators. A literature review was performed on how changes in the workplace affect operators and their capabilities; especially in the case of older operators. The findings of the literature review were used to understand how to support operators, through the lens of sustainability. Moreover, it aided in developing a model for human-system error probability that can provide decision-making support for management based on the concept of entropy.

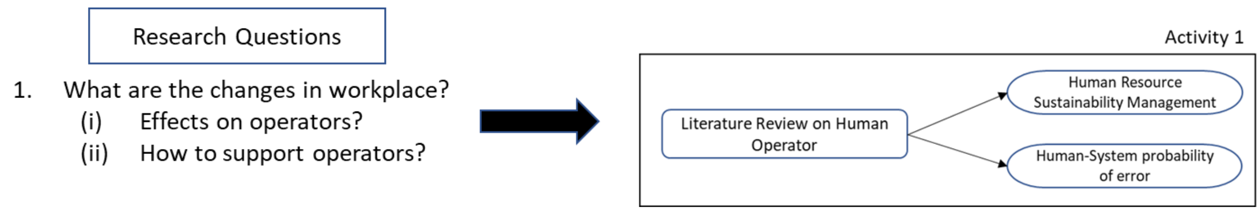


Figure 4. Research questions formed for the 1st research activity and research output..

4.1 Introduction

I4.0 and its enabling technologies heavily focuses on workplace digitisation, HRC and an information based network linking all productive units. While the automation of systems and processes can benefit operation and production it creates a complex environment with dynamic interactions. Consequently, this creates new working conditions and requirements which the human workforce need to adapt. The World Bank published their report *The Changing Nature of Work* in 2019 stating the following changes and arrangements:

- Organisational structure,
- New market and work positions,
- Data protection issues,
- Transformation of sectors and activities affecting employment,
- Flexible work conditions, and
- <u>Change in the working relationship between human and robots</u>.

However, integration of robots and smart technologies in the workplace, apart from the benefits, increase the complexity and dynamic nature of interactions. As such, for those changes to be beneficial, an almost flawless human-robot interaction (HRI) is necessary.

Operators need to adapt and be able to develop in the new environment, through learning, new skills and trust in their robotic co-workers. Although training can be useful for operators to get acquainted with their robot co-workers, it is necessary to consider that each individual operator react differently based on their characteristics. An additional factor affecting operators' perception is age, which raises an issue due to the growing concern for the ageing workforce due to the overall trend of population ageing, globally recognized by governments, economists and institutions alike (EU-OSHA, 2019) and is predicted that by 2060 the workforce population average age will rise significantly if the situation remains as it is (EU-OSHA, 2017, The Economist, 2017).

There are two effects of ageing on operators. The experience gained and the accumulated skills of older operators is considered a valuable asset, in terms of performing tasks, transferring knowledge to their younger counterparts and acting as safeguards in the smooth operation of their workplace (Guvernator et al., 2020, Massingham and Massingham, 2014). However, part of the operators' abilities and skillset deteriorate in terms of physical abilities (e.g. dexterity, muscle strength), mental skills (e.g. fatigue) and cognitive abilities (Van Loo et al., 2001). The change in operator's capabilities and the smart workplace environment is an issue requiring further research, due to the concern for sustainability of human workforce implications coupled with the ageing trend and the new technological advancements being integrated in production lines.

Thus, a literature review was performed to investigate the capability deterioration of ageing operators and workforce management. The research questions guiding this review were the following:

- How industrial engineering research view operators due to their skills in the new workplace, and
- What are the changes of operator capabilities as they age.

4.1.1 Literature search strategy

The methodology to perform the literature review consisted of identifying the most relevant keywords to perform the search query and produce relevant results. Different combinations of those keywords were used in online databases, such as the Scopus and Web of Science databases, while the results were filtered based on their relevance on the research questions. The starting date for the search was set on 2005 until 2021.

The keywords that were identified as most relevant for the literature search were: “ageing/older”, “Human factor/workforce/Operator” and “Industry/Manufacturing/Assembly”. Several combinations of these keywords were used coupled with Boolean operators (e.g. Ageing AND Human Factor AND Industry, Older AND Human Operators AND Manufacturing) on the online databases resulting in a starting total number of 239 papers. Apart from relevance to the research questions, further inclusion criteria were set: articles should be written in English and should be peer-reviewed journal articles. The first screening step consisted of title, abstract and keywords reading, which resulted in 75 articles. Finally, full-text reading followed which resulted in a final number of 46 identified articles (figure 5).

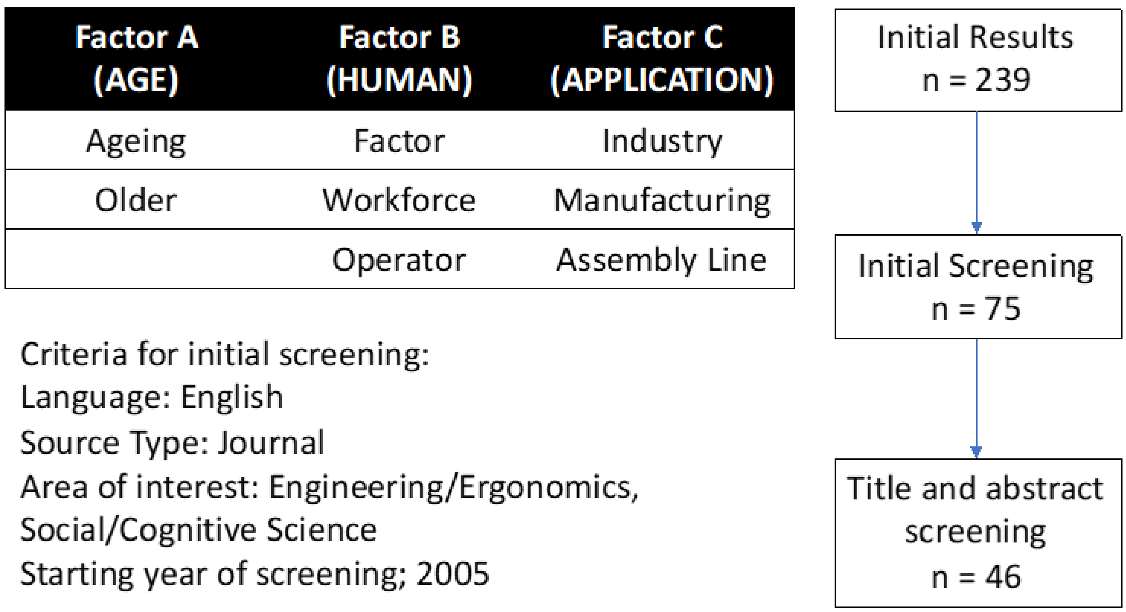


Figure 5. Search keywords and inclusion criteria used for the literature review. On the right, screening procedure and final number of identified articles.

4.1.2 Literature review results

The selected papers were fully read again and examined for information relevant to the research questions. The results focusing on workforce management were then divided into three main categories (table 1): (i) the operators’ capabilities change; referring to physical, mental, psychosocial and behavioural changes, (ii) Knowledge management and how knowledge and experienced operators are valued and positively exploited inside the industry and (iii) Ageing operators management from the hierarchy of industrial management and modelling point of view.

Table 1. Identified categories based on literature analysis for managing operators. Categories defined as capability based management, knowledge based, and managing ageing operators.

Human Operator Capability Change	Knowledge Management	Ageing Operators Management
Rouch et al (2005)	Lombardi et al (2009)	Olstein et al (2005)
Kowalski-Trakofler et al (2005)	Puevo et al (2011)	Kawakami et al (2006)
Schwerha et all (2007)	Arezes et al (2013)	Weichel et al (2010)
Landau et al (2008)	Massingham et al (2014)	Becker et al (2012)
Saremi et al (2008)	Massingham (2018)	Kumashiro et al (2014)
Sorensen et al (2008)	Volberg et al (2017)	Boenzi et al (2015)
Verma et al (2008)	Srilakshmi et al (2018)	Jeon et al (2016)
Wilker et al (2009)	Massingham et al (2018)	Botti et al (2017)
Kawakami et al (2009)	Strasser (2018)	Sokas et al (2019)
Blok et al (2011)	Battini et al (2018)	Calzavara et al (2020)
Landau et al (2011)	Abubakar et al (2019)	
Stamov-Rossagnel et al (2012)	Guvernator et al (2020)	
Fritzsche et al (2014)		
Neupane et al (2014)		
Qin et al (2014)		
Xu et al (2014)		
Thetkathuek et al (2015)		
Van de Ven et al (2016)		
Binoosh et al (2017)		
Chen et al (2017)		
Gilles et al (2017)		
Nardolillo et all (2017)		
Neumann et al (2018)		
Di Pasquale et al (2020)		

4.1.2.1 Operators capability change through age

The level of productivity of operators inside an industrial or manufacturing workplace is closely related to their capabilities, be it physical, mental and psychosocial, and is also affected by their behaviour. As the operators age, functional characteristics start to diminish as shown in several articles (Di Pasquale et al., 2020, Strasser, 2018). However, the experience and knowledge gained can minimize the effects created (Binoosh et al., 2017, Xu et al., 2014). In the transition to the new industrial era, operators need to evolve into smart operators (Operator 4.0 concept, Romero et al., 2020), which raises the question if older operators will have the ability to adapt to what is demanded of them (Becker et al., 2012). However, those aspects need to be examined when considering implementation of technologies, robots or other changes in the workplace (Neumann et al., 2021).

Qin et al., (2014), demonstrated by using electromyography sensors (EMG), that older operators tend to develop muscle fatigue faster, when assigned to heavy tasks that are needed to be repeated several times throughout the working day. The psychological profile of older operators in contrast to younger ones when there is a limit set on their maximum weightlifting was studied by Chen et al**.**, (2017), and Kowalski et al., (2005). Neuman et al., (2018), studied musculoskeletal disorders and injuries of manufacturing operators due to physical demanding working tasks; which has lasting effects on operators as they age. Landau et al. (2008, 2011), researched the long-term effect of musculoskeletal disorders of operators, and showed that older operators continue to suffer from previous trauma in their neck, spine, shoulder and upper limbs. Verma et al., (2008), observed that while older operators have low frequency in getting injured, however the severity of those injuries increases with age.

Workplace changes and environmental conditions inside the workplace have been showcased to have an impact on human workforce. The effect on fatigue level operators due to ongoing noise exposures was researched by Saremi et al., (2008) and Arezes et al., (2013). Back pains can be developed due to ongoing exposure in cold workplace environment as can be seen in the report of Thetkathuek et al., (2015); which can be sever in older operators. Nardolillo et al., **(**2017) studied the effects that different workplace environmental conditions have in operators of varied age, concluding that age-classification (varying from young to old) should be of serious consideration in task and workspace scheduling.

Furthermore, older operator tend to need more training time or more practice trials to learn a new task or a new skill, when it is required for their work than their younger counterparts (Schwerha et al., 2007, Wiker et al., 2009). Fritzsche et al., (2014), and Gilles et al., (2017) reported lower movement performance and slow decision process in older operators. Shift work and its effects have been studied as well (Blok et al., 2011). Rouch et al., (2005), studied the possible difficulties workers may face with shift work as they age; although their work reported no clear indication of any connection between age and shift work. Van de Ven et al., (2016), reported sleep issues, such as short sleep duration, disturbed sleep and possibility of negative mood depending on the quality of sleep of older operators engaged in shift work assignments. Sorensen et al., (2008), studied the relationship between work ability and quality with the age group of workers in shift assignments.

Neupane et al., (2014), in his work reported how different age groups and work satisfaction is related to work environments and work characteristics.

4.1.2.2 Managing knowledge

Older workers and the experience they possess is considered an invaluable asset despite other diminishing abilities (e.g. physical and cognitive). Srilakshmi et al., (2018), reported that experience and knowledge gained from years of practicing at the same working environment and in the same work-tasks, can compensate for the diminishing energy levels and physical capabilities of older workers. Adding to the same point Abubakar et al., (2019) reported that experience and knowledge is considered in many aspects a more valuable aspect in the operators' skillset than younger age, higher cognitive functions or individual performances. Volberg et al., (2017), showcased a decrease in certain type of injuries related to experienced operators due to the knowledge of their workplace and assignment-related tasks. Moreover, older operators are more conscious of using their work-related protective gear and adherence to safety regulations (Arezes et al., 2013, Battini et al., 2018, Lombardi et al., 2009). Strasser (2018), showcased that experienced workers plan their working tasks ahead of time and in a quick manner, they are highly autonomous inside their workplace and can identify when situations may become critical. Massingham (2014, 2018) demonstrated that knowledge management is an effective tool in knowledge transfer between older workers and their younger counterparts.

4.1.2.3 Ageing operators

Industrial engineering and decision-making can benefit by managing and supporting the workforce, by considering individuals' operators capabilities (physical, mental, psychosocial, behaviour) and the relevance of experience and strategic knowledge. Scheduling alteration of job rotation by age groups and by high- or low- physically demanding the work task is, was exhibited in several research articles (Boenzi et al., 2015, Botti et al., 2017, Jeon et al., 2016, Weichel et al., 2010). Olstein, (2005), suggested that management should consider retirement policies and the use of new ICT technologies. Kawakami et al., (2006), and Kawakami and Yamanaka (2009), demonstrated that use of automation can be beneficial to older workers in their tasks and the manufacturing/assembly lines. Kumashiro (2014), studied how enabling and designing ergonomic support systems can benefit long-term system designs and the human workforce. Sokas et al., (2019), proposed career training for management position and mentoring younger workers for older workers. Calzavara et al., **(**2020), proposed new ergonomics ideas and management research paths for human factor in the wake of I4.0 era.

Experience and task specific knowledge can be considered a more valuable asset than younger age and capabilities. However, with the implementation of smart technologies and physical collaboration with robots, the operators' reaction and effects on them from the changes needs to be investigated.

The results of the literature review revealed the need to understand how to support operators in the new workplace environment. As I5.0 promotes sustainability and human-centric workplaces, workforce sustainability concept provided the context to integrate the review results. As such using the results of the review, workforce and sustainability was investigated from another perspective, merging HF and the knowledge gained.

4.2 Workforce and sustainability

Due to the introduction of I4.0 enabling technologies and robots in the workplace, operators need to adapt to complex tasks and dynamic interactions. Although those changes can benefit organizations and workplaces with the advantages they offer; e.g. task and process flexibility, modularity and real-time data exchange, operators need to be able to perform their tasks, receive data and information and make decision, adhering to guidelines set by management and also tend to their safety. Those actions and tasks can be taxing to operators and their capabilities which raises the issue of how to support them; especially in the context of I5.0 human-centric framework and sustainable development. This call for research was also highlighted by the research gap of lack of consideration of human factors in engineering research in the I4.0 context, consistent with previous literature (Grosse et al., 2017, Neumann et al., 2021). As such, a proposal was made (Panagou et al., 2021) in how to support and sustain the workforce. In this proposal the operators' states are categorised as follows (figure 6):

<u>I. Behavioral State</u>: behavioural state is mainly related to procedural based actions and decision making, as well as safety. Operators need to be trained in matters of safety and handling equipment as well as introducing measures to avoid critical situations. In the new collaborative environment operators need to be able to trust their robotics co-workers and the information they receive from CPS and other entities, such as logistics, performance and quality assurance. They must also feel

safe inside the workplace, as to avoid making decisions that may lead to loss of productivity and accidents. *"Skills-Rules- Knowledge"* (SRK) acts on the controllability of this situations and processes. Operators must have *"motivation"* to interact and work with new technologies in their workplace environment. Standards for human-robot interactions and human-system interfaces are required and should be differentiated according to individual operators' skills and attitude. Knowledge of the new systems and technologies inside the workplace are required for the safety sustainability of human operators.

II. Mental State: mental state is related and affected by stress and *"fatigue"*. As the level of fatigue increases, operators tend to lose focus or are unable to handle physical demanding tasks, thus increasing safety risks in their work-tasks. *"Cognition"* and cognitive based abilities of the human factor affect the fatigue and stress of operators is also dependent on the age group of operators; younger operators tend to have more cognitive load capacity than older operators and are more capable in learning new work-related skills faster.

III. Physical State: physical state is related to the physical capabilities of operators and is largely affected by the age group they belong to. *"Motor resilience"*, related to optimise or recover motor faction, of older operators is far lower than their younger counterparts and as such, they must be protected from heavily demanding physical task as to avoid injuries. *"Training Experience"* on handling new equipment, such as CPS, sensors and VR/AR tools, as well as learning to cooperate with their robotic counterparts is necessary in learning the required knowledge to avoid safety risks and potential accidents while maintaining the productivity and quality of products as well as learning to trust their new co-workers and their workplace environment; thus, reducing their physical stress. New *"ergonomic"* designs are essential for operators in their tasks, assisting them in heavy workloads while preserving their motor resilience both short-term (work-shift time period) and long-term (help in avoiding physical load will result in less amounts of chronic pains).

IV. Psychosocial State: psychosocial state is dependent both on an individual operator and the workplace environment. With the integration of advanced robotics and technologies in the production of products and services, *"perception"* has a significant role on how human operators react to those changes. As cobots and AR/VR tools replace human workers inside the workplace, loss of social interaction will affect the human workforce. The *"interaction"* factor, which is dependent on the interaction of human with machine and robots rather than other human workers, reports product and process quality outcomes through the IoT based use of CPS rather on personal interactions. Perception and interaction can affect a workers' *"emotion"*. Depending on the personality of an individual operator, it may lead to increased mental fatigue.

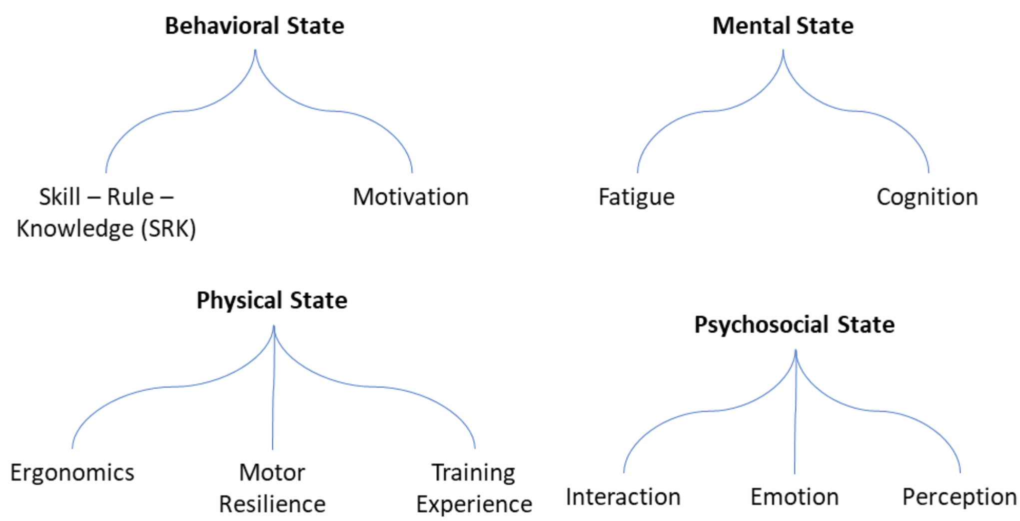


Figure 6. Proposed macro states of operators and their defining factors based on the concept of sustainability.

This categorization is focused on the sustainability concept of operators inside the new industrial and service-oriented framework designs. Moreover, it is closely aligned with the Industry 5.0 concept, which is shifting the focus of smart technologies to support operators inside industry (Breque et al., 2021). With the categorisation of the operator states, the step forward was to integrate them in a way that can be used to support and manage operators in the workplace. The entropy concept was selected, as it provides a means to measure the selected system and its uncertainty. As such, the entropy concept was studied and a method for human-system error probability based on human capabilities and age factor was proposed.

4.3 Entropy and human-system error probability

Due to the new dynamics of the workplace and physical collaboration, the complexity of work tasks increases. In this complex working system, production and services will need to maintain balance between a regular working motion and chaotic interactions. The disorder of those motions, depending on how dynamic and complex their level is, will need rules to be implemented as to maintain the required order for the operators. Those dynamic and complex interactions, raise the question of how efficiently operators will learn to collaborate with robotics and smart technologies in order to keep their productivity and safety. This raises the need to measure uncertainty at work based on operators' capabilities.

