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A SOCIO-TECHNICAL APPROACH FOR ASSISTANTS IN HUMAN-ROBOT COLLABORATION IN INDUSTRY 4.0

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April 2022

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Dedicated to my wife Luz Dary for having accompanied me throughout this time,
and giving me her unconditional support, patience and love.
To my son Sergio Alejandro for being her reason to show him the path of
perseverance, perseverance and patience in life

Abstract

The introduction of technologies disruptive of Industry 4.0 in the workplace integrated through human cyber-physical systems causes operators to face new challenges. These are reflected in the increased demands presented in the operator's capabilities physical, sensory, and cognitive demands. In this research, cognitive demands are the most interesting. In this perspective, assistants are presented as a possible solution, not as a tool but as a set of functions that amplify human capabilities, such as exoskeletons, collaborative robots for physical capabilities, virtual and augmented reality for sensory capabilities. Perhaps chatbots and softbots for cognitive capabilities, then the need arises to ask ourselves: How can operator assistance systems 4.0 be developed in the context of industrial manufacturing? In which capacities does the operator need more assistance? From the current paradigm of systematization, different approaches are used within the context of the workspace in industry 4.0. Thus, the functional resonance analysis method (FRAM) is used to model the workspace from the sociotechnical system approach, where the relationships between the components are the most important among the functions to be developed by the human-robot team. With the use of simulators for both robots and robotic systems, the behavior of the variability of the human-robot team is analyzed. Furthermore, from the perspective of cognitive systems engineering, the workspace can be studied as a joint cognitive system, where cognition is understood as distributed, in a symbiotic relationship between the human and technological agents. The implementation of a case study as a human-robot collaborative workspace allows evaluating the performance of the human-robot team, the impact on the operator's cognitive abilities, and the level of collaboration achieved in the human-robot team through a set of metrics and proven methods in other areas, such as cognitive systems engineering, human-machine interaction, and ergonomics. We conclude by discussing the findings and outlook regarding future research questions and possible developments.

Acknowledgements

It isn't easy to thank all the support received during these three years. However, I would like first to thank the directors, Prof. Cecilio Angulo and Prof Pere Ponsa, of whom I have received unconditional support in the development of this research.

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Chapter 1

Introduction

In this chapter the topic selected under study is motivated from an industry perspective. Next, the problem is state as well as the associated research questions and main objectives. It also presents the publications made in the research process and a guide to the reader of the document developed.

1.1 Motivation

Scientific and technological development is the precursor of the paradigm shift in human beings' lives and work. Today, humanity is experiencing a new paradigm shift from simplest to complexity, from the study of individual parts to the study and development from the system's perspective, a set of interconnected components and technologies working together to solve the complex problems facing modern society into a holistic vision. In the industrial world, these paradigm shifts have been associated to the so-called industrial revolutions. Nowadays, the development of disruptive technologies in the fields of connectivity, intelligence, automation, and advanced engineering such as high performance computers, the internet of things, big data, machine vision, artificial intelligence, collaborative robotics, among others, have motivated the emergence of the fourth industrial revolution, known as Industry 4.0 (Germany) or

Connected Industry (Spain). This fourth industrial revolution is the synergic integration of Information Technologies (IT) with Industrial Operations Technologies (OT) to form an effective, efficient, and safe production system, capable of responding to the demanding needs of today's market, which asks for shorter production times, greater product diversity, higher quality, and high-level safety. From a system perspective, Industry 4.0 is a complex system, where the components of the system are essential as well as the relationships between them. This is where the power and complexity of this intricate and complex system lies. In today's vision this complicated system is seen as a socio-technical system see Figure1.1,it is an approach to complex organizational work design that recognizes the interaction between people and technology in workplaces

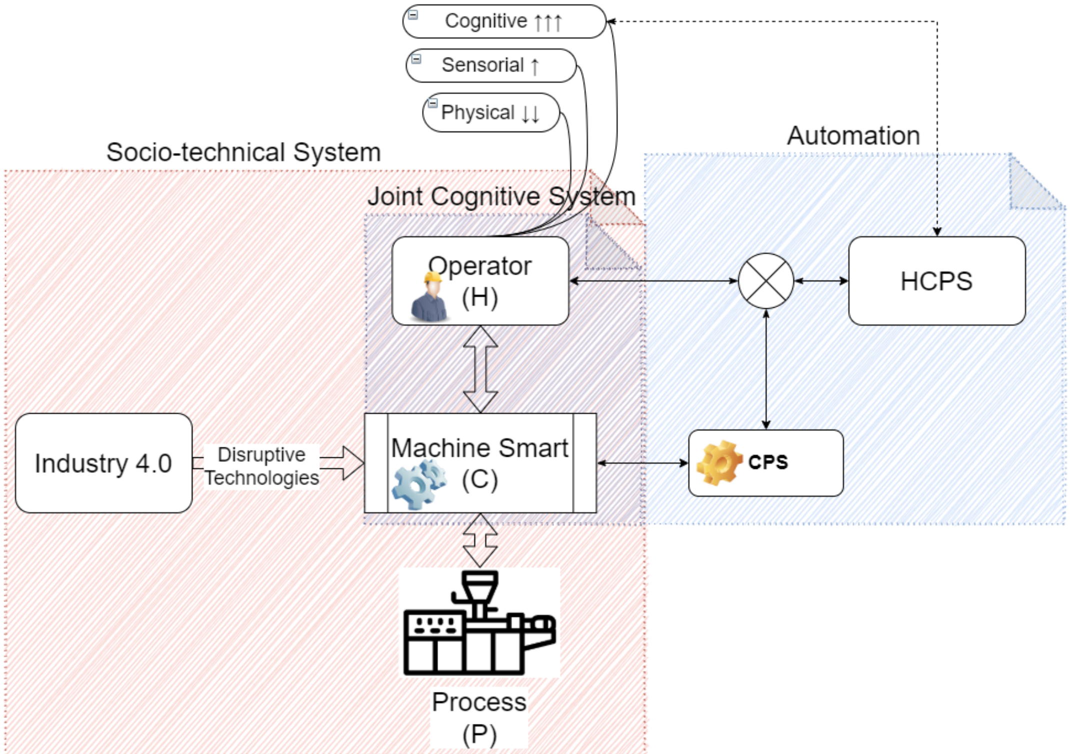


Figure 1.1: Vision from the perspectives of automation and socio-technical systems

In the Industry 4.0 the operator himself, who can be seen as an indispensable resource, is addressed. Not only production lines and processes are changing but also the role of the human is subject to significant changes and turns out to be crucial for developing productive manufacturing systems of the future [1]. One might think that people in the production hall will not be any more needed except for repairs and maintenance that are out of the routine and therefore not stored in the program of the machines. Such theories of ‘unmanned factories’ have instead been discussed decades ago during the CIM era (computer integrated manufacturing). In practice, instead, the factories will not be without humans, not even by introducing Industry 4.0. People will work or operate with robots, machines, cyber physical systems and other humans [78]. The importance to emphasize the role of the human being as a critical driver for a better factory performance has been pointed out by many visions and road maps about the future factory [6]. However, although their role is indisputable, humans can make mistakes that, no matter what their origin, have a direct influence on the cost of non-quality and delays. Some studies have demonstrated that human-caused non-quality is due to three main reasons: lack of appropriate guidelines, gaps in training, and the unavailability of documentation in production lines. As a result of the disruptive technologies of Industry 4.0 the (human) operator must deal with different working situations, see Figure 1.1 operators must be aware of important elements in the situation and to interpret it correctly according to their task of interest. Being constantly aware of all these elements is a difficult task for the workers and may lead to a cognitive overload.

Although most standard situations can be handled by automation a through cyberphysical systems (CPS), operators need to monitor and tune the automated system to keep its functioning within specified bounds. Moreover, automated systems are not capable of dealing with unanticipated situations [78], humans can learn from experience and thus compensate for incomplete knowledge. Humans can also adapt to different situations and prioritize different goals according to current demands. Thus, humans compensate for inevitable design shortcomings by learning and acting in flexible, context-dependent ways [47]. In addition, both the products and the manufacturing environment are becoming increasingly complex.

Investigations about the operator in the industry conducted by Romero et al. [96] propose the emphasis on the principles of human centrality, as part of the Industry 4.0 transformations, with a paradigm shift of independent human and automated activities towards a human-automation symbiosis (or 'human cyber-physical systems' HCPS) . These systems are characterized by the cooperation of machines with humans in work systems and designed not to replace the abilities and skills of humans but rather to coexist with humans and help them be more efficient and effective. In this symbiosis of human and machine team, this research seeks the gain of both parties from a cognitive viewpoint. However the only automation perspective is not enough to deal with the cognitive issue, an additional view is needed.

A socio-technical systems perspective is presented in Cognitive Systems Engineering (CSE) which is dedicated to the careful study of human/machine interaction as the meaningful behavior of a unified system, introduced as the Joint Cognitive System (JCS) [49], offering a principled approach to studying human work with complex technology.

A combined view from automation and JCS systems, proposes the need to support the employee with available assisted technologies in order to cope with the increasing diversity of work tasks and the complexity of industrial production. A major aim is to increase and support existing capabilities of the worker and/or compensate shortages or deficits of the employee. There is currently a need for research on:

- Need for further case study applications of worker assistance systems in manufacturing.
- Missing methodology for the selection of appropriate worker assistance systems for specific user groups

- Missing methodology for a structured evaluation of the suitability of worker assistance systems in manufacturing.

Moreover, according to a study by the Federal Ministry of Economics and Technology, the research for Industry 4.0, this need is shown among the five areas in which Industry 4.0 solutions are developed [92],

- Decentralization and service orientation
- Self-organization / autonomy
- Networking and integration
- Assistance systems

The need of operator assistants from the perspectives of cognition and human-machine symbiosis through HCPS is the motivation for this research.

1.2 Problem Statement and Research Questions

The introduction of different technologies considered disruptive, integrated through human cyber-physical systems (HCPS) in the workplace, force the operator to acquire new knowledge, skills and abilities to deal with the new configuration of their workplace. The current trend is changing from the demand for physical abilities and skills, towards sensory and cognitive abilities and skills, considered the latter of a higher level. However, in general, the operator is not trained in cognitive skills and abilities, causing situations of increased mental load, low performance, and therefore decreasing the efficiency and effectiveness of the process.

To meet these demands and make the complexity of the processes manageable, it is necessary to support them. This support can be provided through digital assistance systems, which help operators in their tasks to face a diversity of systems. Improvement in operators and engineers' cognitive skills is imminent to adapt to Industry 4.0

working environment. Thus, cognitive skills of the smart operators are more required than rather the physical strength.

1.2.1 Research objectives

This research is proposed on the hypothesis of the need to introduce cognitive skills in the service of assistants to the operator for the development of HCPS in the workplace.

Main objective

Defining a methodologies from socio-technical perspective to design, implement, and evaluate cognitive assistance in Human Cyber-Physical Systems (HCPS) that support the operator in Industry 4.0 to do their job into an automation system in a more efficient and effective form.

Specific objectives

This is the list of the associated specific objectives:

- Identify the functions and cognitive processes of a digital assistant during the work shift in the workplace.
- Propose a model of a socio-technical system that allows analysing the relationships of the human-robot team in the workplace.
- Evaluate the performance of the human-robot team, as a joint cognitive system, in the performance of tasks in the workplace.
- Analyse how working with a technological partner in the workplace affects the human operator.

1.2.2 Research Questions

This research focuses on the study of digital assistants that collaborate with the operator in the development of the cognitive tasks required in the workspace together with a technological partner(Human-robot Team). To guide this research, the following questions are proposed,

- What are the cognitive characteristics of a digital assistant in a HCPS in the workplace?
- How can a HCPS be modeled as a Joint Cognitive System (JCS)?
- What parameters should be considered to evaluate the human-machine team from a cognitive point of view?
- How is the introduction of new technologies affecting human-machine system performance in the workplace?

1.3 Publications

Publications made in this research

1.3.1 Journal articles

- Chacón Alejandro, Ponsa Pere , Angulo Cecilio. (2020). On Cognitive Assistant Robots for Reducing Variability in Industrial Human-Robot Activities. Applied Sciences. DOI:10.3390/app10155137
- Chacón Alejandro, Ponsa Pere, Angulo Cecilio. (2021). Cognitive Interaction Analysis in Human–Robot Collaboration Using an Assembly Task. Electronics. DOI: 10. 1317. 10.3390/electronics10111317.

- Chacón Alejandro, Ponsa Pere , Angulo, Cecilio. (2021). Usability Study through a Human-Robot Collaborative Workspace Experience. Designs. 5. 35. DOI:10.3390/designs5020035.

1.3.2 Chapters of Book

- Chacón Alejandro, Angulo Cecilio ,Ponsa, Pere. (2020). Developing Cognitive Advisor Agents for Operators in Industry 4.0, DOI: 10.5772/intechopen.90211.

1.4 Readers Guide

The purpose of the following section is to introduce the reader to the structure of this Ph.D. Thesis and provide a brief reader's guide.

This research work focuses on assistants to the industrial operator in the workspace. The research is presented from the basis of cognition in the operator's tasks. The development is presented in six (6) chapters. In Chapter 1 the introduction text shows the motivation of the present investigation and the research questions. Chapter 2 present the state of the art in relation to Operator 4.0 the human cyber physical (HCPS) system and joint cognitive systems (JCS), as a basis for the study of cognition in the human-robot work team. The work methodology introduced in Chapter 3 presents the FRAM tool for the design of the joint cognitive system. The results obtained in the simulation part and the real experience through a case study are presented in Chapter 4. Chapter 5 discusses about the results obtained. Finally, Chapter 6 presents a list of final conclusions and the future lines .

Chapter 2

State of Art

The state of the art is presented from the perspective of Operator 4.0 and the emerging needs in the Industry 4.0 environment. Advances in cyber-physical systems are presented, and the perspective of the joint cognitive system, as the framework of the human-robot team that is studied as a case study of cyber-physical human systems. Cognition in industry is the area of interest of this research. This research work focuses on the design of assistants in cognitive tasks for the industrial operator in the workplace. To create the reference framework, initially the research context is presented in this chapter. Hence, the concepts of Industry 4.0, human-cyber physical systems, operator assistants and usability and mental load metrics are defined.

2.1 Industry 4.0 and Operator 4.0

The fourth industrial revolution indicates an increase in the quality of industrial production through the combination of machines, products and people. This is done by forming a new production system, which allows a more specific and faster exchange of information. By doing so, we are moving towards a future where robots and people collaborate with the support of smart assisted systems and web technology during the performance of work activities [29]. Anxiety regarding future systems and related new working conditions are the result of a misunderstanding of the role of humans in future manufacturing processes. This raises the question of how and in what way the role of the worker will change in Industry 4.0 [94].

The role of the operator is being greatly affected by the changes produced in the development of Industry 4.0, as evidenced by the investigation in [94]. Figure 2.1 shows how operator's physical and cognitive skills are changing: there are an increase in cognitive skills and a decrease in physical skills, this causing certain misgivings. Much of the unease that operators show in the face of new systems and associated working conditions is due to a lack of understanding or low understanding of the role of the human actor in the new manufacturing processes. How and in what way does Industry 4.0 modify the role of the operator in the production of the future is the question raised in [94]. In a similar way, it is stated in [121], in what way and what assistance needs does the user need? In a first approach to the paradigm shift, oriented to the role of the operator in Industry 4.0, the research in [96] proposes the definition of the *Operator 4.0* as a concept that allows defining the operator of the future in this new environment. This human-centered approach and their role in the production system will be one of the guidelines of this research.

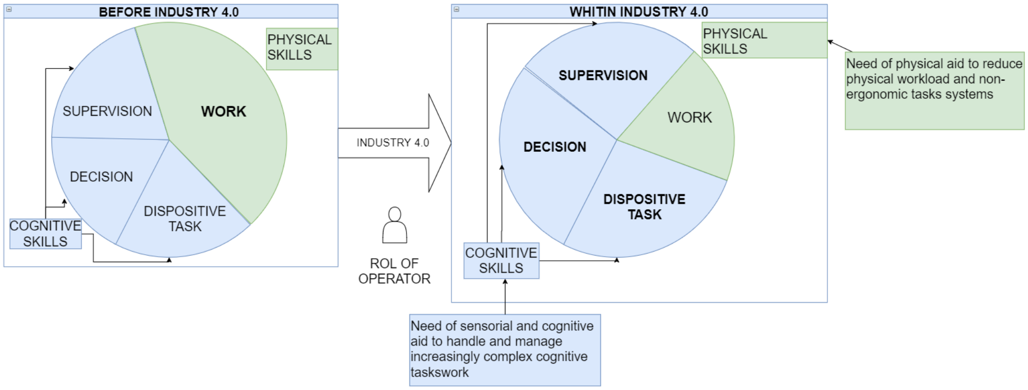


Figure 2.1: Changes in the role of the operator

The *Operator 4.0* concept is defined in [96, 68] in a general form as an operator in an industrial setting assisted by technological tools. Although the increase in the degree of automation in factories reduces costs and improves productivity, in the Industry 4.0 vision, differently of Computer-Integrated Manufacturing (CIM), human operators are yet key elements in the manufacturing systems. In fact, the increasing degree of automation 'per se' does not necessarily lead to enhanced operator performance.

The continuous innovations in the technological areas of Cyber-Physical System (CPS), the Internet of Things (IoT), the Internet of Services (IoS), robotics, big data, cloud and cognitive computing, and augmented reality (AR), result in a significant change in production systems [120, 29]. Empowered with these new skills, HCPS systems can take part, for instance, in tasks of planning and disposition, eventually to manage them. Machines take care of the adequate supply of material, change the production method to the optimal one for the real product, or devise a new plan themselves [121]. This technological evolution generates, among others, the following impacts on the operator:

- the qualification of manual tasks decreases;
- the operator can access all the necessary information in real-time to take decisions;
- intelligent assistance systems allow decisions to be taken more quickly and in a short space of time;
- co-working in the workspace between machines and people requires less effort and attention;
- human implementation and monitoring is more relevant than ever.

The emerging technologies in Industry 4.0 [88] as well as current development of Artificial Intelligent technologies are allowing that cyber-physical systems oriented to human-machine interaction be moving from only a physical interaction vision paradigm to also a cognitive one (see Table 2.1). The operator should be able to take the control and supervise the automated production system. However, the increasing information and communication power of these systems leads to a complexity that is not understandable by the current standard user interfaces employed in the industry. Consequently, the operator would need support to keep the system under stable requirements. Moreover, the operator could get the system work plan (factory, not shift supervisor), and therefore the operator would need additional information during field operation, which requires access to location-independent information as well as a situation-oriented and task-oriented information offer [46].

Table 2.1: Vision of physical and cognitive automation

	Physical	Cognitive
Routine	Traditional Automation	Automated Learning Techniques
Non-Routine	Collaborative Robots	AI (Intelligent Assistants)

As a result of this paradigm shift, new forms of interaction appear in the field of Human-Machine Interface (HMI), in the form of intelligent user interfaces, such as Operator Support Systems (OSS), assistance systems, decision support systems and IPAs (Intelligent Personal Assistants) [94]. In the context of smart, people-centred service systems, cognitive systems can potentially progress from tools to assistants to collaborators to coaches, and be perceived differently depending on the role they play in a service system.

Assistance systems support the operator as follows [82]:

- From a human-centered design approach, expressly considers the identification of user context, the specification of user requirements, the creation of design solutions, and the evaluation of design solutions. Moreover, it provides an appropriate amount of information in a clear way.

- As a decision maker in production control, with information acquisition, data aggregation / analysis of information, and operation choice.

However, it should be clarified that the final decision always remains in the human operator side, thus maintaining the principle of human centrality.

Regarding the tasks and the role of the operator, an increase in the proportion of *complex cognitive tasks* is expected, hence increasing the needs for coordination or organization of production resources, as well as the control and monitoring of complex production systems.

The literature shows that a significant change in this relationship from purely physical to cognitive refers to the human-machine interface, which encompasses the interaction between operators and a set of new forms of collaborative work. The interaction between humans and CPS is produced by either, direct manipulation or with the help of a mediating user interface. Such a close interaction between humans and CPS also raises socio-technological issues regarding autonomy and decision-making power. Cybernetics provides an answer on how a system that controls another system can compensate for more errors in the control process by having more operational variety. As the most flexible entity in the cyber-physical structure, the human will assume the role of a higher-level control instance [29]. Through technological support, it is guaranteed that operators can develop their full potential and adopt the role of strategic decision makers and flexible problem solvers, thus managing the increasing technical complexity. In this research work the inclusion of the human in the CPS will be presented as the latter one, HCPS.

2.2 Socio-technical and Joint Cognitive System

Socio-technical systems theory are concerned with the design of socio-technical systems; being systems that contain both social (human-related) and technical (non-human) aspects that interact to pursue a common goal [116]. The objective of a socio-technical system is to improve the relationship between the technology and the people involved in a defined project.

In the context of socio-technical systems, the interactions between technology and human are mutual, as both of them influence each other. Technology shapes human interactions, relations and societies, and likewise technology is also shaped by social, economic, and political force. The rationale for adopting socio-technical approaches to systems design is that failure to do so can increase the risks that systems will not make their expected contribution to the goals of the organization. Systems often meet their technical 'requirements' but are considered to be a 'failure' because they do not deliver the expected support for the real work in the organization. The source of the problem is that techno-centric approaches to systems design do not properly consider the complex relationships between the organization (industry) , the people (operators) enacting processes and the system that supports these processes (machines). Industry 4.0 is predominant with technology such as connectivity and interaction technology such as smart products, smart machines and smart operators. This causes a rethinking of relationships between human and machine. This interaction is a critical relationship which will be governed by socio-technical transformation. An implementation of CPS in production and the development and use of system-based information management has led to organizations characterized by human-automation symbiosis, where machines cooperate with humans [106, 96].

The result of the inclusion of disruptive Industry 4.0 technologies in the workspace has changed the role of the operator, the Figure 2.2 , shows the existence of a higher demand for the operator's cognitive skills as well as a higher demand for the operator's cognitive skills. In addition the current development of technology allows us to reach the level of cognition in HCPS (see Figure 2.4) [63]. However, the understanding of cognition generates debates because it can be approached from several domains, mainly from psychology through mental models, and from Cognitive Systems Engineering (CSE) to applications in practice. One potential improvement is to treat human operators and automated systems not as autonomous agents but as team members in a Joint Cognitive System (JCS).