In this work, the concept of entropy was used as a framework to identify the dynamics of the human as a natural system in order to quantify the uncertainty and lack of stability of an outcome or process, due to the operators states condition. Identifying the rules and parameters of our micro-states, such as emotion, perception, level of interactions and fatigue, is necessary in understanding the connections and consequences when the status of those states change. Those connections will assist in computing the probability of error of human operators at work. By computing the probability of error, the areas where human operators struggle can be identified and the information can be transferred to management, so strategies in helping the human operators can be designed.

4.3.1 Entropy concept

Statistical mechanics are used as a mean to explore how a natural macro-world or system works by investigating and identifying the microscopic laws that govern the micro-states of the system. Probability theory is then used to link the microscopic laws of the different micro-states together and ultimately identify the macro-system laws and relations. The most fundamental concept that can connect micro- and macro- worlds is entropy. Entropy can be used as a measurement of a system's disorder or uncertainty. This ability gives the entropy concept the flexibility to be used in different fields. Ludwig Boltzmann proposed the classical form of entropy (S_b) to be given by:

$$S_B = k \ln(\Omega) \tag{1}$$

where k is the Boltzmann's constant and Ω is the number of the system's microstates. The generalized entropy equation, named Boltzmann-Gibbs, is given by the following equation:

$$S_{BG} = -k \sum_{i=1}^{\Omega} p_i \ln(p_i) \tag{2}$$

Equations (1) and (2) are used when the microstates are equiprobable. Thus, when using normalization for *i* (state) and *p* (probability) we have:

$$\sum_{i=1}^{\Omega} p_i = 1 \tag{3}$$

This form of entropy is ideal when working with systems that are strongly dependent on all the initial conditions. However, most systems behave quite independently from those conditions.

Thus, Tsallis (1988) proposed a generalized theory for entropy, that describes both extensive and non-extensive systems and can be defined by:

$$S_q = \frac{k}{q-1}\left(1 - \sum_{i=1}^{\Omega} p_i^q\right) \tag{4}$$

4.3.2 Human-system error probability

In the new workplace, operators need to interact with robots to complete their tasks, while also having to deal with an abundance amount of information and data, where some of them may be redundant. Overload of information, lack of social interaction and different workplace environment conditions are some of the issues that can lead operators to deal with decreased productivity or quality and probable critical situations, due to stressful conditions. For that reason, there is a need to understand and measure the uncertainty created by the new conditions and how it affects operators. As a starting consensus, we define the human operator as a natural system described by four categorical states, Behavioral, Mental, Physical and Psychosocial. Each state has its own variables and parameters that defines them.

The foundation of the workplace system is now defined. The interactions taking place inside the workplace are considered the microscopic dynamics, which can be seen as similar to the N-body elements microscopic dynamics. Operator and cobots starting conditions are the initial condition of the system (good condition, operational, in need of maintenance etc.). As time progress (considering long time evolution) the system will reach a stationary or a quasi-stationary state. In that time frame, the initial conditions of the operator can be considered as non-consequential for the measurement. Since the probability of error can be measured, then the overall uncertainty (range of probability) can be defined.

From the workforce management literature review, the major contributing parameters of the operators' states were derived. Perception is considered as the major parameter affecting the states as the operators first perceive the workplace environment and then react. Motivation is hindered by what is perceived and the individual's preferences, thus affecting the mental, physical and psychosocial states. Due to those effects, errors may occur. Personal development is affected, which may lead in increased time on learning new working skills or trust in the robotic co-workers. Workers belonging to different age groups react differently as well. Younger workers, for example, may react more in favour of new integrated technology than older workers. On the other hand, older workers due to their experience tend to be more controlled than the younger workers. Thus, the probability of error is a way to measure those effects and understand the areas where the human operators need to be assisted on.

Assuming same complex working conditions, information received and dynamic interaction for all working age groups, the probability of error can be defined as a complex equation, dependent by age groups. It is comprised by Behavioral (B), Mental (M), Physical (PH) and Psychosocial (PS) states as:

$$PE = f(M, PH, B, PS)^{a} \tag{5}$$

The PE notation stands for probability of error and *a* stand as an index for age group, which for the initial formulation is set as *a*=1 for young workers and *a*=-1 for older workers.

To calculate the uncertainty in the system, the non-extensive statistical form of entropy was considered along the exponential entropy given by Pal N. R and Pal S. K. (1992):

$$H = ln_q \left(\frac{1}{p_i}\right) \tag{6}$$

and,

$$H = \sum_{i=1}^{n} p_i^q e^{1-p_i^q} \tag{7}$$

Given a certain moment in time (work duration or other), the state of the operator is defined by their physical and mental condition, along with the psychosocial state and the behaviour they exhibit at that moment. The condition of the states is further defined by the age group the operators belong to:

$$Operators\ condition \rightarrow \left(\frac{PH \times M}{PS \times B}\right)^{a} \tag{8}$$

Each state and parameter have its own weight, determined by individual operators' parameters and variables (analytic description of what each symbol means in table 2):

$$PS = w_{PS} \times f(I, EM, P) \tag{9}$$

$$M = w_M \times f(F, C) \tag{10}$$

$$PH = w_{PH} \times f(Erg, MR, TE) \tag{11}$$

$$B = w_B \times f(SRK, M) \tag{12}$$

Table 2. Description of the parameters and variables used in the states' formulas. Each state has its own traits that affect its condition during work.

LEGEND

Acronyms	CATEGORY_Traits *description*
$B_{\_SRK}$	BEHAVIOURAL_Skill Rule Knowledge
$B_{\_M}$	BEHAVIOURAL_Motivation
$PH_{\_E}$	PHYSICAL_Ergonomics
$PH_{\_MR}$	PHYSICAL_Motor Resilience
$PH_{\_TE}$	PHYSICAL_Training Experience
$M_{\_F}$	MENTAL_Fatigue
$M_{\_C}$	MENTAL_Cognition
$PS_{\_I}$	PSYCHOSOCIAL_Interaction
$PS_{\_E}$	PSYCHOSOCIAL_Emotion
$PS_{\_P}$	PSYCHOSOCIAL_Perception

4.3.3 Probability of error experimental test

The PE formulation was tested in an automotive cobot workplace scenario (physical and virtual environment) performed over common weekly arrangements, using both young and old workers. The measured variables were heartbeat frequency, blood pressure, pupil dilation and eye movement (Figures 7, 8 and 9). Heartbeat frequency and blood pressure were measured by smartwatch usage, while pupil dilation and eye movement were captured by video recording. Those measurements can provide information on fatigue (linked with mental and physical states), stress (linked with mental and psychosocial states), and the operators reactions and concentration (psychosocial and behavioural states) during the test.

The virtual scenarios were created by ergonomic indexes and fatigue was recreated by standard equations obtained from literature (Di Pasquale et al., 2017, Fruggiero et al., 2018). SHERPA simulator was used as a measurement for breaks and work-shift load. Usage of questionnaires and AHP decision-based approach, assisted in determining the psychosocial factors and work attitude (Fruggiero et al., 2020). Smartwatch recording from the physical experiment were filtered through a discrete time-based control to measure the correlation of data over week tasks.

For the physical scenario, the participants were selected based on age (young and old, 2 categories) and biological sex group. The work-task experiment was performed in different environmental conditions; experiments were performed in different light conditions (300-500 lux) with low ambient noise. The workspace was arranged with minimal complexity and with regard to the operators safety and comfort. The tasks were designed in three complexity (task, guidelines, time for completion) levels; the scheduling over level differentiation was randomized over arrangements to observe the measurement alteration depending on different operator conditions (e.g. well rested, fatigued) in different complexity scenarios. Early morning tests were used for *not fatigue* condition. Late evening - after working days and without resting- were used for *fatigued* collection.

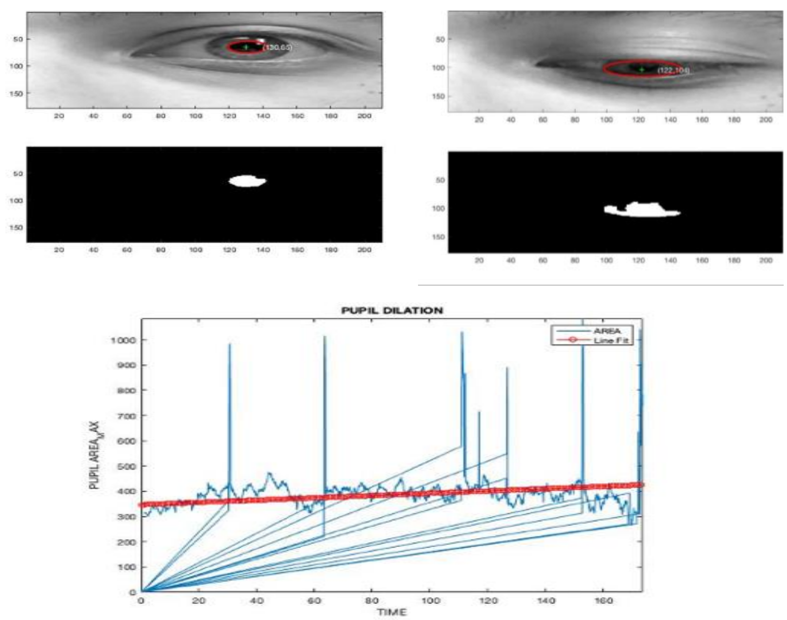


Figure 7. Upper left and right show eye movement and pupil dilation capture by the video recording during the task. The movement and dilation were then used with the PERCLOS method. On the bottom, pupil dilation measurement over time (seconds)for referenced task (eyelid closure/opening in asymptote dilation measurement).

The test was complimented by a set of queries (self-evaluation), to collect well rested and high fatigue conditions. Starting from the recorded video (we are including now information about subject involved in the experimental test - table 3) of the workers' eye, the program evaluated the eyelid using a pixel based quantification for eye movement and closure measurements (figure 7).

Table 3. Information on participants that performed the test and measurements.

	MORNING	EVENING
Number of participants	20 (5 + 15)	16 (6 + 10)
Age range of participants	21- 52	21 -52
Male	13	10
Female	7	6

To measure the mental fatigue, the PERCLOS method was used in combination with eye position controlled by movement probability (figure 8). In this context, the longer the movement the larger the fatigue as correlated with percentage of closure. Major Y movement denotes a head lowering. Variability in X movement reports lack of concentration effect.

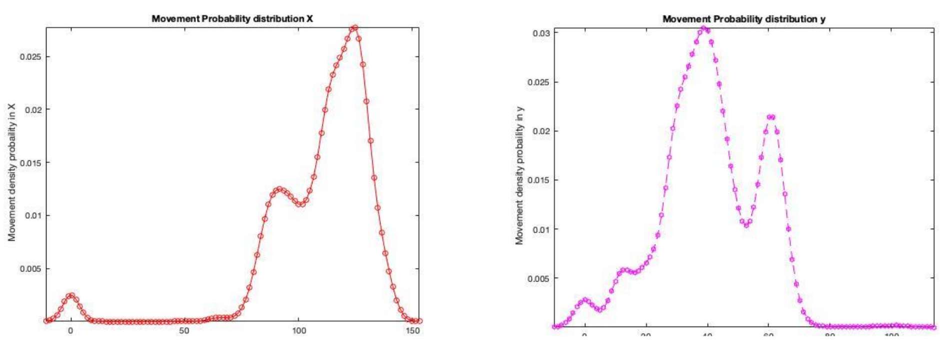


Figure 8. On the left, the probability distribution of eye movement along X direction is depicted. On the right, probability distribution of eye movement along Y direction. X and Y are fixed on absolute references and counted over task time.

PERCLOS (Percentage of eyelid closure) has been found, as shown in the study by Abe et al. (2020), to be an indicator and a valid measuring tool of a persons' drowsiness and alertness. Although, at the current state, the PERCLOS methodology is difficult in its implementation, it is ideal in this approach since it provides flexibility due to not giving an absolute mean value for all workers but enables our methodology since it takes into account the individuals' characteristics. The PERCLOS method is calculated by:

$$PERCLOS = \frac{N_m - N_a}{N_m} \times 100 \tag{13}$$

where N_m represents the total number of record frames and N_a represents the total number of frames where the worker is “awake”.

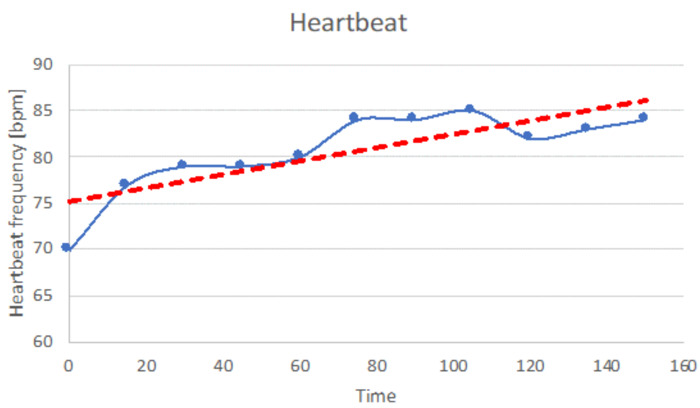


Figure 9. Heartbeat frequency (bpm) over time.

From the experimental results analysis, increased heartbeat frequency (figure 9) and pupil dilation over time and a correlation between both measurements were found. Increased task-complexity showed faster increase of heartbeat frequency and pupil dilation. As heartbeat frequency and pupil dilation rise over time, so does the fatigue levels. While fatigue levels increase, workers tend to react and work slower. Furthermore, as the complexity of working tasks increased, participants had even more slower reactions and slow decision making when performing their usual tasks or when an unexpected event occurred. Moreover, due to increased task complexity, signs of increased mental fatigue show faster than in low complexity tasks. It is worth noting, that although there is correlation between task-complexity and mental fatigue levels, the experimental results report differences between different age groups (Figure 10).

The PE analysis showed that older operators report higher error probability in different work task complexity and changes in working and environment conditions; however, the PE remains stable in a narrow probability area (Figure 10). The analysis for young operators showed lower probability rate (maximum of 0.6), although there is a large variability depending on state conditions. Older operators show increased PE when Physical state condition is low or in critical condition (close to 0.1), which is expected as their physical capabilities decline through age. For the younger operators, behavioural state is a key factor in keeping the PE at low levels, even when the other states are low in condition and stability.

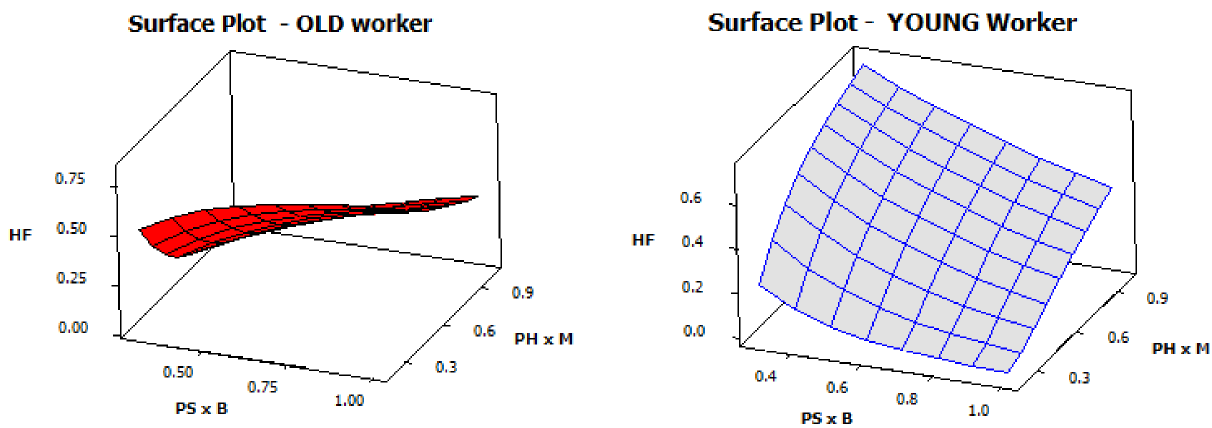


Figure 10. PE analysis for old (on the left) and young (on the right) participants over different state (B,M,PH,PS) conditions (0 to 1).

4.4 Discussion

In this chapter, the research questions aim was to investigate how operators are affected by the workplace changes through the implementation of smart technologies and robots (references can be found in figure 11). In terms of how operators are affected, operators are affected and react based on their perception, personal preferences and capabilities. Capabilities change over operators' due to skill knowledge and experience, but also due to age. A literature review was performed to investigate how those capabilities affect managing operators. The literature review analysis show how operators are affected by workplace changes and environmental conditions due to diminishing capabilities as they age. Moreover, it showed how experience and knowledge are considered valuable as they allow operators to be more cognizant of their workplace. In terms of how to support them; smart technologies can be used to support them as not to lose their experience or knowledge from the workplace environment. However, another solution can be to move experienced older operators from the shop-floor to mentoring younger operators or over to managing positions.

With the results of the literature review, a model was proposed, based on sustainability and HF concept, on how to categorise the operators' condition through the behavioural, mental, physical and psychosocial states. Those states can be described as the macro states of the operator, in the scope of a nature system. As such, using the entropy concept, the human-system probability of error was formulated based on those macro-states and their traits and parameters (micro-states).

The formulation was then tested in an experimental test, to investigate its validity. The task was designed in different task complexity scenarios. Participants were of different age (from 21 to 52 years old). During the test, heartbeat frequency, blood pressure, pupil dilation and eye movement were gathered as to measure the conditions of the macro-states. The results show that although old operators have a more narrow probability range over states' condition, it is higher than that of the younger operators, which however show higher variability due to behavioural state condition.

Although the results confirm what was expected in terms of shape and provide validity in the PE formula, it must be noted that the experiment was also performed to validate the differences in operators' reactions and subsequently the probability of error occurrence. Thus, the next step was to investigate how operators are affected by their robot/cobot co-workers. As such, a research activity was designed, aiming in understanding the effects and outcomes of robot design features on operators.

1st Research Activity - Output

- Fruggiero F., Lambiase A., Panagou S., Sabattini L., 2020, *Cognitive human modeling in collaborative robotics*, Procedia Manufacturing
- Di Pasquale, V., Digiesi, S., Fruggiero F., Longo, F., Miranda, S., Mossa G., Padovano, A. and Panagou S. 2020. Human operator 4.0 performance models in the smart factory: A research framework.
- Panagou S., Fruggiero F., Lambiase A., 2021, "*The Sustainable Role of Human Factor in I4.0 scenar*ios", Procedia Computer Science, 180, pp. 1013-1023,
- Panagou S., Fruggiero F., Neumann W.P., Lambiase A., 2021, "*The Entropic Complexity of Human Factor in Collaborative Technologies*", Lecture Notes in Networks and Systems, 2021, 221 LNNS, pp. 503-510,
- Panagou S., Fruggiero F., Lambiase A., "*Human factor and Entropy evaluation in collaborative workplace environment*"

Figure 11. Publication output of 1st Research Activity.

5. Research activity II: Scoping review on robot design features effect on operators

In this section, the scoping review on robot design features effect on operators is presented (figure 12). The main aim was to investigate how robot design features affect operators and the outcomes. Here, the human robot interaction is investigated as a system and not as individual parts, following the sociotechnical systems approach, as it promotes the joint optimization of the system in question.

This section is structured as follows: first, the scoping review methodology is explained followed by the search strategy. Then, the results are presented starting from general robot features (e.g. appearance) to more specialised (e.g. artificial intelligence & machine learning) ones. Finally, the discussion along with the identified research gaps are presented.

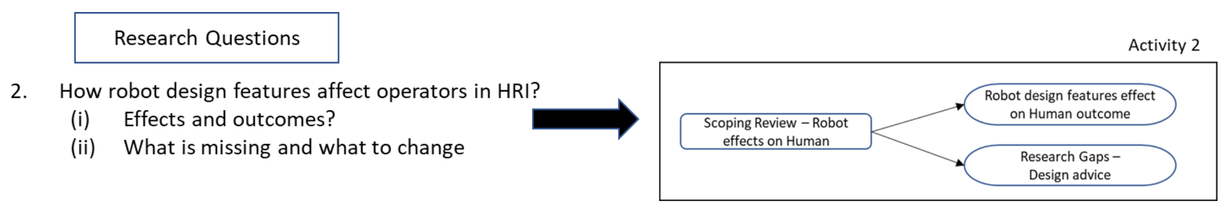


Figure 12. Research questions formed for 2nd research activity and research output.