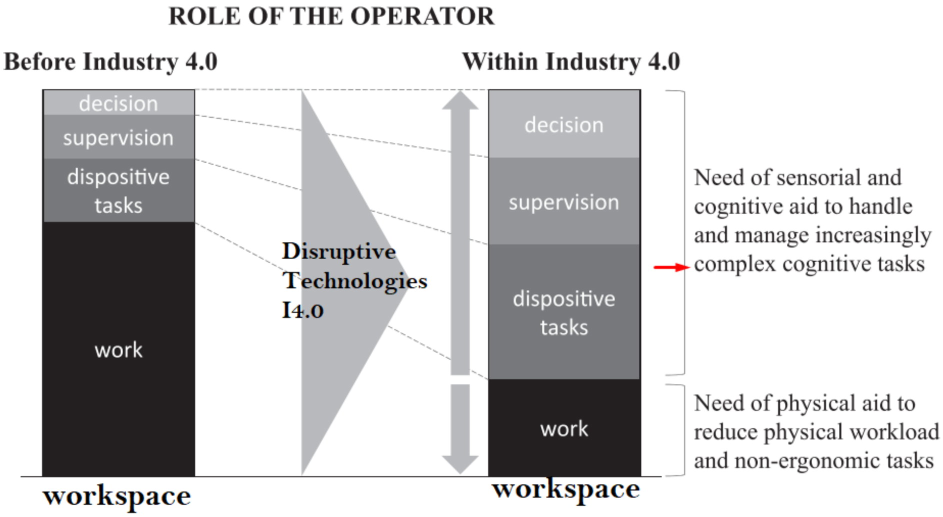


Figure 2.2: Change in the role of the operator adapted from [94]

A Joint Cognitive System (JCS) acknowledges that cognition emerges as goal-oriented interactions of people and artifacts in order to produce work in a specific context, and at the level of the work being conducted. It does not produce models of cognition, but models of **co-agency** that corresponds to the required variety of performance and thereby emphasizes the functional aspects [2].

In this situation, complexity emerges because neither goals, nor resources, nor constraints remain constant, creating dynamic couplings between artifacts, operators and organizations. The CSE approach focuses on analyzing how people manage complexity, understanding how artifacts are used and understanding how people and artifacts work together to create and organize JCS which constitutes a basic unit of analysis in CSE. Human and machine need to be considered together, rather than separate entities linked by human-machine interactions [49].

In the domain of CSE, focus is on the mission that the JCS shall perform, avoiding vagaries into its human resemblances. It performs cognitive work via cognitive functions such as communicating, deciding, planning, and problem solving Figure 2.3. These sorts of cognitive functions are supported by cognitive processes such as perceiving, analyzing, exchanging information, and manipulating.

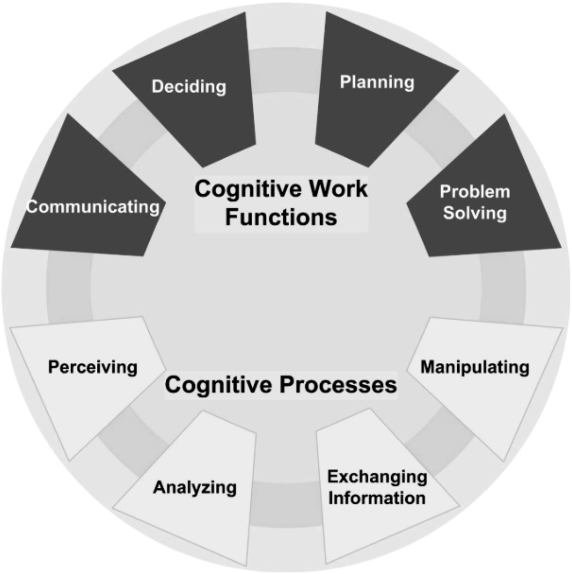


Figure 2.3: Cognitive work functions and cognitive processes

The importance of cognition, regardless of how it is defined, as a necessary part of the work has grown after the industrial revolution:

- Cognition is distributed rather than isolated in the human operator's mind.
- Operator do not passively accept technological artifacts or the original conditions of their work.
- Technological development is rampant, this entails the development of work with inevitably greater *operational complexity*.
- Technology is often used in ways that are not well adapted to the needs of the operator.

There is no turning back, the evolution of Information Technology, Digital Transformation and the Fourth Industrial Revolution requires that processes be more cognitive, automatic and efficient. So one potential improvement is to treat human operators and automated systems nos as autonomous agent but as a team member in a joint cognitive system.

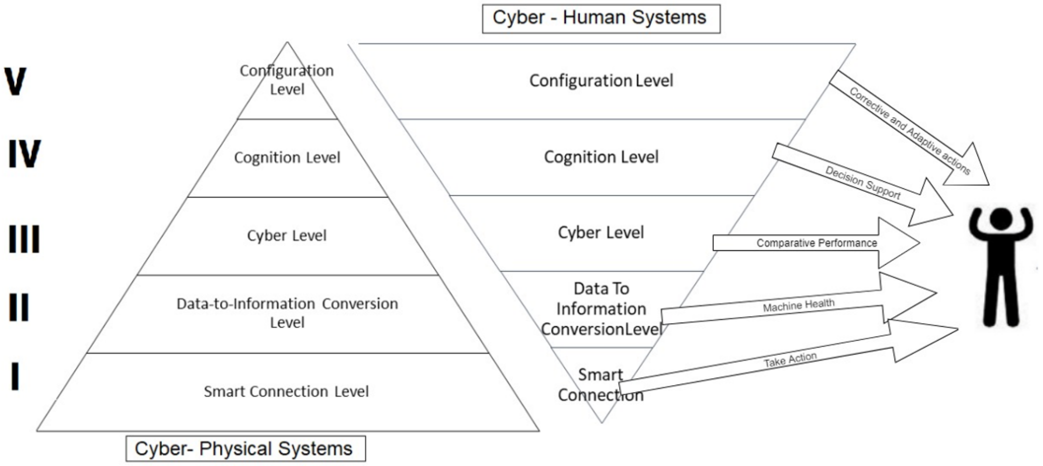


Figure 2.4: CPS vs HCPS model

2.3 Human Cyber-Physical Systems

In the approach with humans in the interaction, a human cyber-physical system (HCPS) [96] is defined as "systems that consist of humans and integrated computational and physical components, creating new levels of socio-technical interactions between humans, machines, materials, and objects" [58]. Our research, however, focuses on HCPS, defined as "a work system that improves the capabilities of operators thanks to a dynamic interaction between humans and machines in the cyber and physical worlds through smart human-machine interfaces". The objectives for HCPS are achieved through the interactions between: the physical system (or process) to be controlled; cybernetic elements (that is, communication links and software modules); and human agents that monitor and influence the functioning of the cyber-physical elements.

In both definitions we can highlight the role of the operator within the control loop. In human-oriented architectures there is the ability to feedback the information (see Figure 2.4) at each level, because inherent intelligence of human operators can be used naturally for self-adaptation, corrective and preventive actions. For the HCPS approach, its levels configuration acts as a supervisory control to ensure that decisions made at the cognitive level are implemented and that corrective or adaptive actions are carried out by the human operator [63].

HCPS are very dynamic and complex systems being subject to a certain degree of unpredictable behaviour of both, the environment and the user. These conditions generate several challenges related to the administration of HCPS that require run-time capabilities allowing the system to detect, monitor, understand, plan and act on those not predicted changes while minimizing (and potentially eliminating) system downtime. In order to develop our cognitive advisor agent for operators, we start by defining three dimensions of HCPS: *Cybernetic*, *Physical* and *Human*. Each dimension is connected to the other ones through intelligent interactions (see Figure 2.5).

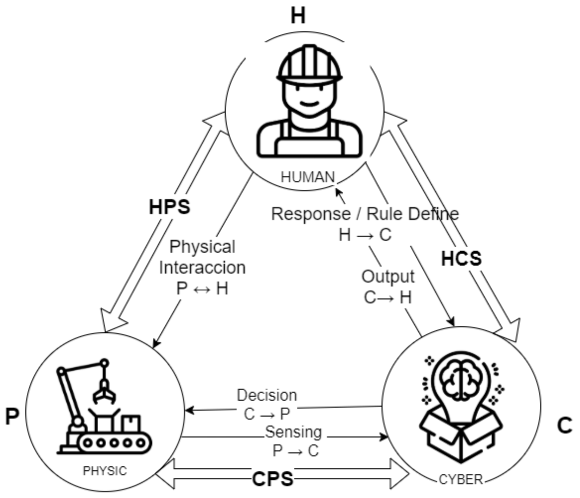


Figure 2.5: Three dimensions of HCPS

The physical dimension includes all the resources connected to the production system through sensors and actuators. The cybernetic dimension describes all computing, network and cloud infrastructures that communicate data, processes and software resources. Finally, the human dimension describes human elements, as well as their situations based on their objectives and context. The human dimension is especially relevant for this research, focused in aligning the objectives of HCPS with the achievement of the personal goals of the users.

2.3.1 Human roles in HCPS

For the moment, the cyber and the physical dimension have been considered in our agent-based approach. However, while in a human-centered architecture, the roles of humans in cyber-physical human systems (HCPS) must be also defined.

In the models of human-automation interaction, attention is paid to whether human assumes control of the system [104]. In HCPS systems, however, human intervention is focused in more aspects: the dialogue with other agents, decision-making and information supply. In this sense, one research line is about the definition of a human model as a part of the full HCPS model. However, human models defined as a transfer function leads to a poor approach. Some researchers expand this approach by developing analytic human models that reflect *cognitive abilities* in the interaction with cyber-physical systems [70]. On the other hand, a HCPS requires flexibility. An adaptive HCPS responds to unexpected or novel situations (re-planning, setting new goals, learn from experience) and the definition of the role of human (passive or active performer) is required [70]. Human roles examples in HCPS are, for instance:

- Supervisor (human on the loop): Approve CPS decisions; Re-allocate tasks between human and CPS
- Controller (human in the loop, Operator 4.0): Interact with sensors, actuators; Use of augmented reality technology; Collaborative task with a cobot

Merging human roles with CPS roles in order to define the functional architecture of a HCPS leads our research to the definition of a *Joint Cognitive System*, its basic aim being to achieve a high level of successful performance managing the human cognitive load in the process.

2.4 Cognition in Industry 4.0

The development of automation technology currently reached levels at which we can have systems such as those offered by IBM Watson, or artifacts with cognitive characteristics. However, the term cognition as such seems to be unclear when we focus on industrial or machine characteristics; therefore, designing these systems requires understanding from which perspective cognition is applied.

There are different definitions of cognition [46, 11] depending on the perspective with which we are working, for this research we will use an explanation from a pragmatic perspective, based on the characteristics of certain types of performance. Human performance is usually ordered (systematic and organized) and directed by objectives. This can be used as a provisional definition of cognition and can be extended to require cognitive tasks to have the following characteristics [46]:

- Cognitive tasks are driven by objectives (purposes and intentions) rather than by events. Cognitive tasks, therefore, are not merely responses based on algorithmic combinations of predefined elements but require advance reflection or planning beyond complex reactions.

- Cognitive tasks are not limited to humans; Cognitive tasks can be found in the functioning of organizations, certain artifacts, and animals.

In this perspective, the aim of designing cognitive tasks is to take advantage of the benefits offered by automation, but in a way that does not prevent operators from carrying out their functions. Achieving this goal is difficult because it requires the combination of two disciplines, systems engineering and human factors engineering, neither of which alone can provide the solution. The operator 4.0 environment is defined within an automation [96] or co-agency [56] symbiosis space, which translates into shared work between operator and automation. In this relationship to find a complete explanation to human behavior is necessary to take into account the interaction between the human and the environment within which it is immersed. This environment is driven as a joint cognitive system (JCS) within a given socio-technical context [46], specifically in its interaction with other cognitive, human and artificial systems in the environment [11].

By looking at the socio-technical system concept, it is not about 'either technology or humans', but more about a coordinated design, which comprises a total socio-technical system. The criterion for definition should always be to use to the fullest capacity the potentialities of the human-oriented design features. In this case the goal is an intersection design whereat the human operator is facilitated by intelligent assisted systems. [21] Such assistance systems do not only offer the possibility to increase the capabilities of workers in the production, but also to create job opportunities. The categorization of the concepts and methods according to the type of aid originates from Romero et al. [96], who in their work have subdivided them into three categories. Physical aid systems primarily serve to decrease the physical workload of a worker in production. Censorial aid systems have the capacity and ability to acquire data from the environment, necessary for orientation and decision-making in the operator's daily work and Cognitive aid systems are defined by the ability to support the mental tasks (e.g. perception, memory, reasoning, decision, motor response, etc.) needed for the job and under certain operational settings.

This research in particular has focus in cognitive aids, Rauch's [94] research indicates that cognitive aids in industry have focused on different fields, before and after Industry 4.0, the Figure 2.6). shows from the point of view of the product life cycle, where cognitive assistance may be required, the main difference in the assistance spaces is the use of modern technologies specific to Industry 4.0.

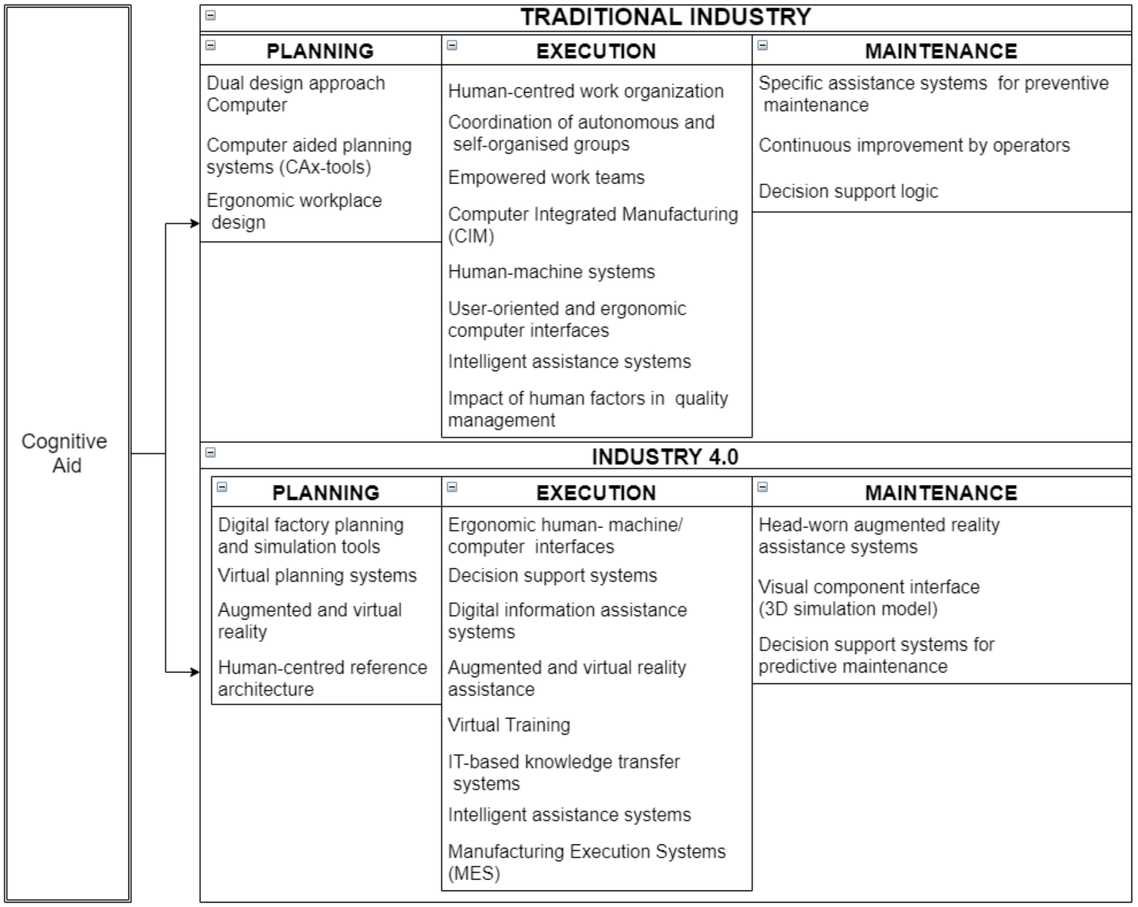


Figure 2.6: Changes in Aid Cognitive from Traditional Industry to Industry 4.0

Cognitive Assistants Cognition is a term referring to the mental processes involved in gaining knowledge and comprehension. In automation processes, the application of solutions have mainly focused on the physical activities of the operator, with which automatic machines and robots have had a great development. Currently, with the introduction of disruptive technologies in the workplace (cobots, virtual reality, augmented reality, smart HMI), the operator faces the need to handle systems with a greater amount of data which must be transformed into information and later into knowledge for the operator's decision-making. This transformation information is made by the cognitive abilities of the operator through different functions (for example, analysis, memory, planning). This research focuses on the concept of distributed cognition proposed by Hollan [44]. Cognition refers to all the processes by which data are transformed, reduced, processed, stored and used to solve events in the workplace, that is, conditions, monitoring, anomaly detection, optimization, prediction of future states [25]. A particular perspective is the concept of cognition in work teams. This perspective, proposed by Fiore [24], allows the understanding of cognitive processes and functions outside the brain. Understanding how cognition is distributed and how it grows by the actions of the different members of the team, leads us to the concept of macrocognition, in addition to understanding that cognition is not a closed function. It can also be understood that artifacts can develop some cognitive processes [49], for which the concept of macrocognition in the workplace emerges from the symbiotic relationship of the human operator and the technological operator. It is this macrocognition when distributed in the workplace which allows the human operator to develop their skills without a mental overload, or stress. Placing artifacts with the ability to perform cognitive processes within the HCPS allows the operator to have assistants in the workplace. In this study, the work team is made up of a human operator and a technological operator (H-R) collaborating in the workplace.

In the industrial domain, one important research activity for cognitive robotics is the development of assistant or advisor robots designed for increasing productivity and effective work organization [52, 14]. In work environments in manufacturing, assistance to skilled workers becomes crucial. Industrial companies, beyond ergonomic or safety issues, are starting to consider new qualification needs and technical competences with regard to operators. Decisions in the overall work processes are communicated to the operators to improve their information and skills [77].

Moreover, the industrial robotics area is currently moving in specific human-robot interaction domains from industrial robots to collaborative robots (*cobots*), specially for small and medium enterprises (SMEs) because affordable costs. Classical robotics approach in industrial settings does not facilitate interaction with humans since people safety and factory resources are priorities, so closed spaces by fencing are only considered [31]. This is the case for mechanical robot arms. The current move from industrial to collaborative robotics scenarios is transforming the safety model, the fencing disappears and shared workplaces are favored for cooperative tasks between human and robot. Hence, the first kind of interaction being under consideration in Industry is the physical one. By *physical interaction* we mean several scenarios considering human and robot [89]: space sharing, proximity, voluntary physical contact (limited in time), involuntary physical contact (collision), reciprocal exchange of forces. At a mechanical level, the robot should meet specifications for limiting force and speed. At the human level, aspects of bio-mechanics, risk prevention and injuries associated with involuntary physical contacts should be analyzed.

One of the purposes of collaborative robotics development is to introduce robot-based solutions in small and medium-sized companies [**?**]. Thus, it is convenient to find out the degree of maturity of the current industrial robotics area towards new interaction models. In these human-machine interaction models there are several functionalities to be developed [105]: planning, monitoring, intervention, learning, interaction between human and artificial agent (trained to have a dialogue with the human), assessment of mental load, levels of automation (manual, shared, and supervised control). Following this innovation path, industrial robotics evolves towards cognitive robotics. Moreover, considering progress in artificial intelligence, the integration of humans with artificial engineering systems is an interesting research area to be analyzed [111, 50].

Research on workers and robots interaction is an emerging area evolving as the current robotics also does it within the framework of the Industry 4.0. At the plant level, the human operator should interact with several devices with changing capabilities as the synergy between artificial intelligence algorithms and electronic devices with fault diagnosis functionalities increases, communications using advanced protocols.

As long as research about increasing social skills of the future human operator is being developed, it should be also ensured that the design of work tasks promotes standardization [53, 55]:

- Ensure that the human-robot team make a significant contribution to task effectiveness and productivity.
- Provide people with the appropriate level of autonomy for make decisions, procedure and task execution.
- Provide opportunities for novice operators for the development of existing skills and acquisition of new skills.
- Provide sufficient feedback for maintain the human operator in the loop.

From a *cognitive or social interaction* approach, the improvement in the development of algorithms should allow the intelligent robot or cognitive agent to know about the operator's working preferences, how to adapt to them, how to suggest better/optional ways of joint working and how to enhance the operator's skills. The dialogue between operator and robot should be changeable and allow advances in operator learning and in the perception of comfort that the operator experiences when working with robots [117]. Hence, one of the functionalities of cognitive robots is that of *cognitive assistance*. However, cognitive assistance in the form of an automatic expert partner is far from the functionality of today's collaborative robots, mainly focused on safety and physical assistance.

Once a cognitive automation platform understands how business processes work autonomously, it can also provide real-time insights and recommendations on actions to take to improve performance and results [96].

2.4.1 Cognition Human-Robot

A comparison among several approaches introduced in recent published works is presented in Table 2.2. Columns show the robotics approach employed (Research, Social and Industry), the interaction level considered (Physical, Cognitive), the employed metrics and some main characteristics of the approach.

The column *Category* in Table 2.2 shows that whether the interaction is Physical, the main concern is to establish safety in the use of collaborative robots, for instance in [4] or ISO TS 15066 standard in [72]. From the robot side, the speed of the robot's terminal element is regulated and the force exerted by the mechanical arm is limited. Talking about the human side, possible collisions between human and robot are analyzed and risk prevention due to the impact on various sensitive parts of the human body [75]. The wide variety of scenarios, the type of terminal element used by the robot, the manipulation that the robot is performing on a part in a task, the proximity of the human, makes very complicated to obtain a generic performance metric [73]. In the case of adding a collaborative robot in a manual workplace, the reduction of human physical fatigue should be measurable. Some authors propose to establish a measure of the level of collaboration [62]. If the percentage of tasks performed by the robot in an H-R system is increased, the human workload is decreasing.