5.1 Scoping review methods

In the initial stages of the scoping review, a literature search was conducted on the SCOPUS and Web of Science databases. This resulted in more than 170,000 papers present in the literature pool with a mention of HRI. As the body of literature is wide and complex, the scoping review approach was selected as a means to scope the literature, clarify and map the concepts, and identify knowledge gaps (Munn et al., 2018). This allows the assessment of the size and scope of available scientific literature for the area of interest and identify the extent of evidence that are of use (Grant and Booth, 2009). Moreover, the scoping review will allow to identify the concepts and gaps of the topic in question (Peters et al., 2015). Another advantage of the scoping approach is that the research questions do not need to be well-defined or based on a hypothesis, allowing for broader and topic focused questions. However, due to the nature of this approach, it requires more time than a systematic review as the number of citations needed to be screened is larger and require a thorough and more comprehensive analysis; although, the scoping approach can provide more structured and defined results.

This work followed the framework defined by Arksey and Malley's (2005), which requires the following steps: (i) Identify the research questions, (ii) Identify relevant articles through review strategy and keyword selection, (iii) Analyse the selected articles obtained, (iv) Chart the data, and (v) Summarise and report the results. The aim of this review is to investigate the effects of robot design features on operators. As such, the research questions formed are as follows:

1. What does the available peer reviewed research reveal about the effects of robot design features in the human-robot interactions?
2. What are the demands placed on the operator's capabilities by the robot design features?
3. What is the outcome of the demands and effects placed on the operator by robot design features?

The main objective was to find keywords that are relevant to the scope of the study in order to maximise the number of scientific articles. A professional librarian helped in selecting the keywords (table 4) and search strategy. Three main categories were identified for the keywords and the search strings to be used: (i) Human-Robot relevant terms, (ii) interaction relevant terms, and (iii) terms relevant to 'work' and 'human operators/workers'. Keywords from the same category were connected by the Boolean operator 'OR', and from different categories with 'AND' (e.g. 'Human Robot' OR 'Human Cobot' AND 'interaction' OR 'collaboration' AND 'work*' OR 'occupation').

Table 4. Strings and keywords used for the scoping review database search. Columns are connected by the AND Boolean operators and rows of same column with an OR operator.

Category A **Human-Robot related terms (separated by OR)**	**Category B** **Interaction related terms (separated by OR)**	**Category C** **Work and human worker related terms (separated by OR)**
i. "Human Robot"	i. Interaction	i. Work*
ii. "Human Cobot"	ii. System	ii. Workforce
iii. "Human Machine"	iii. Collaboration	iii. Employ*
iv. "Human in the loop"	iv. Coexistence	iv. Occupation
	v. Cooperation	v. Work-related
	vi. Communication	vi. Job
		vii. Operat*

The databases, relevant to the search, selected were the SCOPUS database and Web of Science database. The search was performed for articles written between January 2001 and September 2021; January 2001 was selected as the lower limit as it was the year where the implementation of human robot collaboration started (Hoffman and Breazeal, 2004), which was one of the main focuses of this thesis. Moreover, as the case study is related to the manufacturing sector, the search targeted the scientific areas that can bring value in that regard. The major criteria for inclusion to the final list of selected articles were the following:

- Articles must be written in English,
- Articles must address on of the research questions, and
- Articles should be peer-reviewed and published in scientific journals.

The 'snowball' approach, forward and backward, was also used to identify additional articles (Goodman et al., 1961), that may have not been found due to the selected strategy. The backward approach meant using the reference list of the identified articles to track and identify articles not found through the database search strategy. The forward approach refers to identifying new articles based on those articles citing the papers being examined.

A total of 2830 articles were identified and imported to a reference management software. The initial screening procedure, consisting of reading title, abstract and keywords, resulted in the inclusion of 156 articles. The final step of the screening procedure was to fully read the articles; the final number of articles that matched the inclusion criteria was 32 (figure 13)

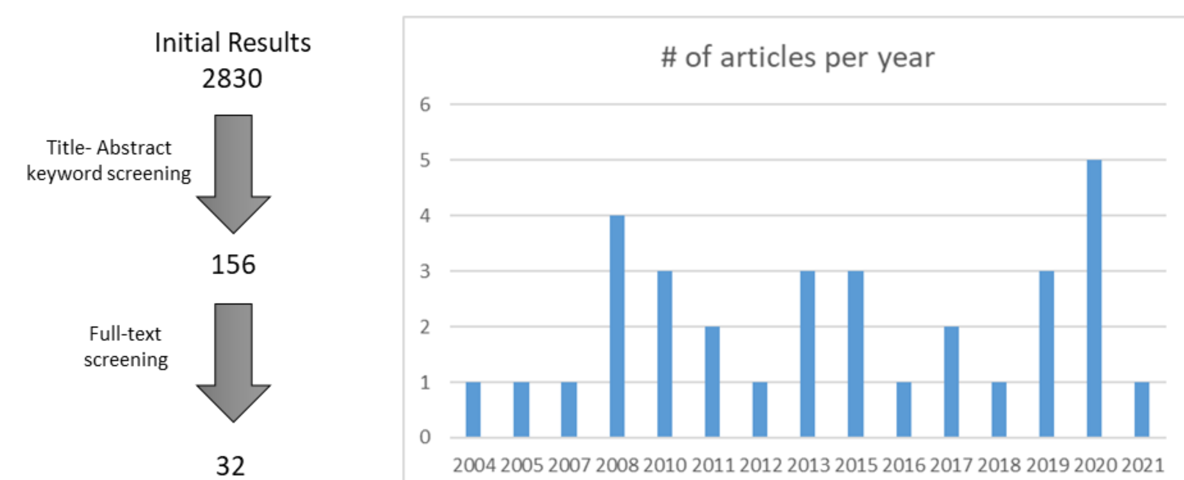


Figure 13. On the left, a flow chart is used to depict the basic steps of the screening progress. On the right, the number of scientific

articles per year is presented.

The selected articles were then fully read again (summary in table 5). Information relevant to the scope, aim and research questions were extracted. In addition, additional information deemed useful to the scope of this thesis, were also extracted based on the following: (i) the focus of each study, (ii) robot design features investigated/used, (iii) operators information relevant to age and sex group, and (iv) operators variables used or investigated in each study. The focus on age here is relevant to the ageing workforce issue recognized by governmental agencies (EU-OSHA, 2019), and as such it is useful to see if and how research approach the issue. The sex term is used in this work inclusively without distinction between the biological or social (gender) aspects. This will allow to collect more information and identify potential issues for better analysis and results (Johnson et al., 2009).

Table 5. Scientific articles included in the scoping review (ID for analysis purposes, Authors, Article title, Journal and year).

ID#	Authors	Title	Journal	Year
1	Hinds P.J., Roberts T.L., Jones H.	Whose job is it anyway? A study of human-robot interaction in a collaborative task	Human-Computer Interaction	2004
2	Besnard D., Cacitti L.	Interface changes causing accidents. An empirical study of negative transfer	International Journal of Human Computer Studies	2005
3	Rani P., Sarkar N., Adams J.	Anxiety-based affective communication for implicit human-machine interaction	Advanced Engineering Informatics	2007
4	Ogorodnikova O.	Human Weaknesses and strengths in collaboration with robots	Periodica Polytechnica Mechanical Engineering	2008
5	Walters M.L., Syrdal D.S., Dautenhahn K., te Boekhorst R., Koay K.L.	Avoiding the uncanny valley: Robot appearance, personality and consistency of behavior in an attention-seeking home scenario for a robot companion	Autonomous Robots	2008
6	Mitsunaga N., Smith C., Kanda T., Ishiguro H., Hagita N.	Adapting robot behavior for human-robot interaction	IEEE Transactions on Robotics	2008
7	Reed K.B., Peshkin M.A.	Physical collaboration of human-human and human-robot teams	IEEE Transactions on Haptics	2008
8	Green S.A., Chase J.G., Chen X.Q., Billinghurst M.	Evaluating the augmented reality human-robot collaboration system	International Journal of Intelligent Systems Technologies and Applications	2010

9	Tan J.T.C., Duan F., Kato R., Arai T.	Safety strategy for human-robot collaboration: Design and development in cellular manufacturing	Advanced Robotics	2010
10	Arai T., Kato R., Fujita M.	Assessment of operator stress induced by robot collaboration in assembly	CIRP Annals – Manufacturing Technology	2010
11	Lee S.-L., Lau I.Y.-M., Hong Y.-Y.	Effects of Appearance and Functions on Likability and Perceived Occupational Suitability of Robots	Journal of Cognitive Engineering and Decision Making	2011
12	Novak D., Mihelj M., Munih M.	Psychophysiological responses to different levels of cognitive and physical workload in haptic interaction	Robotica	2011
13	Duan F., Tan J.T.C., Tong J.G., Kato R., Arai T.	Application of the assembly skill transfer system in an actual cellular manufacturing system	IEEE Transactions on Automation Science and Engineering	2012
14	Cunningham S., Chellali A., Jaffre I., Classe J., Cao C.G.L.	Effects of Experience and Workplace Culture in Human-Robot Team Interaction in Robotic Surgery: A Case Study	International Journal of Social Robotics	2013
15	Zanchettin A.M., Bascetta L., Rocco P.	Acceptability of robotic manipulators in shared working environments through human-like redundancy resolution	Applied Ergonomics	2013
16	Pedrocchi N., Vicentini F., Malosio M., Tosatti L.M.	Safe human-robot cooperation in an industrial environment	International Journal of Advanced Robotic Systems	2013
17	Lasota P.A., Shah J.A.	Analyzing the effects of human-aware motion planning on close-proximity human-robot collaboration	Human Factors	2015
18	Marvel J.A., Falco J., Marstio I.	Characterizing task-based human-robot collaboration safety in manufacturing	IEEE Transactions on Systems, Man, and Cybernetics: Systems	2015
19	Charalambous G., Fletcher S., Webb P.	Identifying the key organizational human factors for introducing human-robot collaboration in industry: an exploratory study	International Journal of Advanced Manufacturing Technology	2015
20	Charalambous G., Fletcher S., Webb P.	The Development of a Scale to Evaluate Trust in Industrial Human-robot Collaboration	International Journal of Social Robotics	2016
21	Maurtua I., Ibarguren A., Kildal J., Susperregi L., Sierra B.	Human-robot collaboration in industrial applications: Safety, interaction and trust	International Journal of Advanced Robotic Systems	2017
22	Peruzzini M., Pellicciari M.	A framework to design a human-centered adaptive manufacturing system for aging workers	Advanced Engineering Informatics	2017

23	Matsas E., Vosniakos G.-C., Batras D.	Prototyping proactive and adaptive techniques for human-robot collaboration in manufacturing using virtual reality	Robotics and Computer-Integrated Manufacturing	2018
24	Oyekan J.O., Hutabarat W., Tiwari A., Grech R., Aung M.H., Mariani M.P., López-Dávalos L., Ricaud T., Singh S., Dupuis C.	The effectiveness of virtual environments in developing collaborative strategies between industrial robots and humans	Robotics and Computer-Integrated Manufacturing	2019
25	Nikolakis N., Maratos V., Makris S.	A cyber physical system (CPS) approach for safe human-robot collaboration in a shared workplace	Robotics and Computer-Integrated Manufacturing	2019
26	Wang W., Li R., Chen Y., Diekel Z.M., Jia Y.	Facilitating Human-Robot Collaborative Tasks by Teaching-Learning-Collaboration from Human Demonstrations	IEEE Transactions on Automation Science and Engineering	2019
27	Meissner A., Trübswetter A., Conti-Kufner A.S., Schmidtler J.	Friend or Foe Understanding Assembly Workers' Acceptance of Human-robot Collaboration	ACM Transactions on Human-Robot Interaction	2020
28	Peruzzini M., Grandi F., Pellicciari M.	Exploring the potential of Operator 4.0 interface and monitoring	Computers and Industrial Engineering	2020
29	Pérez L., Rodríguez-Jiménez S., Rodríguez N., Usamentiaga R., García D.F., Wang L.	Symbiotic human–robot collaborative approach for increased productivity and enhanced safety in the aerospace manufacturing industry	International Journal of Advanced Manufacturing Technology	2020
30	Gervasi R., Mastrogiacomo L., Franceschini F.	A conceptual framework to evaluate human-robot collaboration	International Journal of Advanced Manufacturing Technology	2020
31	Wright J.L., Chen J.Y.C., Lakhmani S.G.	Agent Transparency and Reliability in Human-Robot Interaction: The Influence on User Confidence and Perceived Reliability	IEEE Transactions on Human-Machine Systems	2020
32	Prati E., Peruzzini M., Pellicciari M., Raffaeli R.	How to include User eXperience in the design of Human-Robot Interaction	Robotics and Computer-Integrated Manufacturing	2021

The operators' capabilities were categorised based on the HF domains. As such, this work utilizes the categories formed and used in previous research (Grosse et al., 2015, Neumann et al., 2016 and Sgarbossa et al., 2020) to categorise the terms found in the included articles (table 6): (i) Perceptual, containing terms for awareness (spatial), perception and reaction, (ii) Mental, containing mental fatigue, cognitive load and decision-making, (iii) Physical, containing terms for motor skills and training, and (iv) Psychosocial, containing terms for comfort/discomfort and stress. In this logical set of categories for operators' capabilities we add safety. Safety is crucial for HRI and more importantly for collaboration, as there is no physical barrier between operators and robots and as such, during tasks there are high risks of physical contacts that can lead to accidents if regulations and rules are not set accordingly to protect the operator.

Table 6. Operator capabilities categories based on the inductive approach. Beside each category, the terms used in the articles relevant to each category, are listed.

Categories	Human Operator Capabilities		
Mental	*Mental fatigue*	*Cognitive load*	*Decision-Making*
Physical	*Ergonomics*	*Motor skills*	*Training*
Perceptual	*Awareness*	*Perception*	*Reaction*
Psychosocial	*Comfort*	*Trust*	
Safety	*Safety*		

For the robot design features an inductive approach (Thomas, 2006) was used by identifying relevant terms. Those terms were then grouped in categories by using deductive reasoning and comparison with relevant terms in the literature. Those categories are the following (table 7): i) Appearance, referring to human-like or machine-like appearance or morphology, (ii) Behaviour, referring to behaviour, features, pervasive technology and consistency, (iii) Communication, via action or through interface, (iv) Reliability, referring to reliability, usability, effectiveness and repeatability, (v) Machine Learning, referring to the methods used such as machine learning, vision, natural language processing or reinforcement learning, and (v) Dynamic capabilities, referring to movement (trajectory and speed) and force of contact.

Table 7. Robot design features categories and the terms used in the identified scientific articles.

Categories	*Robot Design Features*				
Appearance	Appearance	Morphology			
Behaviour	Behaviour	Feature	technology	Consistency	
Communication	Communication	Information	Interface		
Reliability	Reliabity	Usability	Effectiveness	Safety	Repeatability
Machine Learning	Machine Learning	Natural Language Processing	Reinforcement Learning	Sensing posture/motion	Machine vision
Physical	Movement	Trajectory	Speed	Force of contact	

5.2 Scoping review results

A full text analysis of the 32 peer-reviewed articles was performed and the effects of robot design features to operators was investigated. Age and sex group information was also extracted from the articles that discussed case studies or experiments and disclosed that information (figure 14). 19 out of 32 articles reported participants age group. From those, 15 of them focused on young operators (mean average age between 25 to 30), 3 used a mixed approach between old and young (19-61 years of age), and only 1 has its focus on older operators (age older than 50). For the sex group, only 22 mentioned the use of both male and female participants, and only 14 provided exact information. From those 14, 9 articles (37%) had more male participation, 2 (8%) had a balanced approach, and 3 articles (13%) had more female participants.

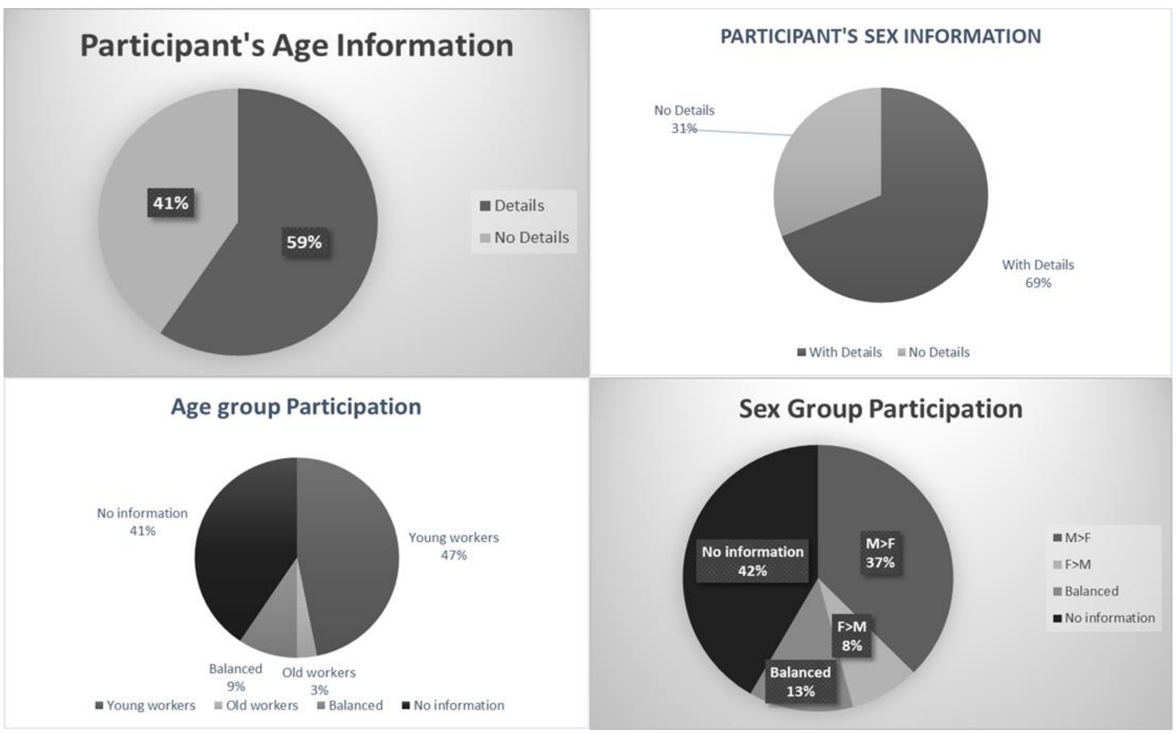


Figure 14. Figure depicts information drawn from the scientific articles on age and sex group of participants in the experimenta studies.

Figure 15 shows the connections between robot design features and their effects on operators as found in the articles. The majority were focused on the dynamic robot features (speed and force) that places demands on the mental and psychosocial status of operators and their safety. Machine learning, a technique with wide research interest due to its versatility and potential for use, was studied mostly in relation to operators' perception of the robots and stress. Communication between operators and robots in the workplace was studied by measuring operators' trust towards the robot and operators' perceived reactions to robot's communication methods and techniques. Varying robot appearances were used to investigate the effects on HF (perception and ergonomics effects). Robot behaviour was investigated through the operator's trust and perception during tasks. Reliability of a robot in the workplace was studied in accordance with operator's perceived safety, ergonomics, and trust.

		Human Operator				
		Mental	***Physical***	***Psychosocial***	***Perceptual***	***Safety***
Robot	***Appearance***	-	15,19,30	1	1,11,31	-
	Behavior	22	22	-	5	-
	Communication	4,13,32	-	-	4,7,8,14,27	-
	Reliability	2	4,28	21	21,31	2
	Machine Learning	3	-	6, 17	3,6,26	17
	Dynamic	10,12,29	9	12,15,20	23,24	9,16,18,23,24,25,29

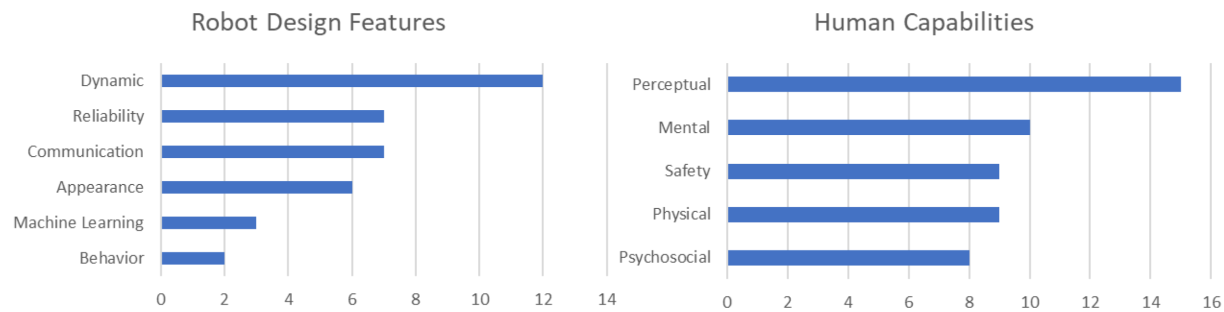


Figure 15. The relations between robot design features and operators' capabilities can be seen in the top figure. Grey cells represent the absence of research in those specific relations or the absence of relation between them. Bar charts present the number of articles that studied the specific category.