When the *Category*'s label for the interaction is Cognitive, it is convenient to employ a measure of the performance of the automatic task planner: what tasks does the human do, what tasks are assigned to the robot [66]. For this kind of interaction, it is a key issue to enhance the perception of the environment. Using sensors, operators can be located, so other robots, predict the human's intention to move, analyze the execution time of the human's tasks and assess whether the robot can optimize sub-tasks initially assigned to the human. It can be also identified human's working styles, the rhythm in which the human performs his/her tasks, changes in this rhythm. Hence, the robot can suggest that operators change their

Table 2.2: A comparison among several Human-Robot Interaction metrics. Columns show the robotics approach, the interaction level, the employed metrics and some particular features. *H, R* notation means human or robot (traded), while *H-R* means human and robot (shared).

Approach	**Category**	**Metrics**	**Features**
Research [108]	Cognitive	H,R task effectiveness, Interaction effort, Situational awareness	Review and Classification of common metrics
Research [73]	Physical and Cognitive	Human - robot teaming performance	Developing a metrology suite
Research [4]	Physical	Subjective metrics in a 7-point Likert scale survey (seven heuristics)	Physical human interaction is modelled as informative and not as a disturbance
Research [35]	Cognitive	Physiological, Task analysis	Model and comparison of H-H team, H-R team
Research [42]	Cognitive	Fluency	H-R teams research
Social [20]	Cognitive	System Usability Scale (SUS) questionnaire	Early detection neurological impairments like dementia
Social [66]	Cognitive	Task effectiveness	H-R model with perception, knowledge, plan and action
Industry [65]	Physical	Human localization, Latency, Performance	Prediction of future locations of H,R for safety
Industry [61]	Physical	Completion task time	Robotic assembly systems
Industry [72]	Physical	H-R distance, speed, performance; Time collision	Algorithm case studies, Standards ISO 13855, ISO TS 15066
Industry [75]	Physical	H-R risk, Degree of collaboration, Task analysis	Assembly line with H-R shared tasks
Industry [62]	Physical and Cognitive	Level of Collaboration; H,R fully controlled, cooperation	Holistic perspective in human-robot cooperation

working behaviors. For instance, the not so noticeable fatigue is mental fatigue. Applying sensors for measuring heart rate, respiratory rate, for example, it is possible to collect data on the state of the human and recommend breaks. All this sensory can become invasive, and traditionally a questionnaire is used when the task is finished, to collect the subjective assessment of the operator. The NASA-TLX questionnaire measures mental load and is suitable for assessing differences in cognitive load when the human is carrying out a main task and a secondary task is added [108, 35].

Thus, an improved workplace setting should take into account the joint framework conformed by human, cognitive agent, and collaborative robot. In this context, we should distinguish two roles for the human: *supervisor* and *operator*. In the case of a human with the role of supervisor, the cognitive agent assists her/him in deciding the best task planning. The cognitive robot can show the performance of the set of operators that work with collaborative robots and can provide guidelines for a better assignment of tasks to operators. Besides, for a human in the role of operator who works with the collaborative robot, the cognitive agent/robot can remind the operator about performance in previous days, and can advise her/him on maintaining the working mode or changing to improve performance. In the case of new operators, the cognitive robot can provide feedback to enhance learning.

2.4.2 The Cognitive Design Problem: The FRAM Tool

As the automation of complex processes becomes more achievable the need for engineering procedures that help decide what and how to automate becomes more important to the safety, flexibility and performance of automation use. The implementation must satisfy general criteria such as *minimizing workload*, *maximizing awareness of what is going on* and *reducing the number of errors*. The basic problem therefore is to reduce the cognitive demands of the tasks being performed by the operators involved in the system while maintaining fully their ability to function within their given roles [95].

The JCS perspective in developing the FRAM model allows an understanding of the effects of task and information propagation, and eventual distributed criticalities, taking advantage of the functional properties of the system [2]. JCSs are characterized by three principles [49]: (a) goal-orientation, (b) control to minimize entropy (i.e., disorder in the system), and (c) co-agency at the service of objectives.

In order to understand the socio-technical system, the Functional Resonance Analysis Method (FRAM) [48] can be used, which allows to have a model generated by the application itself. The FRAM can be described as a method that is used to produce a model, instead of a method that is derived from a model, this method is a way to interpret the phenomenon under study. The objective of FRAM is to build a model of how a set of activities are carried out in a given organization or workplace. It proposes that everyday events and activities can be described in terms of *functions* involved without predefined specific relations, levels, or structures,see Figure 2.7. Instead, the FRAM assumes that the behavior of functions, hence the outcomes of an activity or process,,can be understood in terms of *four basic principles* described in the following. Moreover, the not predefined functions are described using *six aspects.*

The principles of FRAM are:

1. The equivalence of successes and failures: acceptable outcomes as well as unacceptable outcomes are due to the ability of organizations, groups and individuals successfully to adjust to expected and unexpected situations.

2. Approximate adjustments: things predominantly go well, but also they occasionally go wrong.

3. Emergent outcomes: the variability of two or more functions can be combined in unexpected ways that can lead to results that are unpredictable and disproportionate in magnitude, both negative and positive.

4. Functional resonance: The variability of one function may in this way come to affect the variability of other functions in analogy with the phenomenon of resonance (see Figure 2.7)

In FRAM a function represents acts or activities – simple or composite – needed to produce a certain result. Examples of simple human functions are to triage a patient or to fill a glass with water. The organizational function of the emergency room in a hospital, for example, is to treat incoming patients while the function of a restaurant is to serve food. Finally, composite functions include, for instance, a flight management system.

In the description of functions an important distinction can be made between tasks and activities, corresponding to the distinction between Work-as-Imagined (WAI)

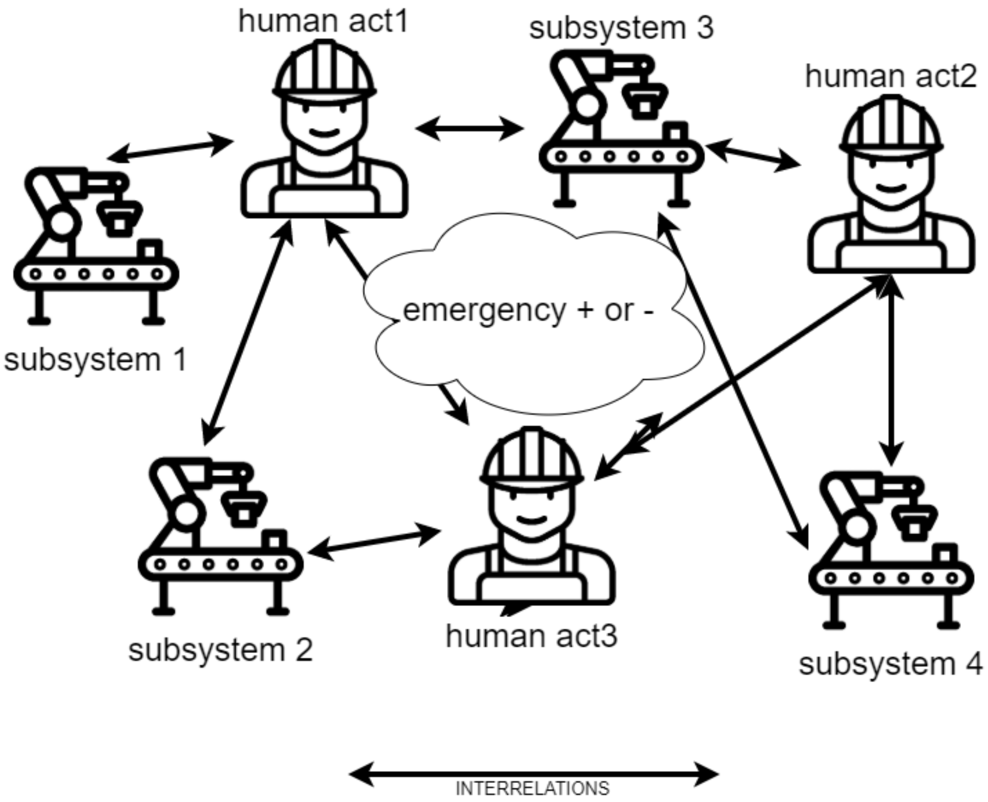


Figure 2.7: success or failure emerges from the variability of system performance as a result of complex interactions and unexpected combinations of actions

and Work-as-Done (WAD). A task describes work as designed, or as imagined by managers. An activity describes work as it is actually performed or done. FRAM primarily focuses on activities as they are done or WAD, but can of course also be used to model WAI.

To basically illustrate the use of FRAM, a pick&place system with a robot is shown in Figure 2.9. The system is based on filling boxes with cylinders. The cylinder supplier is in position *Warehouse* and the destination box in position *Box*. The FRAM model should describe functions and their potential couplings for a typical situation, but not for a specific one. Hence, it is not possible to certainly determine whether a function always will be performed before or after another function. It can only be determined when the model is instantiated. At the start, functions are identified in a first independent version about execution (see Figure 2.10).

The development of the model can continue in several ways – none of them being

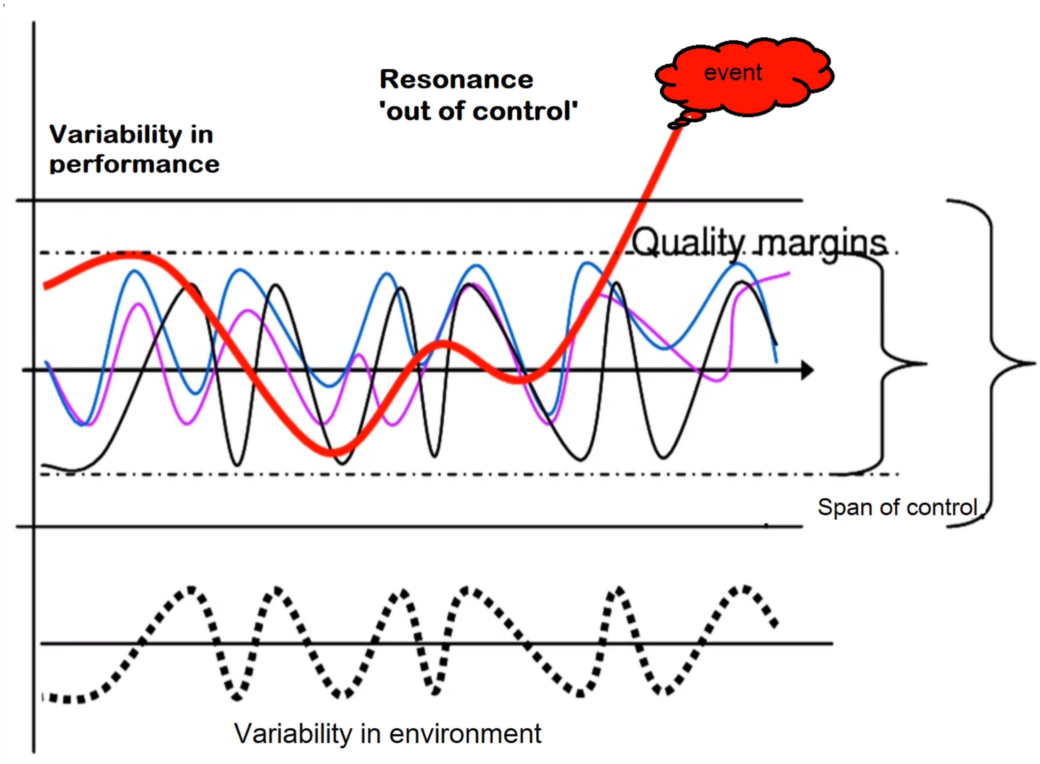


Figure 2.8: The resonance functional

preferable over the others. One way is to look at the other functions in the same way and try to define as many of their aspects as seems reasonable and possible. Another way is try to define aspects that are incompletely described in the current version of the model. The basis of the FRAM is the description of the functions that make up an activity or a process. The functions of different tasks have been assigned depending on who does it, (human, Cobot, Process) in the HCPS (see Figure 2.11). The relationships are not specified nor described directly and the FRAM Model Visualiser (FMV) in fact does not allow lines or connectors to be drawn between functions. Relationships are instead specified indirectly via the descriptions of the aspects of functions. The common technical term for such relations is *couplings*.

Couplings described in a FRAM model through dependencies are called *potential couplings*. This is because a FRAM model describes the potential or possible relationships or dependencies between functions without referring to any particular situation. In an instantiating of a FRAM model, only a subset of the potential couplings can be realized; these represent the *actual couplings* or dependencies that have occurred

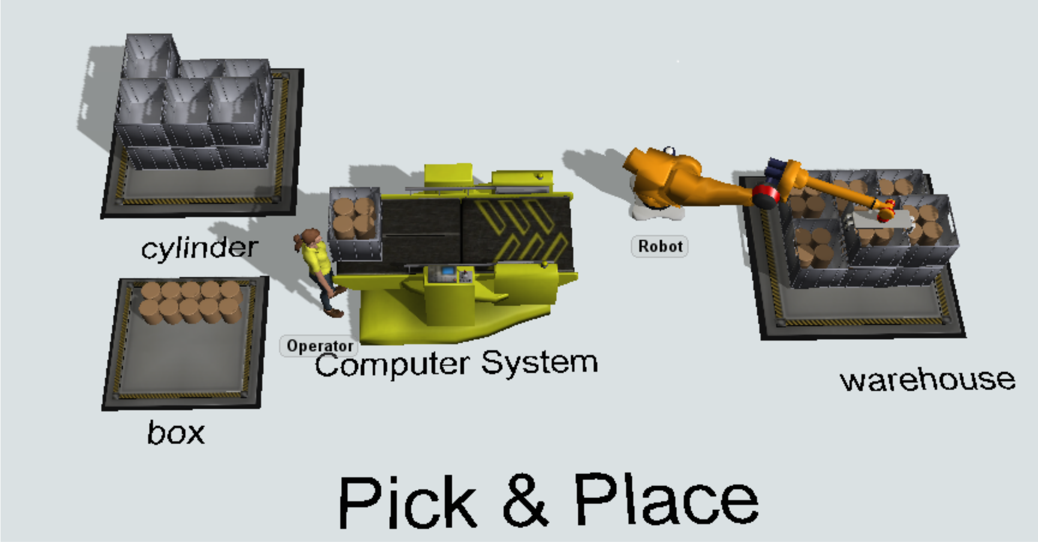


Figure 2.9: Example of a HCPS

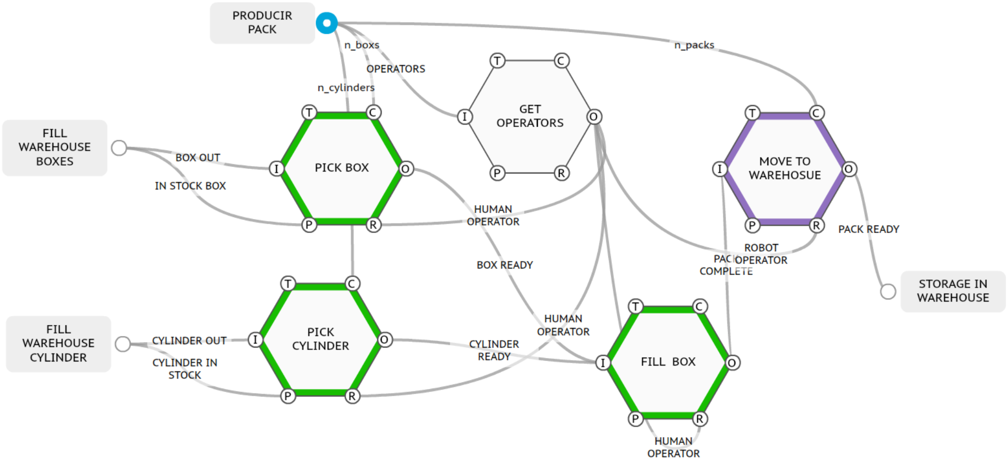


Figure 2.10: The FRAM model for a Pick and Place function ver1.0

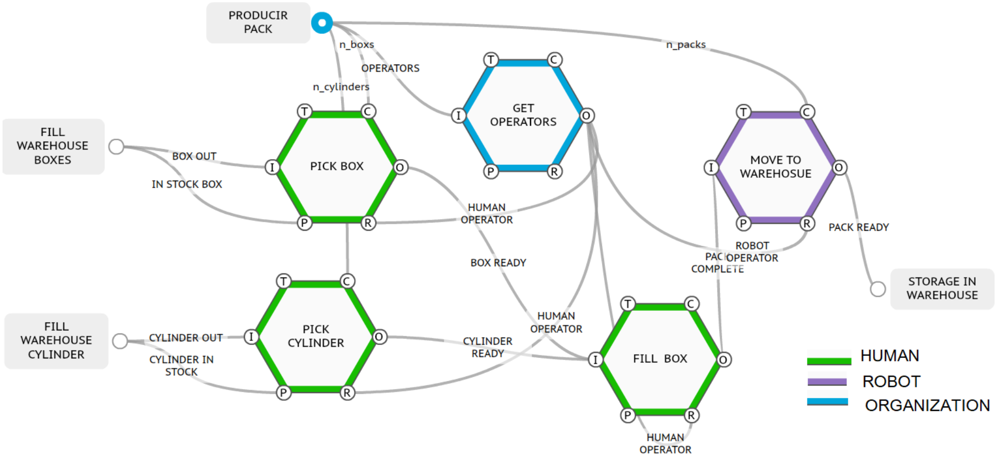


Figure 2.11: The FRAM model for a Pick & Place function / Assignation functions

or are expected to occur in a particular situation or a particular scenario [48].

Hence, basically we can highlight the following useful features for our study:

- PURPOSE: A FRAM analysis aims to identify how the system works (or should work) for everything to succeed (i.e., everyday performance), and to understand how the variability of functions alone or in combination may affect overall performance.

- MODEL: A FRAM model describes a system's functions and the potential couplings among them. The model does not describe or depict an actual sequence of events, such as an accident or a future scenario.

- INSTANTIATION: A concrete scenario is the result of an instantiation of the model. The instantiation is a "map" about functions coupling, or how they may become coupled, under given – favourable or unfavourable – conditions.

The use of FRAM as a tool for the analysis of cognitive tasks would allow us to understand about JCS works, identify its critical points, the propagation of the relationships between functions and understand the distributed cognition and co-agency between the human and the machine.

2.5 Metrics

Measuring the effectiveness, performance, and satisfaction are important to guarantee the effectiveness and efficiency of assistance. To evaluate the latter proposed experiments around HCPS, standardized metrics are used in human work.

2.5.1 Usability

In order to evaluate the performance of the work carried out by a human-robot team, the use of usability as an evaluation metric is proposed, based on the experience of human-computer interaction systems. However, in human-robot work, there are some differences to consider. Robots represent dynamic systems with varying levels of autonomy that operate in real-world environments. In addition, there are differences in the types of interactions and their roles respectively, the physical nature of the robots, the number of systems with which the user may have to interact at the same time and the environment in which these interactions can occur [102].

User research is the systematic study of the goals, needs and capabilities of users. Usability testing is a basic element for determining whether users are accomplishing their goals. Following the international standard definition ISO 9241, Part 11 [54],Figure 2.12 usability is the extend to which a product can be used by specific users to achieve specific goals with (i) effectiveness, (ii) efficiency an (iii) satisfaction in a specified context of use. *Effectiveness* refers to the number of errors, number of successfully completed activities; *efficiency* relates with the task time, physical effort, fatigue, cognitive workload; finally, *satisfaction* is usually measured using subjective questionnaires. It is worth noting that other researchers [15] include usability in a broader methodological framework focused on user experience. A pleasurable user experience is an essential design target of human-collaborative robot interaction and more goals could be added as: fellowship, sympathy, inspiration and accomplishment.

In order to evaluate the usability of collaborative workspaces between humans and robots, in this research a usability test plan is presented. It is developed through a concrete human-robot collaborative workspace experience (HRCWE) to illustrate how this usability test plan can be applied in a real environment. A description of the experience is provided, specifying objectives, roles, and responsibilities of all involved and associated timelines. It should be noted that main outcomes are not about the results obtained for this illustrative usability test plan, but the design of the plan itself.

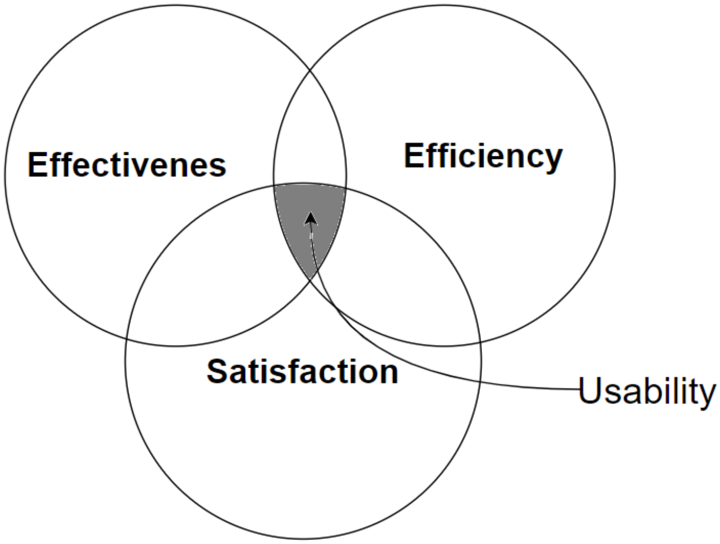


Figure 2.12: Definition usability by ISO9241

2.5.2 Mental Workload

A key element in this transformation to Industry 4.0 is the emphasis on an human-centered approach and full automation. This human-based transformation implies a paradigm shift from independent automated and human activities towards a human-automation symbiosis characterized by the cooperation of machines with humans in workplaces, which are designed not to replace (eventually, overcome) skills and abilities of humans, but rather to co-exist and assist humans in increasing human well-being and production performance [96]. In recent reports, as the Good Work Charter of the European Robotics Industry [22], fusion skills are defined as an interesting challenge: skills that draw on the fusion of human and robots within a business process to create better outcomes than working independently.

In manufacturing systems, the manual assembly task is a routine activity that have been tried to be completely replaced by robotics, unsuccessfully many times [90]. In the case to develop this work in the form of human-robot collaboration, it is detailed in [3] the assessment of the operator stress. In [41], the effects of robot appearance and relative status on human–robot collaboration are investigated to the extent to which people relied on and ceded responsibility to a robot coworker. Negative impact reduction of integrating human-robot teams is investigated in [119], by maintaining human aspects as social interaction, autonomy, problem solving, and task variety. Hence, further studies about the role definition of the human operator in manufacturing applications is required.