The connections found in the literature between robot design features and their effects on operators' capabilities can be seen summarised in figure 15 and are the focus of the analysis as presented below. The subsections are organised based on robot design features, starting from the more general characteristics (appearance, functions) to more specialised ones (AI machine learning and dynamic features).

5.2.1 Robot appearance

A total of 6 articles discussed appearance and suitable characteristics for robot integration in the workplace, based on perceived capabilities and response to appearance by the operators. The morphology and appearance of a robot, being human-like or machine-like, should be considered depending on the workplace and work task. In demanding tasks, either physical or mental, operators are more likely to react positively to a human-like robot than a machine-like one (Hinds et al., 2004). Moreover, the operators may have pre-developed mental models on a robot's appearance for specific tasks, which can influence their perception of the robot's capabilities; human-like features are associated with tasks where robots are expected to have frequent social-like interactions with humans, while robots with machine-like features are expected in situations that are more task-focused, such as lab/workplace assistant and military robots (Lee et al., 2011). Certain physical characteristics can influence the operator's comfort, especially in occupations related to healthcare. The human-like motion of a robot can be considered more acceptable by patients or nurses, which in turn can lower the operator's perceived stress (Zanchettin et al., 2013). Due to perceived capabilities and operators' mental models of how a robot should look, operators should be involved in the implementation of robots in the workplace (Charalambous et al., 2015). Involvement of operators during robot implementation can be crucial, as operators can indicate preferences in robot characteristics. This can result in wider acceptance of a robot due to human input which in turn influences trust (Gervasi et al., 2020). The occurrence of negative events (e.g., misleading information), can also decrease trust and perceived reliability towards robots (Wright et al., 2020).

5.2.2 Adaptable robot behaviour

Three articles discussed robot task behaviour. Robot behaviour is defined as any action the robot can perform and can be categorised based on type (purpose) and level. In the articles found in the literature, robot behaviour is discussed based on robot features, task consistency, pervasive technology, and its ability to adapt depending on the situation in a collaborative environment. For a human-centric and adaptable workplace, human-like behaviour of a robot should stay the same to avoid loss of trust in set tasks and situations (Walters et al., 2008). In adaptable collaborative workplaces, a network of cyber-physical systems can provide information and vision to robots for automatic adjustment for the needs of older operators, improving their perceived safety depending on the work-task (Peruzzini and Pellicciari, 2017). Collaboration with a robot can be beneficial in aiding operators, especially in stressful situations, as the robot can detect changes in human behaviour and adapt its functions and behaviour to support and protect the operator.

5.2.3 Human – Robot Communication

A total of 7 articles discussed the role of communication in HRI. Generally, human-robot communication can be achieved through verbal speech, gesture signalling, haptic communication and through screen-based interfaces. Operators establish their own workplace routines of communication which, when a robot is introduced to the workplace, need to be adjusted. Robots can offer physical support in physically demanding tasks, while operators need to process information and make decisions which in turn puts a load on their mental capabilities. Robots can provide support in that area due to their processing capabilities and can offer information to alleviate the humans' cognitive and physical loads. In that regard, robot additions to the workplace can be beneficial if there is time for operators to train with their new co-workers and understand the information exchange capabilities of the robots (Ogorodnikova, 2008). The addition of robots to the workplace may raise the complexity of the work and task procedures, and sufficient time should be spent in training to avoid errors due to miscommunication (Cunningham et al., 2013). Workplace culture also plays a significant role in the human acceptance of a robot inside the workplace; clear communication protocols, especially for safety issues, are a design feature that can positively affect human's perceived trust in robots (Meissner et al., 2020).

Communication is important in dyads, including both human-human or human-robot, in which case operators should be aware of the team composition. In non-verbal communication HRI scenarios, operators may subconsciously perceive their robotic partner as if they were human. Although it may be useful in terms of efficiency, it may lead to human-system error due to false information, which can lead to loss of trust (Reed and Peshkin, 2008). When a new operator is added to the team, their robot co-workers can provide task information and training information (Duan et al., 2012). Robust communication protocols for augmented reality or teleoperation scenarios can improve spatial awareness, decision making and overall, the team effectiveness (Green et al., 2010). Moreover, in shared tasks, user experience should be considered (Prati et al., 2021) for operators to positively perceive their robot co-worker's usability and effectiveness. In general, results suggest that robot communication ability can play a key role in HRI and human support and can improve workplace reliability, safety, and team cohesion by supporting the HF's perceptual and mental capabilities.

5.2.4 Robot reliability

A total of 5 articles discussed perceived and actual robot reliability and their effects on operators. When changes to robots' functionality or capabilities are introduced to a collaborative workplace, operators should be informed and get trained to avoid potential errors and fatal accidents, thus improving their safety (Besnard and Cacitti, 2005, and Ogorodnikova, 2008). Safety measures should be implemented in collaborative environments for collision avoidance; for example, robot capabilities can be enhanced by receiving information from sensors in the workplace to enhance human safety and the perceived robot reliability (Maurtua et al., 2017, and Peruzzini et al., 2020). Awareness of human location in situations where the robot is operating autonomously, is essential for operators' safety and trust development in robots and perceived robot reliability (Wright et al., 2020). Robot reliability and perceived reliability are directly linked with other robot design features, such as communication and artificial intelligence, as an indicator of positive or negative effects on operators. However, communication and artificial intelligence should be considered independently due to the direct demand or support they place on operators.

5.2.5 Machine Learning & AI

A total of 4 articles present research results on how machine learning and Artificial Intelligence (AI) can play a significant role in the collaborative environment. Their features (e.g., supervised, and unsupervised learning) allow them to handle large amounts of data (historical and real-time) and make decisions based on models programmed by human specialists. Machine learning can be utilised to analyse human behavioural changes, due to fatigue for example, so a robot can adapt to the situation and provide support, especially in cognitive based tasks (Rani et al., 2007). Machine learning and vision capabilities can be used to adjust the robot behaviour to the operators' preferences (Mitsunaga et al., 2008). Moreover, in the same context, machine vision can be useful for a robot to adapt their motion levels to match the operator's preference which can improve human satisfaction and human-robot team cohesion (Lasota and Shah, 2015). Natural Language Processing (NLP) machine learning models can be utilised to improve the effectiveness of human-robot communication, which in turn can increase the operator's perceived safety and performance (Wang et al., 2019). Machine learning and AI can support humans in collaborative environments through models that can be programmed with that capability. Machine learning and AI models can be used to design robots that can adjust their dynamic characteristics depending on the situation and for human support.

5.2.6 Dynamic Robot characteristics

A total of 11 articles discussed dynamic robot characteristics including the robot movement area, velocity and physical force and pressure and how they can influence the HRI. Due to the close proximity between humans and robots in “smart” workplaces, those characteristics can directly affect the safety of operators. Moreover, due to their operational area and speed of movement, operators’ perceived safety can be negatively influenced. In that regard, the area of movement and trajectory along with movement velocity should be optimised (Tan et al., 2010) to improve operators’ perceptions of safety. Close physical collaboration can induce stress to the operator and should be considered in the workplace design process to enhance the human’s perceived safety (Arai et al, 2010). Moreover, in close physical collaboration, such as in picking and placing orders in the shopfloor, the area of movement should be designed with safety measures to avoid collision with operators (Charalambous et al., 2016). In haptic human-robot teams, where the work task includes handling physical load, the support of robots can reduce physical and mental load of operators (Novak et al., 2011). Furthermore, the robot’s ability of repeating tasks with no fatigue issues and their physical strength can be utilised to support operators in physically demanding tasks (Perez et al., 2020), which can minimise the risk of physical injuries. Although, human safety should be considered during physical tasks due to the force and pressure that robots will use or exert (Marvel et al., 2015). A network of sensors (Pedrocchi et al., 2013), or cyber physical systems (CPS) (Zanchettin et al., 2013, and Nikolakis et al., 2019) in connection with robots teamed up with operators, can be used as a safety mechanism and collision avoidance in close physical collaborative tasks. Virtual reality tools (Matsas et al., 2018) can be used in the design process to test for human safety during collaborative tasks where robots have movement tasks. Furthermore, the use of virtual representations of the physical workplace (digital twin) should be considered, for simulations on safety testing for multiple scenarios regarding robot movement speed and trajectory during close physical human robot collaboration (Oyekan et al., 2019). Safety is a crucial aspect for operators in the workplace and minimising risks should be a priority. The dynamic features of a robot, movement and force of contact, can negatively influence the perceived safety and actual safety of an operator and thus, they should be considered and tested in relation to HF and operators’ preferences.

5.2.7 Robot Design effects on operators

Shifting attention from the design effects on operators' capabilities, a deductive approach was followed to identify the outcomes the effects of robot design features have on operators (figure 13). The approach identified 5 outcomes for operators that have been studied in the literature. These concern safety (perceived and actual), reliability (perceived and actual), human and robot team cohesion, comfort and quality of work. Comfort is an overlooked outcome, discussed in a single study, of robot design, only investigated through robot appearance and communication. Interconnection of different features and the HF capabilities affecting outcome can be seen through figure 16. In figure 16, safety under HF capabilities signifies the actual safety of the human, while under human outcome it signifies the perceived safety of the operator. Actual safety is related to robot reliability, dynamic characteristics, and machine learning/AI, while perceived safety is affected by all the HF capabilities, and by extension, the robot design features. Perceived reliability is affected through perception, psychosocial and mental capabilities by 4 robot design features. 13 articles show how robot features can affect team cohesion through the HF perceptual and mental capabilities. 8 articles show the effects on quality of work, through all the HF capabilities by robot features.

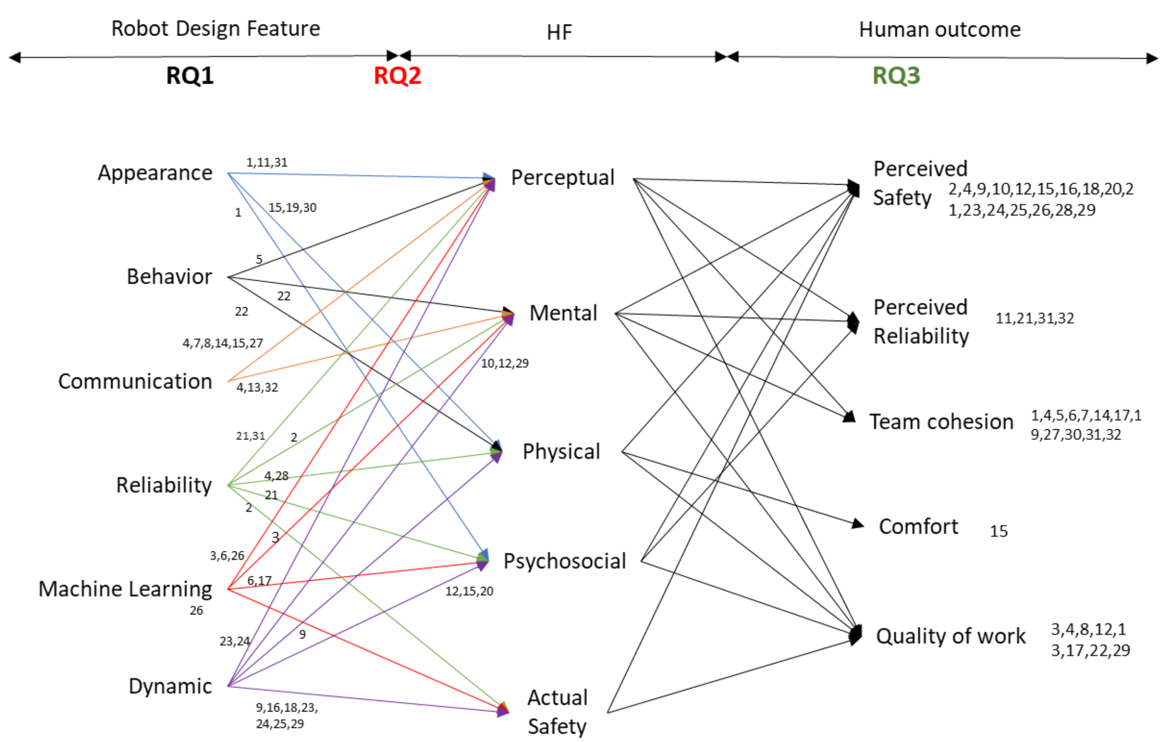


Figure 16. Figure depicts the connections of robot design features effects (RQ1) on operators' capabilities (RQ2) and the outcomes (RQ3).

In figure 17, human outcome is directly linked to the robot design features, based on the literature articles analysis. The links indicate how robot design choices influence the HRI, although the connections are complex due to the interconnections between design features and each human outcome. Moreover, the links between robot design features and outcomes on operators, reveal gaps that could be investigated further to understand if there is connection between them. The connections between robot design features and human outcome can be seen in figure 17, as well the gaps (grey blocks). Those gaps, such as robot behaviour with perceived reliability and safety, dynamic capabilities with perceived reliability and team cohesions, or the outcomes on operators' comfort from behaviour, communication, robot reliability, indicated no research done (and as such present a research gap) on their probable connection in the identified scientific articles.

	Robot Design Feature					
Human Outcome	*Appearance*	*Behavior*	*Communication*	*Reliability*	*Machine Learning*	*Dynamic*
Safety	15		4	2,4,21,28	26	9,10,15,16,18,20,23,24,25
Reliability	11,31		32	21,31		
Team Cohesion	1,19,30,31	5	4,7,14,27,32	4,6,31	17	
Comfort	15					15
Quality of work		22	4,8,13	3,4	3,17	12,29

Figure 17. This figure shows the connections between robot design features and human outcomes. Grey blocks show that no identified scientific article covered them and as such can be considered a research gap for the purposes of this work. Numbers indicate the ID# if articles shown in table 5.

5.3 Implications and discussion points

This sub-section provides the key points of discussion and research gaps found, relevant to the research questions and aim of the thesis. As the study was targeted to the industrial and manufacturing sector, the lack of scientific papers (32 identified articles) focussed on human aspects in robot design is consistent with previous research that shows the systematic absence of attention to human aspects, observed here in cobot design research. This lack of attention severely limits the guidance available to real world cobotic system designers, raising the potential for negative outcomes for operators, as shown by Neumann and Dul (2010), Grosse et al. (2017), and Neumann et al. (2021). The absence of attention to human aspects in research consideration comes into contrast with humans being an integral part in engineering projects from the design, to the implementation and execution. This also comes in contrast with the sociotechnical systems (STS) theory requiring joint optimisation for both technical and social subsystems in design (Van der Zwaan, 1975) and the human centric direction of I5.0 framework.

Many-to-many relationships of robots and human outcomes - Following the analysis, six key features of robot design present in the literature were identified; appearance, behaviour, communication, reliability, machine learning and Dynamic capabilities. Figure 16 shows both the connections and effects between robot design features and demands placed on operators, and in turn the eventual human outcomes or effects. This figure also demonstrates the many-to-many relationships between robot design features and operators' capabilities and outcomes in the HRI. Based on the analysis, those complex relationships and consequences of actions and demands, have not been investigated in their entirety but only in isolation. Furthermore, these interconnections and many-to-many relationships show the complexity of HRI, which is expected following the STS perspective. Thus, it brings into attention the need to investigate those relationships, e.g. investigation on the effects of a design feature should focus on the outcomes on both humans and the system. There is a need to understand and include those aspects, from human perception to psychosocial effects, and through physical and mental traits, as they can be considered as leading indicators of performance. Moreover, there is a need to understand how these HRI dimensions affect different outcomes, such as safety, team cohesion and quality of work, for employees in those situations. In practice, those interactions and relationships should be considered when designing human-robot collaborative workplaces.

Involving human operators in robot implementation – Operators develop mental models on how they perceive the capabilities and suitability of a robot based on its appearance (Lee S-L. et al., 2011). Those mental models can alter the level of trust operators show towards their robot co-workers, depending on how much the robot matches the expectations the human has (Matthews et al., 2020). Current research does not provide much guidance to designers on the form-response patterns of operators. Thus, use of qualitative methodologies could provide insight on the operators' perspective on HRI (Grosse et al., 2016), which then can be tested through quantitative methodologies. Moreover, through human involvement either in the design phase (participatory design, Muller and Kuhn, 1997, Rogers et al., 2022) or control and planning phase (through participatory ergonomics, Burgess-Limerick, 2018) and implementation, the perception of a robot's reliability can be influenced (Lotz et al., 2019, Charalambous et al., 2015), which in turn can improve team cohesion. It may also influence their view on the use of robots, an aspect studied in other engineering design domains (Melkas et al., 2016). Thus, researchers and system designers should investigate the effects of involving operators during the design phase and the eventual implementation of robots in the workplace. Beyond involvement, actual training with robots in workplace scenarios should be considered as a priority as it can improve and benefit the HRI.

Training of human operators with robot co-workers - Several scientific articles noted that by introducing a robot to a workplace, the operators should be trained in the interaction and the new environment (Cunningham et al., 2013, Charalambous et al., 2015, Gervasi et al., 2020). This is beneficial for team cohesion and safety, as operators understand their robot's co-workers' capabilities and functions. Furthermore, when there is an update on a robot's feature or capability, information should be given to the operators and also be allowed to train as to adapt to those changes. Otherwise, there is a high risk of a human-system error that could potentially lead to accidents and possible loss of life, as seen in Besnard and Cacitti (2005) and the recent Boeing 737 MAX crash cases (Herkert et al., 2020). Training and transparency can improve quality of work and perceived safety while reducing the possibility of error. HRI could benefit from further research on how training and transparency is linked with the human's perspective on safety and comfort. Training operators in collaborative contexts can also benefit practitioners, as they can then provide configuration and design information for adjustments. This could improve trust, quality of work and perceived reliability in robot collaborative systems, whereas lack of knowledge and preparedness is a negative influence. This negative influence is evident in the case of acceptance levels of self-driving cars from human drivers (Lee and Kolodge, 2018).

Robot design features for human support - The analysis (figure 17) reinforces the notion that the robot's dynamic characteristics (such as strength and speed) pose a safety concern for operators (i.e. Tan et al., 2010, Charalambous et al., 2016), while also showing that they affect comfort (Zanchettin et al., 2013) and quality (Novak et al., 2011). In the complex HRI environments, human safety protocols should be in place to protect the operator (Lasota & Shah, 2015). Due to the robot's speed and potential force of contact, a collision could induce injuries to an operator (OSHA 2018), which requires safety measures to be taken in order to protect the operators, considering as well the robot's potential speed and area of movement. Fear of collision with robots generates mental strain and distrust due to their dynamic capabilities (Arai et al., 2010). In their literature review on safe HRI, Robla-Gomez et al., (2017), summarise classifications of safety in collaborative environments, including collision avoidance strategies. Use of sensor networks is already used as a deterrent of collisions, with the robot halting operations and movement to avoid injuring an operator. However, there is an issue on how the robot will respond in case the operator moves towards it; in such case a collision leading to an injury may occur, an inaction which would contradict the first law of robotics introduced by Asimov in his work; *a robot may not injure a human being, or, through inaction, allow a human being to come to harm*. Robot situational awareness (Endsley et al., 2003) could be developed further by giving them the autonomy to pro- and re- actively perform collision avoidance manoeuvres. This could be achieved by allowing them to (i) understand the situation, (ii) forecast the future state of the situation and (iii) selection of appropriate action to avoid potential problems (e.g. move out of the way or provide support). Cyber physical systems can be utilised for enhancing robots' sensing capabilities (Nikolakis et al., 2019) along with the implementation of computer vision through machine learning/AI (Mitsunaga et al., 2008). Virtual reality tools can provide a safe environment to test critical situations (Oyekan et al., 2019) and optimise human robot collaboration. Safety should be a priority for practitioners and workplace designers for smart manufacturing, as pointed out in the COMEST report on Robotics ethics (UNESCO, 2017).

Research gaps. Analysis of the literature articles identified several research gaps. The blank cells in the matrix analyses in figures 15 and 17 reveal areas in research that could be investigated in order to explore potential issues and solutions. For example, robot behaviour and connection with operators' comfort need to be examined. Robots' behavioural characteristics demands on an operator's psychosocial state and safety, or outcomes on perceived safety and reliability could be of use for workplace design and management. Robot communication functions and the effects on psychosocial state and human comfort in the workplace could be of potential interest to practitioners for quality and process optimization. Moreover, human comfort was investigated as an effect of robot features in only one of the identified articles. As comfort relates to a state free from distress, physical and mental discomfort recognized in medical research (Kolcaba and Kolcaba, 1991), and also psychological stress (related to discomfort), it is an important psychological factor of humans that needs evaluation (Taniguchi et al., 2009) as it directly affects work safety and human work quality (Zanchettin et al., 2013). This conforms with the I5.0 framework call for human-centred systems. Although safety, actual and perceptual, is discussed in the identified articles, it is still an open issue for workplace design. This is for collaboration, as humans and robots operate in close physical proximity and dependability of the interaction should be guaranteed for successful implementation (De Santis et al, 2008). In the articles containing experimental studies, common metrics are used as indicators for humans or robots (e.g. NASA TLX, EMG, task performance, effectiveness, reaction time), however there is a lack of metrics to evaluate the performance of the interaction as a system and/or process and team performance (e.g. Annet et al., 2010). Introducing metrics by either developing new ones or using metrics developed for other purposes could be beneficial for HRI as it could provide indicators on areas that need improvements. For example, the works of Steinfeld et al. (2006), and Murphy and Schreckenghost (2013) provide metrics for operators and robots; those metrics can be investigated in how they fit the purposes of HRI as a system. Our analysis also showed that there is no representation of ageing workers. This highlights the need to research those aspects due to the ageing workforce trend, as seen in the EU-OSHA report (2019). It is estimated that workers aged between 55 to 64 will constitute 25% of the workforce population by 2030. Research including experienced and older operators can improve collaborative conditions (Di Pasquale et al., 2020) and acceptance for robots in HRI (Rogers et al., 2022). Another gap shown in the analysis, is the discrepancy between female and male representation in HRI (figure 14) and is consistent with the findings of Perez (2019). Sex and gender analysis is important, especially in the case of collaboration, as it could provide more insights and improve design as is shown in the work of Tannenbaum et al. (2019) and could support advancement of theory and practice as reported by Sperber et al (2022).

The research output during this activity can be seen in figure 18. The next step of this research project was to investigate a collaborative assembly scenario. As cobots are taking over physical tasks, it allows operators to have less physical strain in their workload. As such it was decided that the focus of the experimental study should be on HRC effects on cognitive load (and mental fatigue) and quality (product, process and human work); with human work quality being one of the findings of the scoping review. The next chapter presents the review performed on cognitive load and task complexity, the development of the experimental study framework, and finally the experiment itself on human robot collaborative assembly.

2nd Research Activity - Output

- Panagou S., Fruggiero F., Lambiase A., "*Human gesture system in Human Robot Interaction for reliability analysis*",
- Panagou S., Fruggiero F., Lerra M., del Vecchio C., Menchetti F., Piedimonte L., Natale O.R., Passariello S., "*Feature investigation with Digital Twin for predictive maintenance following a machine learning approach*"
- Panagou S., Fruggiero F., del Vecchio C., Sarda K., Menchetti F., Piedimonte L., Natale O.R. and Passariello S., 2022. *Explorative hybrid digital twin framework for predictive maintenance in steel industry*, IFAC-PapersOnLine, 55(40), pp- 289-294.
- Panagou S., Neumann W.P., Fruggiero F., 2023, A scoping review on human robot interaction research towards Industry 5.0 human-centric workplaces, International Journal of Production Research, pp. 1-17.

Figure 18. Publication output of 2nd Research Activity.

6. Research Activity III: Experimental study on human robot collaborative assembly

Up to this point, this works presents the research activities that focused firstly, on workplace changes, due to I4.0 framework and its enabling technologies, and the effects on operators and their capabilities and secondly on the effects of robot design features on operators. As HRI, and HRC in particular, is becoming the norm in the workplace, the effects of robot design features on operators were investigated through a scoping review. The results of the scoping review showed that the outcomes are related to operators perceived safety and perceived reliability, comfort (mental and physical) issues, team cohesion and operators' work quality.

The next step of the thesis was to perform an experimental study to investigate those outcomes in a collaborative scenario. The main focus was to investigate the effects of collaborative assembly on cognitive load and in turn the quality of product, process and human work (figure 19). The participants' perception of the robots before and after the experiment were investigated through questionnaires, as well as team cohesion and the level of comfort working with the robot and new technologies. As the experiment was performed during the COVID-19 pandemic, some restrictions were placed in terms of participation and execution of the experiment. This chapter starts with an introduction to HRC, followed by a state of the art review in cognitive load measurements and task complexity. Next, the experimental framework, data gathering and setup are shown. Finally, the results of the experiment are presented.

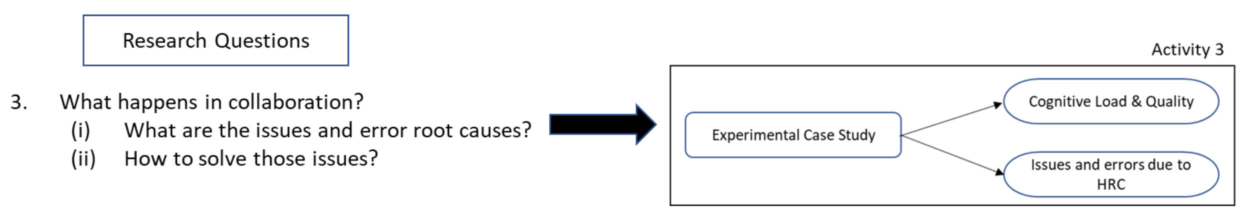


Figure 19. Research questions formed for 3rd research activity and research output.

6.1 Introduction

Human robot collaboration is a complex and dynamic system and is a critical part in assembly lines. It can benefit production and quality and allow for flexibility in roles and processes; e.g. robots can now perform heavy physical tasks allowing operators to concentrate on other tasks. In that regard, HF is critical in both production and quality as operators are an integral part of the system due to their capabilities. As the operators need to collaborate closely with robots, receive information and updates on the work process and be aware of potential issues, HF can provide insights and possible solutions in this dynamic environment.

In the collaborative industrial assembly scenario, mental fatigue and cognitive load of an operator can negatively influence the outcome of production. The operator is being overloaded with new information and rules set by the management, be it task or process related, while performing tasks with their robot co-worker (figure 20). Those information impact the mental effort needed, and consequently the cognitive load as the operator spends working memory resources (Sweller et al., 1988). As the HRC is complex and dynamic, investigating the factors that affect cognitive load during collaboration is needed. This will allow for better understanding of what is needed to support operators and provide insights for task and process related design purposes.

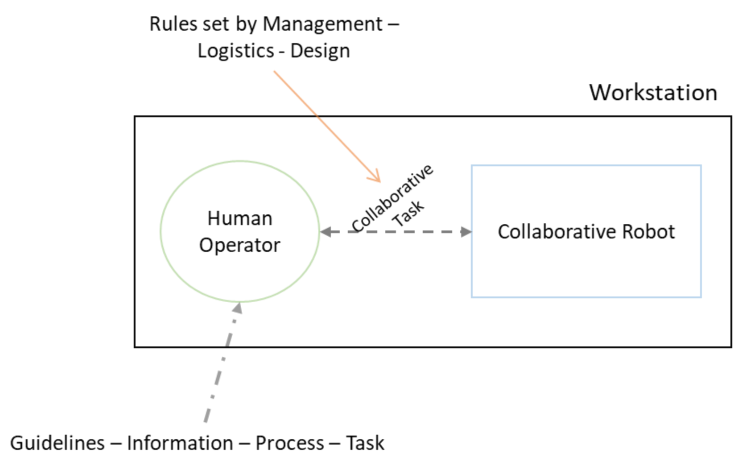


Figure 20. Schematic representation of human robot collaboration and inputs based on management, guidelines and demands.

6.2 Cognitive load and task complexity

Apart from the benefits they can bring to an industry in terms of productivity and quality, robots can benefit operators in the workplace. In collaboration with operators, robots can assist in tasks requiring moving physical objects, lowering the physical demands of operators. They are fitted with sensory capabilities, and can provide information related to the task, system and processes, or warn operators of potential risks or errors. Moreover, robots should be programmed with collision avoidance manoeuvres and fitted with force sensitive parts to lower their impact in case of contact with an operator or parts they need to interact with. However, apart from the benefits, robots add another layer of complexity and create a more dynamic environment that operators have to work in.

Robots' presence in the workplace affect operators both in an objective and subjective manner. From a subjective point, operators have their own preferences and their perception of robots and their capabilities vary. In a more objective manner, robots affect other aspects in their interaction with operators such as team cohesion and work quality. Apart from the issues created by the presence of robots, the collaboration and the work tasks they need to perform operators have to also deal with:

i. information and data sent to them by sensors and robots, which impact the mental demands and cognition,
ii. guidelines and rules set by management, which they have to conform with and follow, and
iii. most important of all their safety; impacting their capabilities, such as their perception (e.g. keep track of developing issues and position of robot).

Meanwhile, operators need to perform their tasks, that now have an added layer of complexity, keeping productivity and quality at same or higher levels than before, as well as make decisions during tasks and act as safeguards. As such, it places a burden on their mental capabilities and increasing mental fatigue, which leads to cognitive load impacting their decision-making capabilities and can lead to human-system error.

With collaboration becoming the norm in manufacturing industries and assembly lines, and with the focus of manufacturing moving towards adaptable assembly lines that can change their production target and product depending on market, this creates a scenario where operators need to adapt to and be able to stay productive. Moving towards the human centric workplace of the I5.0 framework, it is important to understand how collaboration affects operators in order to support them. With the help of the industrial partner, the experimental study focused on the effects of collaboration and subsequent cognitive load during assembly tasks in quality (product, process, human work). Complexity is often highlighted in this thesis due to workplace integration of robots and effects of collaboration. As such, quantifying task complexity can be of use to identify issues and effects of complexity (Calinescu et al., 1988), and improve shop-floor quality and productivity (Hu and Stecke, 2009). The research questions for this part of the thesis are:

(i) how can cognitive load of an operator during a collaborative task be measured?
(ii) how to measure task complexity?

6.2.1 Cognitive Load

In this work, the dimension of cognitive load (CL) examined is the amount of working memory used during a task. In the literature, CL is classified into three distinct types, (i) intrinsic load, (ii) extraneous load and (iii) germane load (Paas et al., 2003). Intrinsic CL is a function of task complexity and is dependent on the inherent difficulty of said task. Extraneous CL is generated by presentation of the task to the user, the more irrelevant information presented, the more the CL. Germane CL is load generated by the need of a human operator to create new mental schemas due to interactions with a task, system design or another entity in the workplace. The three CL types and the factors influencing them can be seen in summary in figure 21.

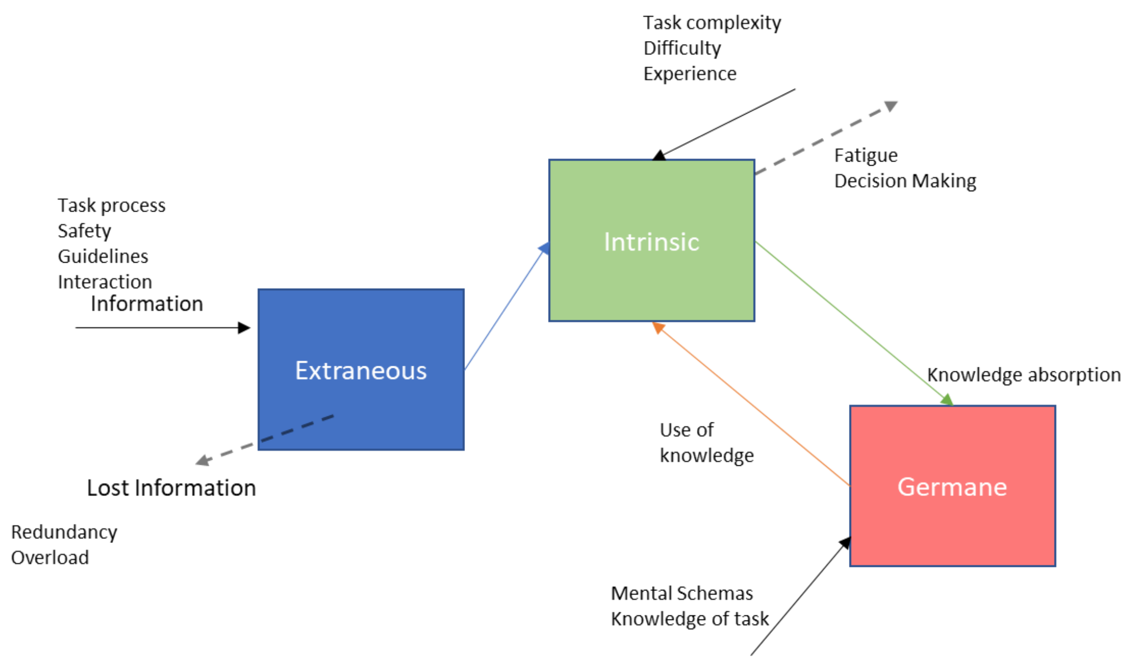


Figure 21. Cognitive load distinct types. In the figure connections between them are drawn along with the factors influencing them.

CL measurement is a complex issue, as it is dependent on the human operator and thus, while a unified approach is hard to develop, general effects and trends can be observed. In that regard, questionnaires have been developed for individual filling and rating of CL, although it should be noted that this is a subjective method and prone to personal bias. The most commonly used questionnaire is the NASA Task Load Index (NASA-TLX), which consists of rating six parts: mental demand, physical demand, temporal demand, frustration, effort and performance (Hart, 2006). Another known questionnaire is the Cognitive Load Component which aims in rating the three types of CL (Lepping et al, 2013). However, use of questionnaires should not be the only measure of CL, as it is subjective and changes are momentary, and thus, should be used along with other methods. Additional methods for CL measurements are through task performance (Fridman et al., 2018) and through response time, error-rate and accuracy are highly sensitive to changes (Paas et al., 2003). However, those two methods they are task-dependent and may not provide useful results in case of human-robot collaboration.

Physiological behavioural changes during a task are most commonly used for CL measurement. Specifically, changes in the activity of four physiological human organs are used: (i) heart, through heart rate (HR) and heart rate variability (HRV) that can indicate fatigue (physical and mental), (ii) brain, through neurological activity by using an electroencephalogram (EEG), (iii) eyes, through eye movement (e.g. PERCLOS method for measurements), blinking rate or mean pupil diameter change, and (iv) skin, through galvanic skin conductance measurements. Research has shown that reduction in HRV indicates higher CL (Mukherjee et al., 2011), while higher HR activity indicates higher task difficulty, which indicates higher CL (Cranford et al., 2014). Blinking rate decreases in case of increasing mental load (Reilly et al., 2018), while in the same context mean pupil diameter increases (Holland and Tarlow, 1972). EEG theta wave activity increases when CL increases (Gevins et al., 1998); the same activity was reported for galvanic skin conductance measurements (Shu et al., 2007).

With the advancement of technology and machine learning (ML), researchers investigated potential use of ML for CL measurements. Zhang et al., (2007), proposed a support vector machine based method for mental workload classification by using EEG, electrocardiogram and electrooculography signals. Heard et al., (2018), investigated the use of workload assessment algorithms to predict workload levels. Apart from the above techniques, Kumar and Kumar (2019) proposed a methodology of measuring CL by taking into account demographics and the amount of information that the operator processes during a task.

6.2.2 Task Complexity

Complexity can be defined as the interrelation between product variants, task content, workstation layout, tools and support tools, and work instructions. With smart manufacturing and the introduction of robots and I4.0 enabling technologies in the workplace, the complexity and dynamic nature of the processes involved in production increases. To mitigate the effects of task complexity it is necessary to understand the factors involved. Task complexity assessment can increase awareness of the issues, causes and effects (Calinescu et al., 1998). Increased complexity in tasks and production affect quality (Falck et al., 2012), reliability (Grote, 2004), performance (Perona and Miragliotta, 2004) and production time (Urbanic and ElMaraghy, 2006). Moreover, increased task complexity affects the human operator, in both actual task complexity and perceived complexity, which is subjective and is dependent on the individual (Gullander et al., 2011). However, managing complexity can help increase productivity, quality and competitiveness (Samy and ElMaraghy, 2012).

In assembly systems, complexity is further increased due to product designs and processes along with mass customization, which affects the tasks needed to be performed by the operators. Task complexity affects physical and cognitive factors and affect performance and condition of an operator, which may lead to mistakes and human-system error (Kolus et al., 2018). Increased time of completion due to complexity is related to the amount of information the operator needs to process; the more the amount of information, the higher the probability of an error (Panagou et al., 2021). Task complexity variant categories can be defined as:

i. Management induced, related to time perspective, regulations and role,
ii. Subjective, related to task allocation, roles of the human-robot team, processes and functions, and
iii. Objective defined, divided into static and dynamic complexity.

Complexity can be further defined by: (i) task variants, number of variants needed for task processes, (ii) work related content and amount of instructions on how to perform assembly, (iii) workplace layout, concerning stations, handling equipment and ergonomics, (iv) tools and support tools, (v) work instructions, concerning details and usefulness (e.g. daily usage or general information), and (vi) human perspective, concerning general view on task and station and personal preferences. A summary of task complexity variants with effects on operators and final outcomes for the system can be seen in figure 22.

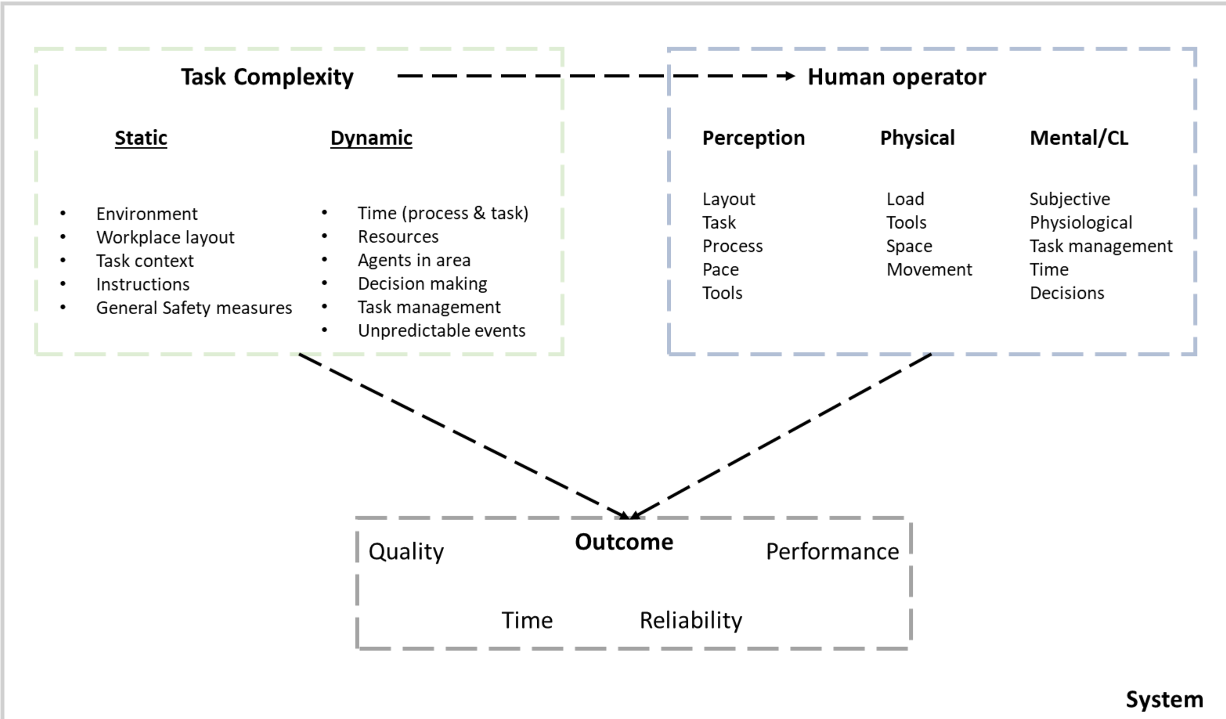


Figure 22. Task complexity variants based on static or dynamic nature and their link with human operator and effect on the system and task.