Cognitive skills should be not only considered for the operators, but also for the robotics systems. Human-robot interaction design at a cognitive level is a key element for the success of the collaborative workplace [81]. In some cases, the operator could get help from an assistant with cognitive skills to improve the operator's understanding of technology equipment. Hence, in [87] a cognitive work analysis method is applied for the design of an assistance system to support human in the control of intelligent manufacturing systems. In [112] an intelligent decision making method is developed that allows human-robot task allocation using the robot operating system (ROS) framework. With the aim to decrease the workload of the human and maximize the user adaptation, it is developed in [60] a set of cognitive models (task model, truth-maintenance model, interaction model, and intention rule-base). A mathematical model is introduced in [93] relating human low workload (physical, mental) to high performance in a human-robot collaboration framework depending on the complexity of the task, and whether the robot task is performed successfully or with errors (human intervention is required).

For cognitive interaction between an operator and a station, what type of interface allows efficient dialogue should be considered. In [74] a framework (methods, metrics, design recommendations) is developed for the study of effective interface designs in collaborative human-robot interaction. Moreover, when collaborative robots progress towards cognitive robotics, the human operator should be trained to be at that same level of competence. In this context, cognitive architectures for human-robot teaming interaction must be developed and tested [103].

From the cognitive point of view, workload and attention must be assessed. A priory, semi-automatic systems (collaborative systems) should facilitate effective teamwork between robots and humans. The human task must be adequately balanced so as not to excessively increase the assigned load. With regard to attention, it is necessary to analyze what type of attention is appropriate for the tasks that are being performed (sustained, selective, divided). If a task has high priority then it is preferable sustained attention: the human is focused and motivated to continue this task and complete it. In other cases, is preferable selective attention: the human is developing the task even when there are distractions around him. In some situations the operator needs to have attention in multiple places. Divided attention helps the human retain information while successfully completing two or more tasks at the same time.

Having to intervene in various places can cause stress for the operator and make it difficult for the chosen task to be carried out successfully. To understand in detail how humans behave when faced with the challenge of completing a task or interrupting it to carry out a direct intervention at the station, the following section shows how to prepare a laboratory scenario on which to perform and evaluate human-robot collaboration tasks.

Chapter 3

Methodology

The two portions of the study consisted of evaluating the usability as operator performed two tasks at workspace and the mental load that the development of these tasks causes in the operator. This section begins with descriptions of methodology we used for design, implement and evaluating the workspace and the evaluation environment we used for both portions of the study.

The developed research methodology is adapted from the User Centered Design method. Considering in the first place as a user the Operator 4.0, this methodology promotes a framework that has four steps.

- Understand and specify context of use.
- Specify the user requirements.
- Produce design solutions.
- Evaluate the design solutions.

For the development of the user-centered approach, the definition of the operator4.0 has been considered, understood as a smart, skilled operator who performs not only cooperative work with robots but also aided work by machines as and if

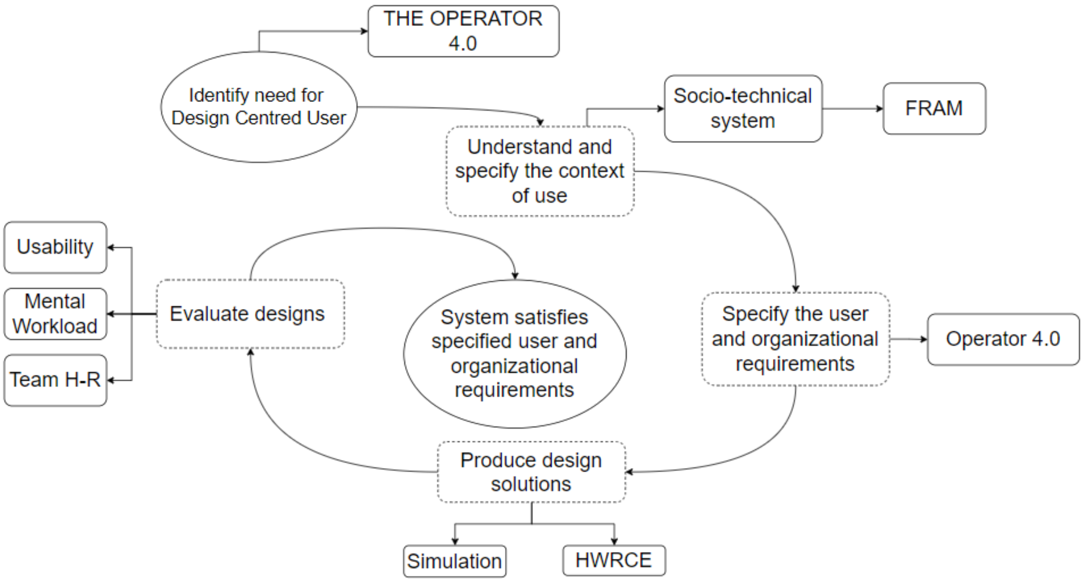


Figure 3.1: Methodology for research.

needed by means of human cyber-physical systems, advanced human-machine interaction technologies and adaptive automation towards achieving human-automation symbiosis work systems [97], the different technologies of Industry 4.0 create a new work environment that is much more qualified.A more interesting working environment, greater autonomy and opportunities for self-development where the central element is human-centricity [57] from this description we obtain that the focus must be focused on the user, as the main executor of activities in the workspace.

3.1 Understand and specify context of use

The workspace can be considered as a set of working conditions as show Table3.1 and ergonomic principles and human factors, which can be considered as a space for improving the cognitive and physical abilities of the operator, it will be necessary to develop methodologies and technologies to create a suitable working environment for efficient operator work 4.0, which entails the concept of the Workplace of the Future [27]

Table 3.1: The working environment with Operator 4.0 concept, adapted from[85]

Aspects	Description
Operator duty	Collaboration with the machine.
Task complication	High.
Situation Awareness (SA)	Second Level.
Speed	Very High.
Decision making dependency	Independent operators and work groups
Operator jobs	Entire manufacturing.
Data supply	Real time decision assistance to operators.

For the development of the research, the Human Cyber Physical system (HCPS) has been identified as the unit of analysis [49, 96] in a common framework. In order to develop our approach and work on the research questions, this HCPS is implemented in the form of a case study as a human-robot collaborative workspace experience (HRCWE), through an academic prototype.

To understand the context of use, it has been conceptualized the HCPS-based as a socio-technical system, the modeling is performed through the FRAM tool; then, a first validation of the model through simulation and statistical assessment will be performed. The study focuses on work variability. The next step is the implementation of the prototype in a laboratory and the design of experiments in the form of HRCWE, to collect data associated with the human part, such as usability, then the data of the machine through metrics, and teamwork data. These measurements allow understanding and evaluating performance from the perspective of the human-machine work team or more specifically in the experiment the human-robot team.

3.2 Specify the user requirements

We start from the premise that for the concept of Industry 4.0, the operation of a process or a processing plant requires the participation of an operator [47]. The objective is therefore to analyze the social construction of robots as co-workers in collaborative work environments to better understand how the distribution of tasks and the organization of work will be affected by the introduction of this new form of robots, thus the table shows the characteristics of the workspace to be implemented.

3.3 Produce design solutions

3.3.1 Value Sensitive Design

Future production workplaces will be augmented with multiple types of worker assistance systems that will combine technologies such as collaborative robotics, voice interaction, augmented reality, and more, thus giving rise to digital assistants [69]. In part, this drive toward these new types of symbiotic technologies is a consequence of increased needs in manufacturing industries, with a consequent increased need for production workers. However, like all technologies, these systems also embody human values. More specifically, the design decisions made in the engineering of these HCPS imply a series of human values, even if they are not explicit. The philosophy of technology has long held that technologies are neither value-neutral, nor purely instrumental, nor purely deterministic. The Value Sensitive Design (VSD) approach is a principled framework to illustrate how technologies enabling human–machine symbiosis in the Factory of the Future can be designed to embody elicited human values [69]. The question is, How to align humans, technology and organization to ensure human well-being and system performance in industrial work systems in the transition to Industry 4.0? for this research propose VSD identifies are show in Table3.3

In order to support the development of human values, the Figure 3.2 3.3 3.4, proposed a set of specifications in accordance with the standard established for the corresponding value.

Table 3.2: Workspace Characteristics

Operator qualification and training	
Level of education	Low (no dedicated job training)
Training contents	Brief introduction to the machines and tasks
On-the-job training	Often the only source of training
Conditions for learning	Poor (few permanent jobs)
Routine task characteristics	
Content	Keeping production going, meeting specifications, quality control, dealing with faults
Specificity of interventions	Qualitative, few instrumental measurements
Human-automation task sharing	Operators provide the preconditions and collaborate with assembly
Frequency of interventions	High
Repetitiveness	High
Types of control	Production control, compensatory control, corrective control
Monitoring	Vigilance and scanning, need for mental models, perceiving effects of process in products, reacting to alarms
Dealing with abnormal situations	
Detecting	Easy
Dealing with faults	Compensatory control (stopping, restarting), often just removing symptoms, procedural knowledge gained from experience
Challenges for operators	
Understanding the process	Basic
Complex interactions	No complex system dynamics but limited understanding of interconnections between machines, product properties, and environment
Goal state	Fully specified, clear hierarchy of constraint
Time pressure	High

Table 3.3: Values from VSD for HWRCE.

Value	**Definition**
ACCESSIBILITY	Refers to making all workers successful users of technology.
CONFORMITY	Support the workers to respect rules and expectations, thus demonstrating social discipline and loyalty. At the same time, it shall restrict one's actions and/or conditioning one's choice, inclinations, impulses and desires.
HUMAN WELFARE	Refers to ensure workers' health (physical well-being and peaceful psychological state) also thanks to a proper work-life balance, a balanced workload and a comfortable and pleasant work environment.