To measure complexity, the existing methodologies can be divided into two general approaches: through information flow and through computation. Sivadasan et al. (2006) proposed a method focusing on monitoring information flow based on dynamic complexity factors: flow variation, product, reasons and variation states. Urbanic and ElMaraghy (2006) propose a model to measure complexity based on information flow, regarding quantity, diversity and content of information. Meyer and Curley (1993), proposed a computational approach, using knowledge and technology complexity by studying the subjective factors of complexity. Frizelle and Suhov (2001, 2008), proposed a method for complexity calculation through the use of entropy concept. As entropy allows for uncertainty and randomness measurement of a system, Frizelle and Suhov applied it in the production system, regarding the tasks and choices of a station or in the assembly line and system. Zhu et al. (2008) presented their operator choice complexity, which utilizes entropy to measure the uncertainty in stations to calculate the complexity of the system. Falck and Rosenqvist (2012) proposed a complexity tool focused in measuring how high or low is the complexity in method stations of automotive industries as a means to increase productivity and decrease costs. Zeltzer et al. (2013) proposed an objective-based method, CXC, aimed at characterizing the complexity of manual operator workstations. Mattsson et al. (2012, 2014), proposed a complexity measurement method, CXI, based on operators' experience within the system. In this method, a questionnaire is used separated into different sections based on a study by Fässberg et al. (2011).

The smart technologies concept (implementation of advanced technologies, robots and collaboration) benefits manufacturing by offering flexibility, adaptability and productivity. Robots can (i) take over tasks that are physically demanding, and (ii) process data and provide information during tasks due to their programming. However, workplaces are more dynamic in nature, raising complexity which affects operators and their capabilities. In this new workplace environment, operators need to perform their tasks, make decisions on received information and ongoing processes, work with or collaborate with robots and be a safeguard entity in the workplace. Depending on the task complexity, it can result in high mental fatigue and cognitive load, affecting their ability to perform their tasks, which can result in human-system error and impact their safety. An investigation on measurement methodologies for cognitive load and task complexity was performed in order to select the appropriate method for use in the experimental study.

6.3 Experimental study set up and methodologies

6.3.1 Hypothesis and main variables

The investigated scenario of the experimental study was designed along with the industrial partner (automotive industry). The main hypothesis of this study is the following: due to the complex and dynamic nature of HRC, cognitive load is affected which in turn affects the quality of product, task process and human work; cognitive load is correlated with quality. It is important to clarify here that below only the terminologies and main variables are presented and not how they are quantified or measured; those are given later some. The terminologies used in the hypothesis are:

(i) Adaptable assembly lines and product design, refers to manufacturers adapting to market and customers' demands and needs by changing production; this means that product design can change in short-term (e.g. yearly), leading to changes in the assembly line (adaptable), which consequently affects operators as they will need to adapt to the changes fast in order to maintain same or higher productivity level, and

(ii) Quality; the investigated *quality*, is not targeted only on the final product, but also on the process quality during assembly and operators' work quality.

Quality is not an easy quantity to be measured as it is dependent on the sector (e.g. manufacturing or healthcare) and the organization. In healthcare for example, quality is linked with the care provided to the patient, the outcome and the perspective of the patient. For manufacturing, it is linked with the processes, the product and the customers respond to the product. As such, each organization sets quality standards catered to their own needs. However, there are some metrics that can be used to measure quality: reliability, efficiency, security and maintainability. Another way to set up quality measurement are the following steps: i) decide the relevant factors, and ii) determine the measuring method. As the purpose of this experiment was to measure quality of product, process and human work the following metrics were decided:

i. Product quality: For the main product (collaborative assembly), quality was linked with inspecting the final result and (i) is the product finished, and (ii) were the assembly steps followed correctly. For the secondary products (manual assembly) the factors related to quality were the number of scraps and errors made in the finished products.
ii. Process quality: for process quality the important factors that were considered were mishandling of components, collaboration issues, robot downtime due to participants not picking up the delivered component and safety issues (participants moving into the robot moving area or breaking down the robot sequence).
iii. Human work quality, the factors considered were the (i) participant's posture during the experiment, as the guidelines stated a certain procedure to pick up items, and (ii) if participants were having issues performing what was expected of them. The issues mentioned here refers to how they performed the experiment; were they relaxed or were they moving in a fast way indicating they were behind the schedule.

The errors participants made during the experiment, related to process and work quality, were categorized in the following categories:

a) Mishandling components (process related); in this category errors related to components are included, such as not correct handling of components (e.g. during pick up or transfer),

b) Collaboration issues (process related); in this category errors related to working with the robots are included. For example, not following the guidelines correctly which constitute safety concerns, or not comfortable with the cobot, resulting in the component being delivered to fall due to the participant not placed correctly for the delivery,
c) Cobot downtime (process related); this category relates to participants not tending to the cobot when it delivers a component, resulting in the cobot standing in place for more than 5 seconds, and
d) Work related; this category includes errors related to the participant. This includes guideline errors and posture errors from the participants (related to not following instructions on how to perform tasks, pick up components).

(iii)

The main variables that were used for the study are task complexity and cognitive load, while participants' experience and perception on safety and trust on robots were taken into consideration. For task complexity the static and dynamic categorisation was utilised and measurements were taken for the operator's perceived task complexity. The measured task complexity should be high enough to warrant mental fatigue and cognitive load. Moreover, task complexity of subsequent runs should be, almost, the same; this will allow for better investigation of cognitive load and quality issues without altering static complexity variables. The classified factors of static complexity in this study are the following: (i) workplace layout, (ii) task context (product assembly), (iii) Instructions on task and guidelines, (iv) tools and components, (v) agents involved (operator – robot), and (vi) ergonomics. The classified dynamic factors of this study are the following: (i) time (e.g. to complete the process), (ii) agents present in the area, (iii) perceived safety and robot reliability, (iv) decision making, as it is dependent on the operator, and (v) unpredictable events, such as technical issues and errors.

Participants' experience is also classified into the following dimensions:

a) Experience, regarding work related tasks (knowledge and learning process) and familiarity with the task, and
b) Expertise, which is further differentiated into i) technical expertise, familiarity with the task (e.g. working with robots or assembly), ii) maintenance, familiarity with task-related

issues, and iii) collaboration, regarding actual working experience with robots and smart technology.

Participants with different experience and/or expertise, can provide information regarding the task and collaboration from the perspective of an operator. With knowledge gained by performing the experimental tasks, the participants can also provide insight for task design purposes, collaboration and the system in general.

6.3.2 Task complexity and cognitive load experimental framework

Here, the framework developed for the experimental study is presented. It should be noted for clarity, that the methodologies, set up and data gathering methods of the experiment itself will be shown after the framework presentation.

The experimental study was developed with the assistance of the industrial partner and its based on an industrial collaborative assembly process. During an assembly apart from collaboration, operators need to perform secondary tasks. Those secondary tasks can vary from picking another (support) tool necessary to complete a task, pick up components needed for the product (e.g. bolts and screws), log finished processes, or move over to a different area of the workbench for task purposes. Initially the experiment was to be performed in one of the industrial partner's production line with a group of their operators, but due to the COVID-19 situation and the restrictions imposed, it was not feasible. As such, the experiment was performed in the university lab with students as participants. To avoid potential issues due to COVID the university's regulations were strictly followed (e.g. mask and glove use, tests, and thorough cleaning of the workplace area).

The main task of the experiment required from the participants to assemble a product through collaboration with a cobot. In this process, the cobot picks the components (one-by-one) from a designated area (robot pick-up Area), and delivers the components to the operator in the designated collaborative area. The operator then performs the assembly in the designated assembly area. To emulate a real industrial collaborative assembly process, the operators had to perform secondary tasks as well. The secondary tasks involved picking up secondary components from two separate areas; one of these areas was located behind the operator. As such the operator had to turn around to pick the component and then return back to the starting place to finish the secondary task (designated assembly area). The general schematic for the experiment, locations of cobot and participant, and designated areas can be seen in figure 23.

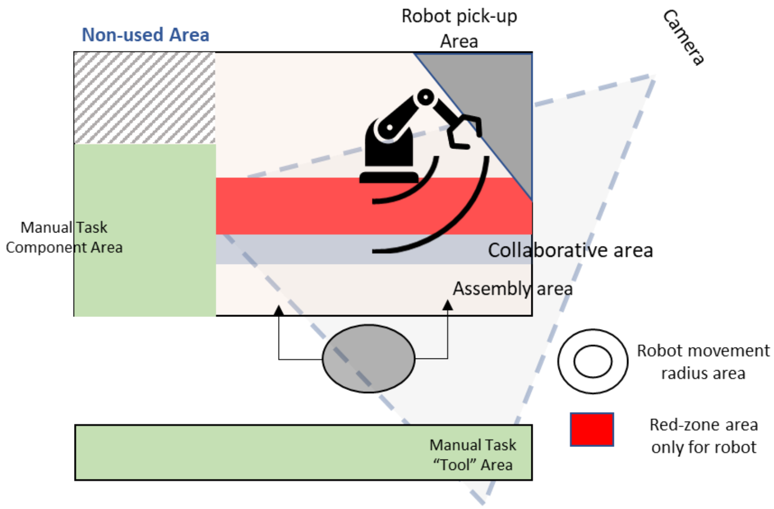


Figure 23. Schematic representation of the experiment along with the designated areas for human, robot and collaboration.

Both main and secondary tasks involve assembly. In both tasks the components consist of different colours and the assembly had to be performed with a specific sequence; the participants were given a detailed description beforehand and were reminded of it before their turn. The differentiation of colours increases task complexity as it requires from the participants to remember the steps and patterns provided to them. The task process can be seen as steps in figure 24.

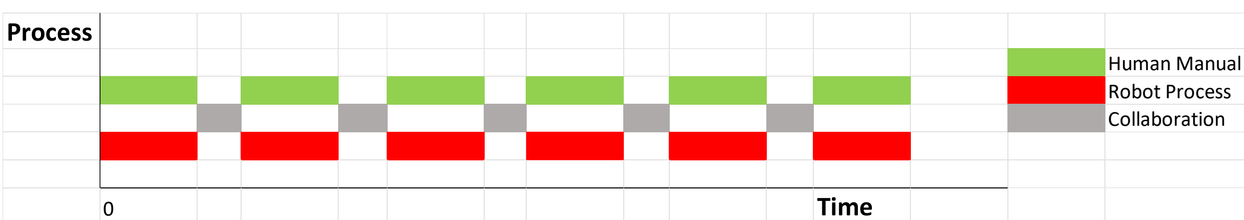


Figure 24. Experimental process over time. The sequence of events between collaboration and human manual and robot process is shown.

The main task involves collaborative product assembly as discussed before. Between the time it takes for the robot to pick a new component and deliver it, the operator performs the secondary task. The operator needs to pick up components from either the area on the left of them or behind them (see figure 23) and perform a manual assembly in the designated assembly area, from shop-orders given to them. Apart from different colours, the components are smaller in size than the components of the main task, requiring precision and careful assembly; further increasing task and complexity. It should be noted that the participants had to attend to the robot and pick up the delivered to them component without delay (no downtime for the robot rule).

6.3.3 Equipment and data collection

The cobot used in this experiment was the Franka Emika Panda (FEP) robot arm. FEP has a powerful and intuitive interface and is adaptable to any task design, as it can be easily programmed through a web interface that comes with it. Moreover, it provides flexibility for grasping objects of various shapes and size, and stable delivery of said objects through a predefined path to its target (Sileo et al., 2021), by using a gripper characterized by parallel fingers, that can exert a maximum force of 100 N. FEP has 7 degrees of freedom in its joints and is equipped with torque sensors in all 7 axes, allowing for more sensitivity in manipulation. In addition, it comes with an external activation device that can be used to stop its movement, at any time, during the execution adding another safety layer in collaboration. For the purposes of the experimental study, the robot motion was programmed by setting the grasping pose for each component of the main task product, placed in the robot pick-up area in a fixed position, and the pose for delivering the component in the collaborative area.

As the purpose of the experimental study was to emulate a real industrial collaborative assembly, it was decided, along with the industrial partner, that the tools and methodologies used to gather data should be non-intrusive to the operator and in accordance with personal data protection laws and regulations of Italy and European Union. Only a camera was used for video purposes that served two purposes: first, video recordings could be of use to recognize errors and quality issues (the approach is explained below) and to monitor the experiment for safety purposes. To gather data related to participants and the experiment they performed, three sets of questionnaires were used along with an interview (provided in the Appendix at the end) at the end of each experimental run (details below).

A Stereo Labs™ ZED-2 stereo camera was used to record the experiment. The video recordings were then used to identify errors and assess quality issues during the process; errors and quality issues were logged in separate fields correlated to the participant. Moreover, each video was analysed in order to estimate and track, in real-time, the 3D human body motion using the MocapNET2 method based on the monocular 2D color (RGB) images of the input video (Qammaz and Argyros, 2021). To estimate the skeletal based pose the following procedure is utilised: a video is a sequence of N images showing the process, and thus, firstly the OpenPose method (Cao et al., 2019) is employed to obtain a set of 2D image coordinates (x,y), that is the locations of 25 skeletal body joints according to the BODY25 pose output model. This procedure is required as the MocapNet2 approach relies on the estimations of the 2D body motion to drive ensembles of Deep Neural Networks that are able to efficiently regress a view-invariant skeleton-based body pose in 3D space. Moreover, the hierarchy of the 3D skeletal body model is split into the upper and the lower body parts that are estimated independently, in order to tackle cases where the presence of severe and possibly long-term occlusions of the human body deteriorates the quality of estimation and tracking of the human poses. The output of the MocapNet2 method is a Biovision Hierarchy (BVH) character animation file format (Meredith and Maddock, 2001) representing the estimated 3D human motion observed in the input image sequence. For each input image, the estimated 3D human pose comprises the 3D location and orientation of 25 main body joints (including the base/middle/upper of spine, neck, head and both left and right shoulder, elbow, wrist, hand, tip of hand, thumb, hip, knee, ankle and foot). This rich information can then be used to estimate the human body orientation through skeletal tracking, to perform physical (posture-based) ergonomics analysis, estimate reactions and analyse further considerations related to human motion and physical condition. The information drawn from this procedure in relation to the experimental study were body posture, issues occurred during the experimental process and errors participants made.

The questionnaires covered three areas: general information related to the participant, perceived task complexity and cognitive load. In the general information questionnaire, the participants had to fill information on their study subject, prior experience with robots, comfort and trust level on robots and technology and questions on their view on robots. The task complexity questionnaire was based on the CXI index by Mattsson et al. (2012). This questionnaire allowed investigation of perceived complexity by dividing the experiment into six separate categories for investigation: product complexity, work related complexity, station and layout related complexity, complexity of HRC, complexity added by the instructions and general complexity (two questions). For this questionnaire the participants had to answer questions (22 in total) based on those complexity categories using a Likert scale (1-10). For cognitive load, the participants had to complete the NASA-TLX questionnaire (Hart, 2006), which utilizes Likert scale (1-10 for this experiment) and divides cognitive load into the following areas: mental demand, physical demand, frustration, temporal demand and performance.

6.3.4 Experimental methods

The experimental framework and processes involved are presented here; from participant selection up to the final task. As the experiment was performed in the university of Basilicata, students from the schools of Engineering and Computer Science were asked to volunteer. Students were shown a presentation of the study and were then asked at the end to read a form of interest that included details of the study, data gathered from them and what is expected. Students that wanted to partake in the experiment had to express their consent and agreement.

A total of 28 participants volunteered for the experiment from the schools of engineering and computer science of University of Basilicata. While all participants performed the first task run, only 23 of them performed the second run due to COVID-19 reasons. As such, and it was decided to use only the data for those 23 participants for the final results, 17 male and 6 female students. The level of education of participants ranged from bachelor level to PhD; 3 in bachelor, 14 in their master studies, 3 in between PhD study, and 3 researchers. Next step included sending to the participants a guideline and general information file, that included a description of the study, questionnaires (purpose and how to fill them) and collaboration. Along with this file, the participants were sent the general questionnaire to complete.

The participants had to perform the procedure two separate times (run 1 and run 2). Each run was identical in purpose, context, workplace (layout and environment) and tasks. The main task involved collaboration with a robot to assemble a product (figure 25) using LEGO pieces. To pick up the object delivered by the cobot, the participants needed to use the button on the upper part of the cobot arm, so that the gripper would release the component and the task can continue. The release actions must be performed when the robot is out of its “executing task” mode. The participants were aware of the robot’s mode by checking the lights on its base that indicate its status. Interaction must happen under blue light status and there must not be any interaction when the status is green (“executing task”). The participant could only assembly in the dedicated assembly area and interact with the robot in the dedicated collaborative area. Movements towards the main robot parts was designated as a red zone, for collision avoidance and safety reasons; to ensure safety in case a participant moved into the red zone two measures were put in place: (i) the researchers could stop the cobot manually in case of safety risk and red zone overlap, and (ii) a programmed collision avoidance system.

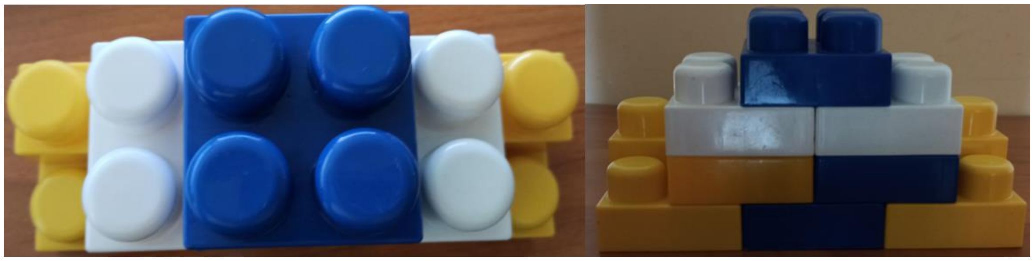
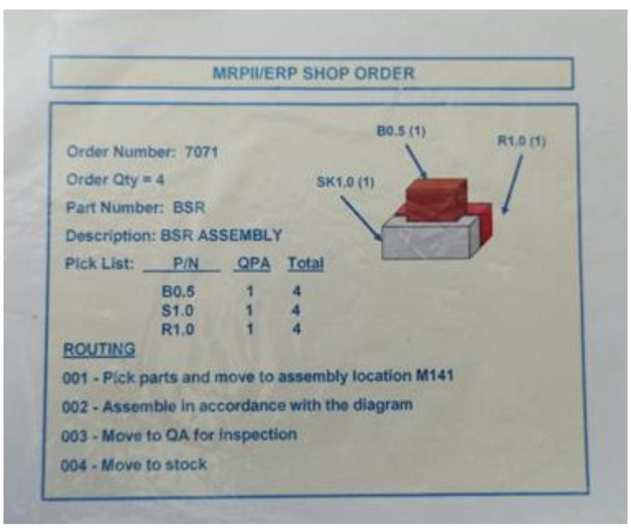


Figure 25. Participants had to assembly this 'product' through collaboration with the robot.

During the waiting period between cobot picking a component and delivering it, the participants had to assemble secondary products, with instructions given to them in the form of shop-orders, (figure 26); the purpose was to emulate an operator performing secondary tasks (e.g. moving to pick a tool, or sub-variant components like bolts and screws). The participants were given a number of shop-orders that they had to complete before the final component of the main product was delivered to them by the cobot. The shop-orders were available and in front of the participants during both runs.



MRPII/ERP SHOP ORDER

Order Number: 7071
Order Qty = 4
Part Number: BSR
Description: BSR ASSEMBLY
Pick List:

P/N	QPA	Total
B0.5	1	4
S1.0	1	4
R1.0	1	4

ROUTING
001 - Pick parts and move to assembly location M141
002 - Assemble in accordance with the diagram
003 - Move to QA for inspection
004 - Move to stock

Figure 26. One of the shop orders given to the participants to perform. In total participants had to complete manually six different shop orders.

When each participant finished their run they were asked to fill the task complexity questionnaire and NASA-TLX for cognitive load. After the questionnaires, the participants had to answer four questions in a small interview regarding the following:

i. What they believe is the main cause of any errors they made during the task,
ii. What is their thought on collaboration with a cobot,
iii. How did they perceive the tasks in terms of difficulty or demands, and
iv. Did they believe they had enough time to perform the tasks and why.

In this section the experimental tasks and data gathering processes were discussed. In the next section the results from the experiment are presented.

6.4 Experimental study results

At the start of the experimental study the participants completed the general questionnaire. Only 4 participants had prior experience with robots, but not related to collaboration. All participants answered that they trust technology and robots, with only 4 of them expressing mild concerns depending on the context; 2 of them were concerned with robots assisting in a surgery, and 2 were concerned with collaboration. In the matter of comfort, 4 of them expressed some discomfort in working with a robot, while the rest answered that they will be comfortable. In the question if they perceive robots as a threat or an opportunity for humans, 19 participants view them as opportunity, 3 either way depending on the scenario they are used, while 1 answered that robots are both a threat and opportunity.

With the general questionnaire done, the next step was to perform the experiment. The experiment was performed in the AREA (Automation, Robotics and Applied Electromagnetism) laboratory in the university of Basilicata. The participants had to perform two runs of the experimental task and in accordance with the regulations, the participants had to wear a mask at all times and were given gloves to perform the task. The participants were divided into two groups and performed the experimental runs on different days. This space between the groups and experimental runs, was used to thoroughly clean the components and areas used during the experiment. Before each participant performed their task, they were given a presentation on how to perform the task and guidelines. Moreover, they were shown how to collaborate with the robot and were able to train with it. The total amount of time allotted for this activity was 10 minutes.

Participants had to assemble the main product (collaborative assembly) following the procedure given to them in form of instructions when they volunteered (figure 27), and also explained to them right before performing the experiment. In addition they had to assemble manually secondary products from shop-orders, given to them before the experiment. The participants were given enough time to understand how to assemble them before performing the experiment.

Figure 27. Collaborative product assembly divided into three separate levels as given to the participants in the instructions.

After a participant finished performing the experiment, a visual inspection on both main and secondary products was performed to check for errors in assembly or other issues. In addition, a further inspection was performed on the recordings taken during the experiment, to observe errors and other issues for each participant. After each run, the participants had to complete the task complexity and NASA-TLX questionnaires and take part in an interview on their thoughts and perception on the experiment, collaboration/teamwork and issues they faced.

6.4.1 Task complexity

The hypothesis for task complexity was that it will be the same or almost the same in both runs. This was in accordance with emulating an industrial assembly line, as operators perform the same tasks and processes without changes in between days. For this experimental study the CXI index was selected for perceived task complexity measurements as it divided task complexity into six major categories and as such, it allows for in depth investigation in case there were large differences between the first and second run. Figure 28 shows the results of the task complexity questionnaire the participants had to complete after each run. For the first run, the overall CXI index was 5.08, while for the second run was 4.82.

Although the difference between the two runs is not that large (0.27), the results showed there are also three subcategories of task complexity (collaboration, instructions and general) that increased in the second run, and also a larger, than the other categories, difference in work complexity category (0.78). As such, statistical analysis was performed to investigate the possibility of significant difference between the two runs in those categories. The t-test analysis showed no significant difference (lower than 0.05) and as such the hypothesis for task complexity can be accepted.

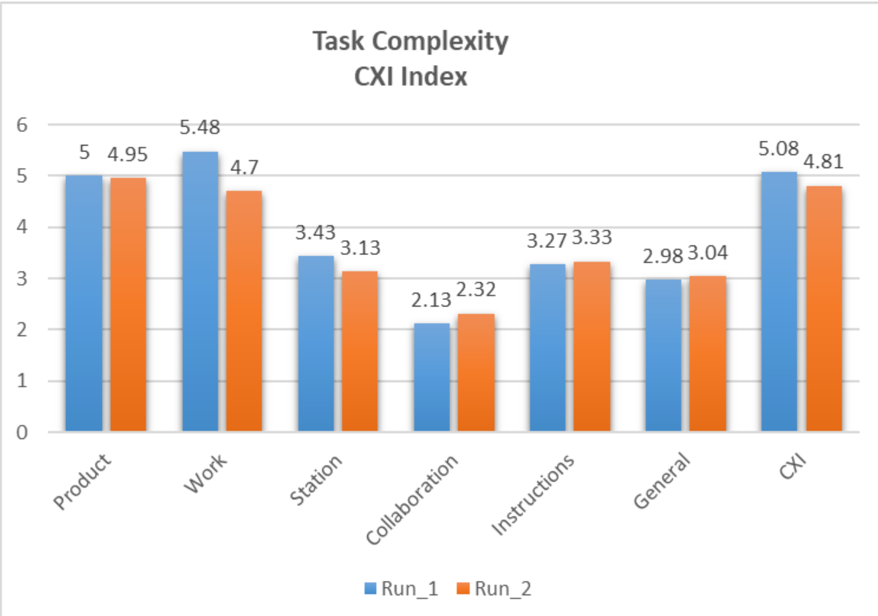


Figure 28. Average value for CXI indices for runs 1 and 2.

6.4.2 Cognitive Load

In order to investigate the main hypothesis (H0) that cognitive load affects quality, a secondary hypothesis was made for cognitive load. Due to knowledge gained and experience (learning effect) from the first run, cognitive load of the second run should be lower than the first one (H1). As stated before, the participants had to complete the NASA-TLX questionnaire after each run. NASA-TLX utilizes Likert scale (here the 1-10 scale was used) and divides the factors influencing cognitive load into six categories: mental demand, physical demand, frustration, temporal demand, performance and effort. Apart from the Likert scale, the participants were asked to answer 15 questions. In each question the participants had to choose one of the two categories; those answers were then used to assign weights to the categories. With the questionnaire and the weights filled, the cognitive load can then be calculated.

Table 8 shows the calculated cognitive load for each participant, and the mean average cognitive load, for both runs. Although it was expected that cognitive load will be lower in the second run due to the learning effect (H1), results show an increase in the second run. This is shown both in the individual scores and the mean average cognitive load. As such, a look into individual cognitive load categories is needed to see if this is a general issue in all of them or there are individual categories that showcase the issue.

Table 8. Cognitive Load scores for each individual participant for both experimental runs, along with the average score of each run.

	Cognitive Load	
ID	**Run_1**	**Run_2**
1	45	65
4	40	55
5	42	64
6	42	63
9	66	55
10	56	57
12	49	55
13	67	65
14	40	73
15	42	29
16	37	26
17	85	91
18	58	69
19	52	23
20	23	39
21	68	68
22	55	23
23	64	60
24	61	53
25	49	53
26	56	53
27	71	73
28	49	46
M.Avg	53	55

In figure 29 the categories average score for both runs is shown along with the standard deviation and the weights average score. From the mean average it can be seen that physical demand, frustration and temporal demand show an increase on the second run. However, as the physical demand weight score is lower than 1 (from a maximum of 5 points), it can be considered as not significant in the final score. As such, an analysis on frustration and temporal demand is needed to investigate if there is any statistical significance for those categories and the impact on cognitive load between the experimental runs.

	Standard Deviation		**Mean Average**		**Weights**
Category	*Run_1*	*Run_2*	*Run_1*	*Run_2*	*Average*
Mental	11.92	10.91	10.04	17.13	3.21
Physical	2.36	2.94	1.39	1.56	0.56
Frustration	8.72	9.79	9	10.78	2
Temporal	11.67	13.26	24.56	29.48	4.13
Performance	11.32	10.652432	20.48	19.26	3.91
Effort	3.4	2.5	4.3	3.65	1.21

Figure 29. Standard deviation, mean average and weights score for each NASA-TLX category.

Frustration category had an average weight score of 2, with a calculated mean average of 9 for run_1 and 10.78 for run_2, and standard deviation of 8.72 for run_1 and 9.79 for run_2. The normal distribution and boxplot graphs were plotted (figure 30) and statistical tests (ANOVA and paired samples t-test) were performed with the hypothesis that there is significant difference between the two runs. The results of the ANOVA test show a p-value of 0.54, and for the paired samples t-test show a p-value of 0.38. As the p-value is larger than the alpha value of 0.05 the hypothesis that there is significant difference can be rejected.

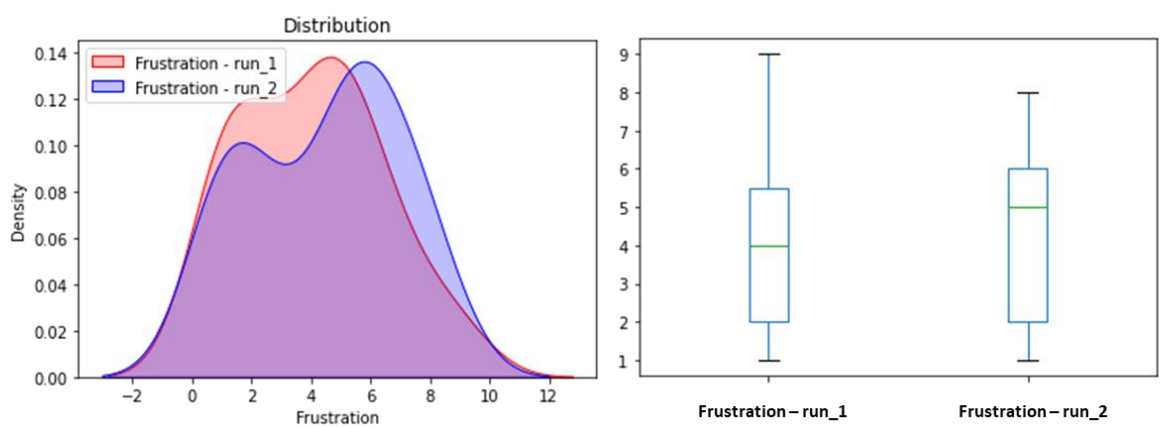


Figure 30. Left: Distribution of Frustration category over both runs. Right: Box plots for frustration after statistical analysis.

Temporal category had the highest average weight score of 4.13. This score provides an indication that the temporal demand of the robot was an issue for the participants. The mean average of run_1 was 24.56 and for run_2 was 29.48. Standard deviation for run_1 was 11.67 and 13.26 for run_2.

Normal distribution and boxplot graphs were plotted (figure 31) and again statistical tests were performed, same as in frustration category, with the hypothesis that there is significant difference between the two runs. The p-value for ANOVA test is 0.08, while for the paired samples t-test the p-value is 0.007. As the values do not 'agree' (one above alpha value and the other below), another statistical test was used. Firstly, the f-statistic value was calculated as a means to assess the variability between the two runs. F-statistic value is 3.04 and confirms the variability between the two runs, as it is larger than 1. The Wilcoxon paired samples test (Wilcoxon, 1945), a nonparametric statistical test, was then selected to further test the hypothesis. Wilcoxon test advantage is that it makes use of the magnitude of differences rather than just the value. Results of the test show a p-value of 0.01, and as such the hypothesis is accepted, which shows significant difference between run_1 and run_2 for temporal value.

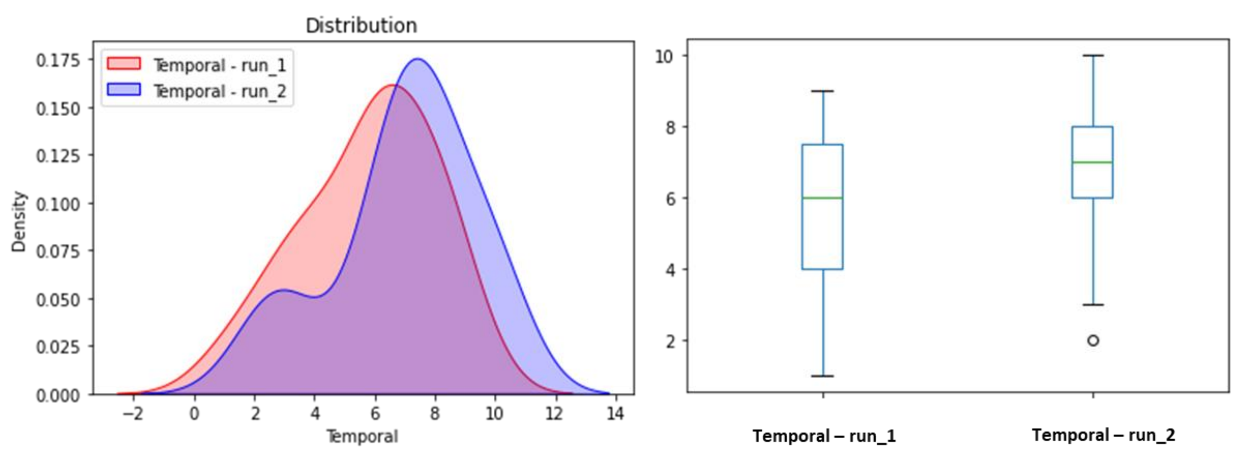


Figure 31. Left: Distribution of temporal category over both runs. Right: Box plots for temporal value after statistical analysis.

As a final remark, the H1 hypothesis that cognitive load will be lower in the second run due to the learning effect was rejected, as cognitive load was increased (53 in run_1 and 55 in run_2) and there was significant different in the temporal value. This prompted an in-depth analysis on the categories used in the NASA-TLX questionnaire. The analysis showed that temporal demand was the significant factor of the issues faced by the participants which affected the overall cognitive load.

6.4.3 Quality

Table 9. Participants information related to collaborative and secondary task. 1 shows that participants made an error, while 0 shows that participants performed the respective task correctly. Green colour show that the participant performed better in the second run, while grey show that participant performed worse in the second run.

	Collaborative Task		Secondary Task	
ID	**Run_1**	**Run_2**	**Run_1**	**Run_2**
1	0	1	0	1
4	x	1	1	1
5	0	0	1	1
6	0	0	1	1
9	x	1	0	1
10	0	0	1	1
12	0	0	1	1
13	x	0	1	1
14	x	0	1	1
15	0	0	1	1
16	0	0	1	0
17	0	0	1	1
18	0	0	1	1
19	0	0	1	0
20	0	0	1	0
21	0	0	1	1
22	0	0	1	1
23	0	0	1	1
24	0	0	1	1
25	0	1	1	0
26	1	0	1	1
27	1	1	1	1
28	1	0	1	1
Total	7	5	21	19

The hypothesis related to quality is that in the second run, all or most of participants will complete the experiment with fewer or with no errors/mistakes and thus the overall quality will be improved. In the context of product quality, in the first run 4 of the participants did not finish the collaborative product. The participants triggered the collision avoidance mechanisms of the cobot due to them either not waiting for the cobot to get into position or not using the mechanism to release the component correctly. In both cases, if this issue happened only once, the participant was allowed to redo the task, otherwise they had to stop and move on to the next stage of the experiment (questionnaires and interview). Table 9 shows the results for both collaborative and secondary task (product assembly) in respect to which of the participants made a mistake/error. In the first run of the collaborative task, apart from the four that did not finish, only 3 participants made an error (for a total of 7 participants), while in the second run, 5 participants made an error. For the secondary task, 2 and 4 participants did not make a mistake in the first and second run respectively.

Video recordings were used to investigate the process and human work related issues and errors. Table 10 summarises the results of the investigation. Most common issues for the participants were mishandling the components, either from dropping them or from misuse (handling both main and secondary components at the same time), and work related issues (e.g. bad posture during assembly). Although in the second run, the number of mishandling and collaboration issues were almost the same, cobot downtime and work related issues were fewer than the first run. This result can indicate that participants became more familiar with the task and what was expected from them.

Based on the results of the error investigation, quality can be considered not optimal as what was expected from the hypothesis that in the second run the overall errors will be close to none. In the context of product quality, 18 out of 23 (78%) participants finished the collaborative assembly, however only 4 (17%) finished the secondary tasks (manual assembly). For process quality only one category was improved in the second run and is related with the cobot downtime issue. Although in the other two categories, mishandling and collaboration issues, the number of participants that made mistakes were low in both runs (8 and 7 for mishandling, 4 and 5 for collaboration issue), there was no improvement. For work related issues, in the second run only 11 (47%) of the participants performed the experiment with no issues.

The lack of improvement in all three category related issues, results in rejecting the hypothesis related to quality and indicates the need to investigate the root cause. From the cognitive load results, temporal demand seems to be a reason for the participants errors during the experiment. The next step was to analyse the participants' answers during the interview, that were centered on finding the participants' perception on the experiment, collaboration/teamwork and the issues they faced.

Table 10. Table shows if and in which error category participants made an error for both experimental runs. At the end the total

number of participants is calculated. A legend is provided to link symbols with the error category.

	Run_1				Run_2				M	Mishandling
ID	*M*	*C.I*	*C.D*	*W.R*	*M*	*C.I*	*C.D*	*W.R*	C.I	Collaboration Issues
1	x	x		x		x			C.D	Cobot Downtime
4	x		x	x	x				W.R	Work Related
5				x		x				
6	x	x		x	x					
9	x		x	x		x		x		
10				x				x		
12			x	x	x	x		x		
13										
14				x				x		
15										
16	x			x	x			x		
17			x	x			x	x		
18				x				x		
19	x	x			x					
20	x		x	x	x			x		
21										
22	x	x		x				x		
23				x	x			x		
24										
25						x				
26				x				x		
27				x				x		
28										
Total	8	4	5	16	7	5	1	12		

6.4.4 Interview results

The interview was the final task of the experiment and the questions were formulated using the results of the scoping review on robot design features effects on operators. The participants had to answer five questions related to their perception on the collaboration, their level of comfort during the experiment, issues they faced on the experiment and if their view on robots changed after collaborating with one of them.

For the view on robotics, in the general questionnaire that participants had to fill at the start of the experiment, all of the participants answered that they trust robots and will not have an issue collaborating with one. The results of the interview show that no participant changed their perception on robots after the experiment. On the same topic, all participant stated that they viewed the collaboration as beneficial, in general, for completing the task and they were comfortable with robots as the experiment progressed.

However, participants stated that the main issue they faced and resulted in errors and mistakes (per their perception) was lack of time to complete their tasks. Firstly, they were not sure if they have time to perform the secondary assembly. The reason for that issue was that they were unsure of when the cobot would arrive at the collaboration zone. This resulted in confusion and slow decision making, which further resulted in mishandling components, assembly mistakes and task management issues. Although the assembly steps were not complex, they felt they had to rush to complete the products, resulting in task management issues.

During the interview, the participants were also asked what would they change in the collaboration and task design to improve it, in relation to their experience with the experiment and collaboration. The participants were positive with collaboration, however indicated that more training with robots and time to perform the tasks will be beneficial for better experience and performance.

6.4.5 Experimental hypothesis (H0) result

As stated the main hypothesis of the experimental study was that cognitive load affects quality of product, process and human work. The cognitive load results section shows that while cognitive load was almost the same in both runs (average of 53 in run_1, 55 in run_2), the temporal demand factor of cognitive load was increased in the second run and statistical tests showed significant difference from the first run. For quality, the error analysis in both experimental runs showed errors in all aspects of investigated quality (product, process and human work) and also showed no improvement in the second run; participants made the same amount mistakes as they did in the first run. During the interviews, participants stated that temporal demand of the task was high and it impacted their performance and decision making; this created issues in performing the secondary tasks as they were unsure how much time they had before the cobot was in place for component delivery. The results show that temporal demand impacted cognitive load and decision making which in turn impacted performance and resulted in errors/issues, thus impacting quality. This result also provides an indication that cognitive load affects quality and that there is a correlation between them. Thus, the hypothesis H0 is accepted and in conclusion it validates the experimental framework developed. As such, future expanded experimental tests can be performed in a real industrial scenario with larger participation.

6.5 Experimental study discussion

An experimental study was designed, with the support of the industrial partner, as a means to investigate the outcomes of robot design features on operators in collaborative scenarios. In both previous research activities, the mental fatigue and cognitive load were of interest due to the consequences in task performing, decision making, errors and safety risks. As such, the main hypothesis for the study was that there is a correlation between cognitive load and quality of product, process and human work. A review was performed on cognitive load and task complexity measurements as to choose the methodologies that are in line with the aims of this experiment.

The study targeted the collaborative assembly scenario and the tasks designed were in accordance with an industrial scenario. The main task involved a collaborative assembly while the secondary tasks involved manual assembly as a way to emulate the secondary tasks performed by operators in industrial assembly lines. For data gathering purposes, participants had to fill three questionnaires related to general topics (e.g. experience with robots, trust in robots, comfort), task complexity and cognitive load (NASA-TLX questionnaire). Moreover, they had to answer five more questions in an interview after each experimental run. Apart from the questionnaires, a stereo video camera was used to record the experiment, and the recordings were then inspected for issues and errors for each participant. After each experimental run, a visual inspection on the finished (and/or unfinished) products was performed to collect information for quality purposes.

The results show that task complexity remained almost the same between the two experimental runs, which was the purpose. Cognitive load was increased in the second run. An investigation on the questionnaire answers showed that temporal demand and frustration were higher on the second run. From the statistical analysis, temporal demand showed significant difference while frustration did not. For quality purposes, it was expected that there would be fewer issues and errors in the second run as the participants had some experience and understanding of the tasks they had to perform (learning effect). However, the error analysis shows almost no difference between the two experimental runs. In the interview participants stated that although the cobot had a positive influence in the collaboration, the time they had to perform their tasks was not enough. This lack of time resulted in them not knowing in what order to perform their tasks (task management), resulting in confusion at times (seen also from the video recordings), and slow decision making.

The results shown an indication of the correlation between cognitive load and quality and as such, the hypothesis is accepted. Potential solutions were identified, such as involving operators in the task design phase as to give their opinion based on their expertise, more training with their robot co-worker as to learn the task procedures, and implement direct communication methods between operator and robot to increase efficiency. The next step of the experimental study is to perform in an industrial assembly line with participants with different set of skills, expertise and experience working with robots.

The experimental study concludes the work performed and presented here (figure 32). As such, the next chapter includes the final discussion along with conclusions and possible future directions of this work.

3rd Research Activity - Output

- Panagou S., Fruggiero F., Mancusi F., 2022, *A methodological framework to assess mental fatigue in assembly lines with a collaborative robot,* LNME
- Mancusi F., Fruggiero F., *Panagou S.*, 2022, *A cloud-aided remanufacturing framework to assess the relative complexity,* IFAC-PapersOnLine, 55(10)
- Panagou S., Fruggiero F., Iannone R., Gnoni M.G., 2022, *The CACTUS approach: Organizational approach for sustainability*
- Panagou S., Sileo M., Papoutsakis K., Fruggiero F., Qammaz A., Argyros A., 2023, *Complexity based investigation in collaborative assembly scenarios via non intrusive techniques, Procedia Computer Science, 217, pp.478-485*

Figure 32. Publication output of 3rd Research Activity.

7. Conclusion & Future Directions

This section includes the conclusion of the presented work. The following subsection discusses and concludes the steps that were taken and research activities performed, to fulfil the research aim. In the end an outlook on possible future research directions is given.

7.1 Discussion

The initial aim of this work initial was to investigate the effects on operators in the smart manufacturing era introduced by I4.0 and I5.0 and human robot collaboration. Moreover, it aimed in identifying guidelines for possible solution both in workplace context and design (table 11). As such, the initial search on the status of operators in the new environment, showed that there is a disconnection between industrial and robotics engineering and human factors. Thus, the first review was targeted on operators' cognitive load in collaboration scenarios and the mapping of said scenarios (Fruggiero et al., 2020). The results of this review assisted in proceeding with the research activities based on the main aim. It also focused the thesis on mental fatigue and cognitive load of operators in collaborative scenarios.

Table 11. Potential design guidelines/advice identified through research activity, and the linked HRI system factors.

Design guideline/advice for human-centric HRI		
Research activity I	Smart technologies for human support	
	Accommodate operators in workplace relevant to their skills, knowledge and experience	
Research activity II	Involve operators in implementation and layout for HRI/C task & workplace design	Reliability, safety, comfort, work quality
	Improve training for HRI task processes	Team cohesion, safety
	Improve knowledge of operators regarding capabilities and functions of their robot co-worker	Safety, reliability, trust
Research activity III	Involve operators to improve task processes in collaboration	Quality, decision making
	More training for collaborative tasks	Reduce errors, quality

A literature review was then performed to investigate the effects of workplace changes, due to the introduction of smart technologies and robots, on operators' capabilities. Although smart technologies can benefit organizations and operators alike, by improving performance and productivity, or through alleviating operators from physical demanding tasks, it also creates a complex and dynamic environment. The analysis on the identified scientific articles for this literature search showed that operators need to improve their skills in preparation for the challenges created, which can be taxing to older operators since their capabilities diminish as they age. As such, a model was proposed to measure the probability of human-system error (Panagou et al., 2021). This model is based on the view that operators are a natural system with four macro states. The macro states used are behavioural, mental, physical and psychosocial states, with each one having its own parameters and traits. With the help of those states the model can be used for collaborative scenarios to identify in which areas an operator has issues or will have issues and thus, supportive actions can be introduced for them, such as assist with more training, improve skills or introduce tools or systems (e.g. sensors or supportive robot tools). The validation of the probabilistic model was then explored through an experimental test in collaborative scenarios (Panagou et al., 2021).

The results of the review on workplace changes and their effects on operators along with the probabilistic model, showed the need to explore the human robot interaction and collaboration. As such, a scoping review was performed to investigate the effects and outcomes of robot design features on operators. The analysis on the identified scientific literature showed the many-to-many relationships between robot design features and effects on operators. A further analysis showed the outcomes of those effects, namely (i) the perceived safety in collaborative scenarios, (ii) perceived reliability of robots, (iii) team cohesion, (ii) comfort and discomfort of operators working with robots, and (iii) human quality of work. The analysis allowed to identify directions on how to approach HRC from a design perspective. Example of those directions are the following: (i) operators' involvement in the design phase or control and planning phase for perceived safety and reliability, and team cohesion, (ii) training with robots for HRI or HRC scenarios for team cohesion, quality and safety and also when changes are implemented either in the workplace or in the robots' capabilities. Moreover, in line with the call for human centric workplace of I5.0 framework, robots' features should be designed with the operators in mind. For example, robots' vision through sensors can be enhanced to monitor operators and react in case of critical situations.

The results of both literature reviews were then used to develop an experimental study along with the help of the industrial partner. The formulated hypothesis of this experimental study, was that due to the changes in the workplace and human robot collaboration, the cognitive load of operators affects quality of product, process and human work. In the experimental study, participants had to work with a cobot to assemble a product (collaborative assemble), while also performing other tasks (secondary tasks, manual assembly). The participants had to fill a general questionnaire before the experimental tasks, which revolved around their perception of robots, trust and comfort working with robots. As the participants had to perform the experimental tasks in two separate runs, after each run they had to fill two more questionnaires, one regarding perceived task complexity and the other perceived cognitive load. Finally they had to participate in an interview, where they answered questions revolved around collaboration, the task and the issues they faced. The results of this experimental task showed that although the participants felt that the collaboration was beneficial, the temporal demand factor of the cognitive load was the main issue. From both the NASA-TLX questionnaire for cognitive load and interview, the temporal value was identified as the main reason for the issues created in task management and decision making which in turn was the root cause of the errors made during the experiment. Thus, the hypothesis that there is a correlation between cognitive load and quality was accepted.

7.2 Conclusion

The research planned during this work was performed in order to fulfil the requirements of this work. As discussed, the main aim was to investigate the effects of smart manufacturing and collaboration on operators and investigate guidelines and possible solutions. The first and second activity fulfilled the requirement of investigating the effects, while the third activity was focused on the issues operators face in HRC to investigate the root cause which can then be used to identify possible solutions. The main outputs of this work are the following. From the investigation of workplace changes effects on operators, a probabilistic model was developed and tested in order to measure the error probability based on operator’s condition in smart manufacturing (Panagou et al., 2021). This model can be used to identify the areas where operators need to be supported (e.g. training or skill improvement). The scoping review (second research activity) on robot design features effects on operators in HRI resulted in identifying probable design guidelines based on human and robot capabilities and characteristics. Through the results of the scoping review, there were two additional outputs. In the first one, the communication between human and robot during collaboration was investigated; a simple hand gesture model was developed and tested in a collaborative scenario (Panagou et al., 2022a). The second one involved the use of Digital Twins and machine learning to investigate how the use of those methods can improve decision-making of operators and management for predictive maintenance purposes (Panagou et al., 2022b). The results of the experimental study (third research activity) identified an issue that operators face with collaboration. The temporal demand of collaboration creates issues in task management and decision making processes, which in turn results in mistakes and thus lowers the quality. Here, probable solutions can be to improve task design with input from operators, and also task training as a means to minimize human-system error. It needs to be stated that an expanded experiment in real industrial collaborative assembly scenarios with operators could provide more insights into further issues and solutions. However, the experiment achieved in identifying a root cause of the issues that operators face and allowed for a better understanding on what operators face when they are asked to perform collaborative tasks.

As a final note, the results of this work are in line with the main aim. The changes of the workplace in relation to operators were mapped. Human robot collaboration was identified to have effects on operators due to the close proximity between human and robot, and the changes it brings to the task procedures. As such, the effects of robot design features on operators were investigated. From this investigation the outcomes on operators for task purposes were identified. An experimental study was developed to investigate those outcomes in a collaborative assembly scenario. The results of the study show that the changes in task complexity and management due to HRC impact cognitive load and in turn the quality in the workplace. Moreover, the experimental results showed that temporal demand in collaboration is the one most affecting operators and as such solutions were identified from the interview with the participants stating that more training and better time allocation is needed for successful collaboration. However, the limitations of this study should be noted as well to help in further investigation. In the scoping review, the investigation was limited to peer-reviewed articles that discusses HRI system for manufacturing and industrial settings and excluded most of medical, social and other sectors. An investigation including them could potentially reveal useful information. The experimental study was performed in the laboratory, due to the recent COVID-19 pandemic, with university students as participants, which helped understand the issues inexperienced participants face with collaboration. However, this limited the results on inexperienced operators and an investigation with experienced operators that have knowledge on industrial tasks and processes can potentially reveal separate and more detailed information on issues for experienced operators.

As such, the aim of this work was reached and this work is concluded with possible future directions.

7.3 Future Direction

This section provides an outlook for future direction of this work. The directions are focused on the results of all three research activities focused not only in assembly but also in other sectors, such as remanufacturing with disassembly scenarios, predictive maintenance and logistics and warehouse management.

1. *Dynamic learning between human and robot*

One aspect that can increase team cohesion, quality and safety is for both humans and robots to actively learn during work tasks. Although the concept of reciprocal learning exists (Nixdorf et al., 2022), it is not used for active learning during tasks. As such, dynamic learning can be beneficial as operators and robots can both learn from each other in order to adjust their approach and work techniques during work. It can also be applied for safety reasons in parallel with collision avoidance, as it will allow the robot and human to be able not to only to react to situations but also be more proactive to avoid critical situations.

2. *Experimental studies on industrial collaborative settings*

Being able to observe and collect data during work-shifts in multiple arrangements and scenarios, could better help in understanding issues and identifying their root causes. This activity can support developing guidelines and solutions from involving experience operators to provide their insights by including them in the procedures.

3. *Evaluation of human robot collaboration in different scenarios*

This work was focused on collaborative assembly scenarios and as such, it creates the need to investigate HRC in different context. For example, healthcare and robots, warehouse logistics, and social settings. This could improve knowledge in general, allowing for a better understanding of the effects of robots on human, and for insights on design guidelines.

4. *Research activity in human-multi robot collaboration*

The effects of working with multiple robots should be explored as it can be beneficial in many scenarios, such as in warehouse logistics where multiple robots are already used and interact with operators. As such, the concept of physical collaboration of multiple robots with operators to perform tasks should be explored, as it can benefit both performance and the operators.

5. *Remanufacturing and HRC*

This is in accordance with the circular economy model of I5.0. Here, investigation on optimizing the HRC on disassembly and returned product condition can benefit the overall process minimizing time, waste and lost material.

6. *Long-term study on adaptable assembly lines and effects*

As manufacturers look towards adaptable assembly line and product design, operators will have to also adapt to the changes in shorter time frames (e.g. changes every year). This will affect operators as they will have to learn each time a new procedure and adapt to the changes. This can probably affect the learning rate, as they will need to continuously change the learning target. As such, an investigation in this case could provide information on those effects and issues created by this strategy.

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Appendix

1. TASK COMPLEXITY QUESTIONNAIRE

TASK COMPLEXITY ID: ____________

Questo questionario è progettato con lo scopo di valutare la complessità del compito. La complessità in generale, caratterizza il comportamento di un sistema o di un'attività i cui componenti interagiscono in più modi e seguono regole locali che non sono definite da una regola o da un agente esterno. La complessità del compito coinvolge il prodotto, il lavoro necessario per eseguire l'assemblaggio, le domande relative all'ambiente in cui è stata eseguita l'attività, gli strumenti, le istruzioni e le informazioni ricevute prima dell'attività, le domande generali relative all'attività e infine è possibile lasciare commenti e raccomandazioni sull'attività. I quesiti sono valutati tra Completamente in disaccordo (0) e Completamente d'accordo (10). Grazie per la tua partecipazione!

1. Complessità correlata al prodotto

1. Ci sono vari component del prodotto nell'ambiente di lavoro (che sono o non sono necessari nell'assieme)

1	2	3	4	5	6	7	8	9	10
Completamente d'accordo								Completamente non d'accordo	

2. Ci sono componenti nell'ambiente di lavoro che sono simili e possono essere utilizzati allo stesso modo (che provocano confusione)

1	2	3	4	5	6	7	8	9	10
Completamente d'accordo								Completamente non d'accordo	

3. Ci sono componenti che non sono necessari per l'attività

1	2	3	4	5	6	7	8	9	10
Completamente d'accordo								Completamente non d'accordo	

4. Ci sono molti oggetti diversi nell'ambiente di lavoro (componenti di attività, strumenti, componenti, specifici del robot)

1	2	3	4	5	6	7	8	9	10
Completamente d'accordo								Completamente non d'accordo	

2. Lavoro correlato

1. Ho familiarità con il processo di assemblaggio (esperienza precedente)

1	2	3	4	5	6	7	8	9	10
Completamente d'accordo								Completamente non d'accordo	

2. Ho abbastanza tempo per eseguire l’attività a un ritmo normale

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

3. Devo eseguire altre attività oltre al processo di assemblaggio (passaggi ed errori delle attività del documento, spostare componenti o altro)

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

4. Ci sono stati eventi non pianificati durante l’attività del documento, spostare componenti o altro)

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

3. Ambiente e layout

1. L’ambiente è stato ben progettata per quanto riguarda la raggiungibilità (raggiungere facilmente le parti, lo spazio di assemblaggio era vicino, non ci si doveva girare per raggiungere le parti)

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

2. I passaggi necessari per eseguire l’attività sono stati

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

3. L’ergonomia in questo compito è stata ben implementata (nessun allungamento non c’è bisogno di piegarsi o girarsi per raggiungere una parte o un’altra)

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

4. Il posizionamento delle parti, la scelta di un semplice componente e i passaggi di assemblaggio sono stati ben progettati

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

4. Collaborazione

1. Il movimento del robot è stato ben progettato

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

2. La gestione robotizzata delle parti è stata ben progettato

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

3. La collaborazione con il robot è stata positiva per il completamento delle attività

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

4. La collaborazione è sembrata più rilassante e utile

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

5. Istruzioni

1. Le istruzioni erano dettagliate e utili

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

2. Le istruzioni erano facili da capire

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

3. Le istruzioni hanno semplificato il processo

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

4. Le istruzioni sono state utili per lavorare con il robot

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

5. Il tempo per capire e imparare il compito dalle’struzioni è stati lungo

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

6. Generale

1. Per lavorare in questo compito, è necessaria esperienza

1	2	3	4	5	6	7	8	9	10

Completamente d’accordo									Completamente non d’accordo

2. L’attività di assemblaggio è stata ben progettata e spiegata

1	2	3	4	5	6	7	8	9	10
Completamente d’accordo								Completamente non d’accordo	

Saresti disposto a prendere parte a un altro caso di studio con un compito diverso ma collaborando con un robot? Si prega di fornire una risposta e le proprie ragioni, se possibile, di seguito:

Si prega di scrivere eventuali commenti e raccomandazioni che hai in base alla tua esperienza con l'attività di seguito:

NASA-TLX QUESTIONNAIRE

COGNITIVE LOAD ASSESSMENT QUESTIONNAIRE ID:__________

Thank you for your participation!

Scegli tra le due opzioni - Quale delle due credi ti abbia influenzato

Temporale – richiesta temporale, mentale – richiesta mentale, fisico – richiesta fisica

1. Sforzo ò Performance -………………………
2. Temporale o Frustrazione - ………………….
3. Temporale ò Sforzo - ……………..
4. Fisico o Frustrazione - ……………
5. Performance ò Frustrazione - ……………
6. Fisico ò Temporale - ……………….
7. Fisico ò Performance - ……………..
8. Temporale ò Mentale - …………………
9. Frustrazione ò Sforzo - ……………….
10. Performance ò Mentale - ……………….
11. Performance ò Temporale - ……………….
12. Mentale o Sforzo - ………………………
13. Mentale o Fisico - …………….
14. Sforzo o Fisico - ………………
15. Frustrazione o Mentale - …………………

1. Mental Demand - Mentale

1	2	3	4	5	6	7	8	9	10
Low									High

2. Physical Demand - Fisico

1	2	3	4	5	6	7	8	9	10
Low									High

3. Frustration - Frustrazione

1	2	3	4	5	6	7	8	9	10

Low High

4. Temporal Demand - Temporale

1	2	3	4	5	6	7	8	9	10

Low High

5. Performance - Performance

1	2	3	4	5	6	7	8	9	10

Low High

6. Effort - Sforzo

1	2	3	4	5	6	7	8	9	10

Low High

List of Publications

1. Fruggiero, F., Lambiase, A., Panagou, S., Sabattini, L. 2020. Cognitive human modeling in collaborative robotics. *Procedia Manufacturing*, 51, pp. 584-591.
2. Di Pasquale, V., Digiesi, S., Fruggiero F., Longo, F., Miranda, S., Mossa G., Padovano, A. and Panagou S. 2020. Human operator 4.0 performance models in the smart factory: A research framework. In *Proceedings of the Summer School Francesco Turco 2020*.
3. Panagou, S., Fruggiero, F. and Lambiase, A. 2021. The Sustainable Role of Human Factor in I4.0 scenarios. *Procedia Computer Science*, 180, pp. 1013-1023.
4. Panagou, S., Fruggiero, F., Neumann, W.P. and Lambiase, A. 2021. The Entropic Complexity of Human Factor in Collaborative Technologies. In *Congress of the International Ergonomics Association*, Springer, pp. 503-510.
5. Panagou, S., Fruggiero, F. and Lambiase, A. 2021. Human factor and entropy evaluation in collaborative workplace environment. *International Journal of Simulation and Process Modelling*, 17(2-3), pp. 187-203.
6. Panagou, S., Fruggiero, F. and Lambiase, A. 2022. Human gesture system in Human Robot Interaction for reliability analysis. *Procedia Computer Science*, 200, pp. 1788-1795.
7. Panagou, S., Fruggiero, F., Lerra, M., del Vecchio, C., Mechetti, F., Piedimonte, L., Natale, O.R, and Passariello, S. 2022. Feature investigation with Digital Twin for predictive maintenance following a machine learning approach. *IFAC-PapersOnLine*, 55(2), pp. 132-137.
8. Panagou S., Fruggiero, F., Iannone, R., Gnoni, M.G. 2022. The CACTUS approach: Organizational approach for sustainability. In *Proceedings of the Summer School Francesco Turco 2022*.
9. Mancusi, F., Fruggiero, F. and Panagou, S. 2022. A cloud-aided remanufacturing framework to assess the relative complexity. *IFAC-PapersOnLine*, 55(10), pp. 1025-1030.
10. Panagou, S., Fruggiero, F. and Mancusi, F. 2023. A methodological framework to assess mental fatigue in assembly lines with a collaborative robot. *Lecture Notes in Mechanical Engineering.*
11. Panagou S., Fruggiero F., del Vecchio C., Sarda K., Menchetti F., Piedimonte L., Natale O.R. and Passariello S., 2022. *Explorative hybrid digital twin framework for predictive maintenance in steel industry*, IFAC-PapersOnLine, 55(40), pp- 289-294.
12. Panagou, S., Sileo, M., Papoutsakis, K., Fruggiero, F., Qammaz A. and Argyros, A. 2023. Complexity based investigation in collaborative assembly scenarios via non intrusive techniques. *Procedia Computer Science*, 217C, pp. 478-485.

13. Panagou S., Neumann W.P., Fruggiero F., 2023, A scoping review on human robot interaction research towards Industry 5.0 human-centric workplaces, International Journal of Production Research, pp.1-17.