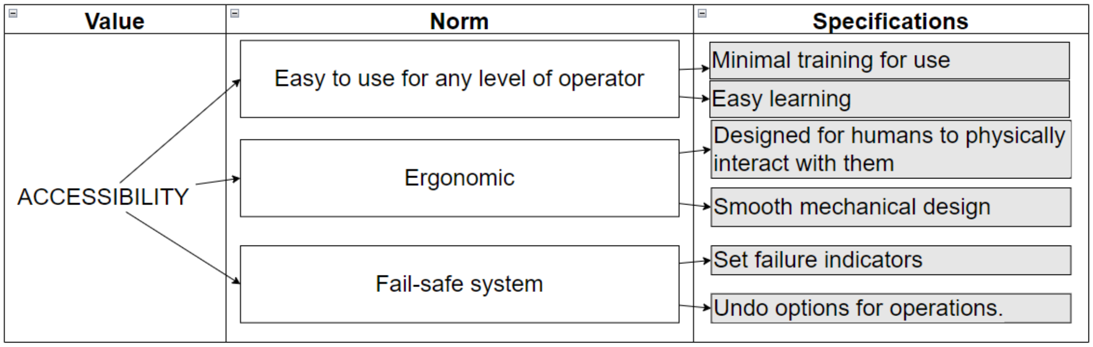


Figure 3.2: Accessibility

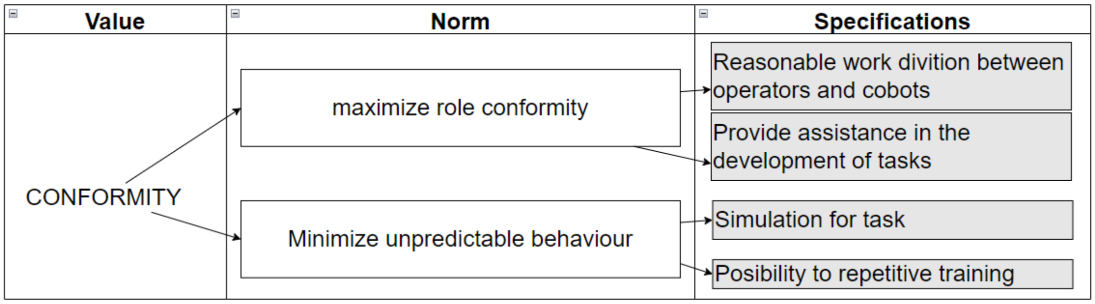


Figure 3.3: Conformity

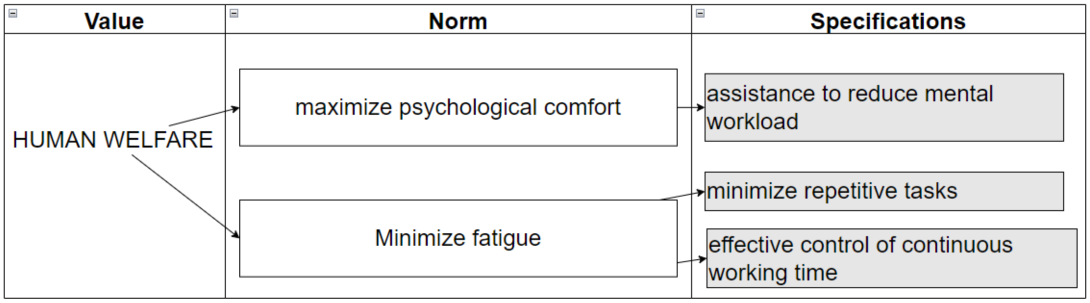


Figure 3.4: Human welfare

3.3.2 Functional Resonance Analysis Methodology

The variability of human behavior during plan execution poses a difficult challenge for human-robot teams. Some researchers use the theory of mind (ToM), or the ability to infer beliefs, desires and intentions of others [40]. The Functional Resonance Analysis Method (FRAM) allows modelling complex socio-technical systems by collecting data from real/simulated work practices. It provides a tool to describe system outcomes using the idea of resonance arising from the *variability* of everyday performance. By understanding sources of human variability using FRAM it could be possible design cognitive assistant robots with the aim to balance this variability.

In the context of human-robot interactive systems, the application of FRAM when modeling H-R tasks in order to get task allocation/configuration between human operator and robot allows in a straightforward form to evaluate variability as a performance measure. Whit this aim in mind, some analysis steps are necessary,

1. Identify and describe system activities into a task, and characterize each one using a six basic characteristics (*aspects*) schema: *Resource*, *Precondition*, *Input*, *Time*, *Control*, *Output*. See Figure 3.5 and Table 3.4.

2. Check the completeness/consistency of the model. In this point, a discussion about the work of human-robot teams is required.

3. Characterize the potential variability of the activities in the FRAM human-

robot model.

4. Define useful variability metrics.
5. Identify an effective task allocation/configuration between human and robots.

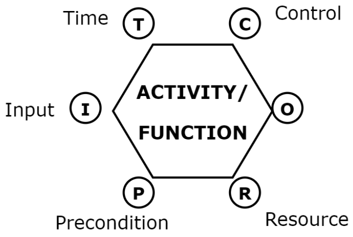


Figure 3.5: FRAM activity/function representation [47] in order to graphically represent instances in a FRAM study.

Table 3.4: Aspects related to an `<ACTIVITY>`.

Aspects	Description
Input (I)	It activates the activity and/or is used or transformed to produce the Output. Constitutes the link to upstream activities.
Output (O)	It is the result of the activity. Constitutes the link to downstream activities.
Precondition (P)	Conditions to be fulfilled before the activity can be performed.
Resource (R)	Components needed or consumed by the activity when it is active.
Control (C)	Supervises or regulates the activity such that it derives the desired Output.
Time (T)	Temporal aspects that affect how the activity is carried out.

The variability of an activity's output is revealed by the variability occurred in its outputs, and is referred to the deviation of one or several of the following dimensions such as: timing, duration, magnitude, object, and so on, with respect to an expected value. Thus, the variability occurred in the upstream functions affects the performance of the downstream function. The subsequent propagation of the variability in the system may lead to nonlinear effect called resonance generating unexpected/uncontrolled consequences. However, the impact of such variability over the system cannot be determined by observing the variability of the upstream function output only. In fact, it also depends on the variability acceptance capacity of the function receiving inputs (downstream). Thus, the functional resonance effect is triggered by the output variability of the upstream function exceeding the variability dumping capacity of the downstream function [7].

All the elements highlighted in Figure **??** have been now defined: human and robotics activities will be modelled using FRAM, because this methodology allows the evaluation of the variability in quantitative measures. Modelling configures a task in several activities, which will be simulated using FlexSim, RodoDK and UR robots simulator, and executed to get information about this variability in the measure. According to the obtained performance, feedback is provided to improve human skills and robot behavior. Eventually, this feedback will generate new interaction models for the task. In the next section, all these elements will be implemented in the form of a manual assembly task and results obtained from the executed simulation will be analyzed.

3.3.3 Environment Modelling and Simulation

This section will provide a precise description of the experimental setup, in the form of collaborative manual assembly; metrics under consideration, mainly variability depending on user preferences and selected process strategies, impacting on product/process quality; modelling of the task, using the FRAM method, in the form of activities; obtained results in a simulated environment; their interpretation, as well as the experimental conclusions that are drawn from the simulated experiences of the manual assembly task. For easiness of the discussion, FRAM principles of failures and emergence are out of the scope in this article.

3.3.4 Experimental Setup: A Manual Assembly Task

The production process to be automated is an assembly system for a turning mechanism, which is part of a whole production system. In Figure 3.6, the components of the assembly task are shown. The product to be assembled (see Figure 3.20) requires three parts: a *base* on which a *bearing* is placed and finally the assembly is sealed with a *cap*. As an initial stage it is assumed that the raw material is always available. The workstation process is described as follows (Work as Imagined, WAI [47]):

1. It is verified that there is a base, a bearing and a cap from the stock to start the assembly.
2. Get a base from the stock, get the bearing and pre-assemble on the base.
3. Next, get the cover and assemble the product.
4. Take the assembly and store it in a stock.

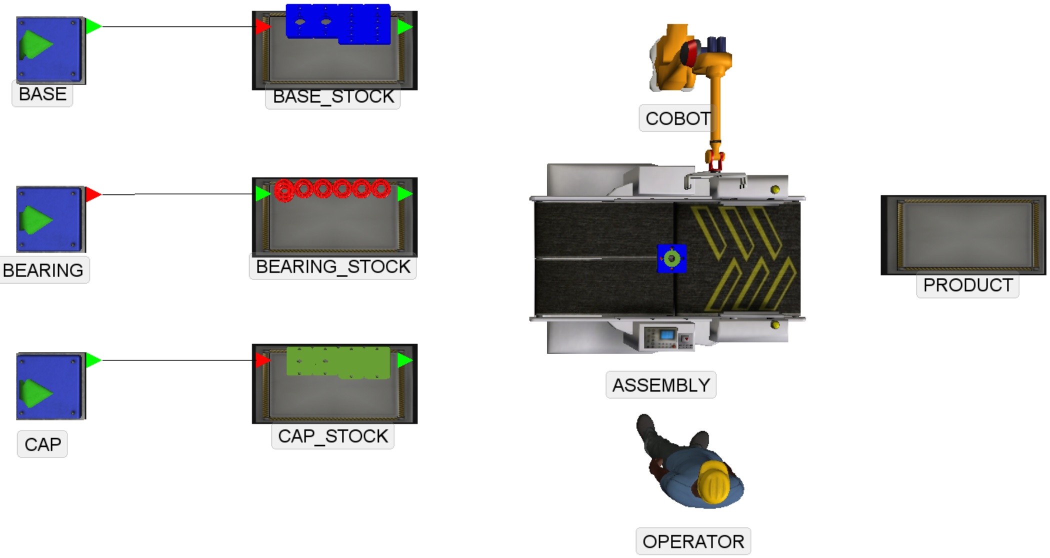


Figure 3.6: Simulated layout of an assembly task.

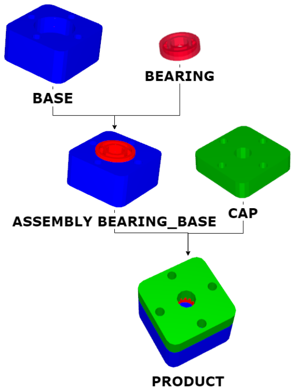


Figure 3.7: Product (Turning Mechanism) and assembly steps.

This process of assembly will continue until completing the production order, or until the end of the work shift. Input and output stocks can be into either, the same or different location.

3.3.5 Activities Modelling for the Manual Assembly Task

The goal of the model is the allocation of functions needed to perform product assembly, and to assign functions to the operator or robot within the workplace in a collaborative human-robot environment. For the modelling, first a basic model of the necessary functions of the process is created, without considering who performs the function, and then 3 scenarios are established for the execution,

- Scenario 1. Fully manual task.
- Scenario 2. Fully automated task with a robot (a cobot is supposed).
- Scenario 3. The process is executed in a collaborative manner, human-robot shared task.

The FRAM methodology (Functional Resonance Analysis Method) [83] is followed for modelling, based on the 4 steps describe above.

Identify and Describe Functions

Based on the description of the process, the following are the `<ACTIVITIES>` associated to the `[MANUAL ASSEMBLY]` Task. Each work task in the process is divided into activities, assignable to H, R, or both H-Rs. In the context of the FRAM model, activities are also referred as *Functionalities*,

- `<ASSEMBLY PRODUCT>`
- `<ASSEMBLY BEARING_BASE>`
- `<GET BASE>`
- `<GET BEARING>`
- `<GET CAP>`
- `<CHECK PRODUCT>`
- `<START PRODUCTION>`
- `<CHECK PARTS>`
- `<PROVIDE PARTS>`
- `<STORE ASSEMBLY>`

These Activities or Functionalities are described in a FRAM form. For illustrative purposes, the `<ASSEMBLY PRODUCT>` activity is shown in Table 3.5. Function Type is not initially described as far as it can be either 'Human', when performed by an operator, or 'Technological', when is a cobot under consideration. An instance of the model in the FRAM visualisation tool, shown in Figure 3.8, highlights the `<ASSEMBLY PRODUCT>` function considered as an objective function of the system.

Table 3.5: Function `<ASSEMBLY PRODUCT>`.

Name of Function	`<ASSEMBLY PRODUCT>`
Description	Assembly the PRODUCT, put the CAP in the ASSEMBLY BEARING_BASE, end of process
Function Type	Not initially described
Aspect	**Description of Aspect**
Input	(BASE_BEARING) in position
Input	(CAP) in position
Output	PRODUCT
Time	Assembly Process

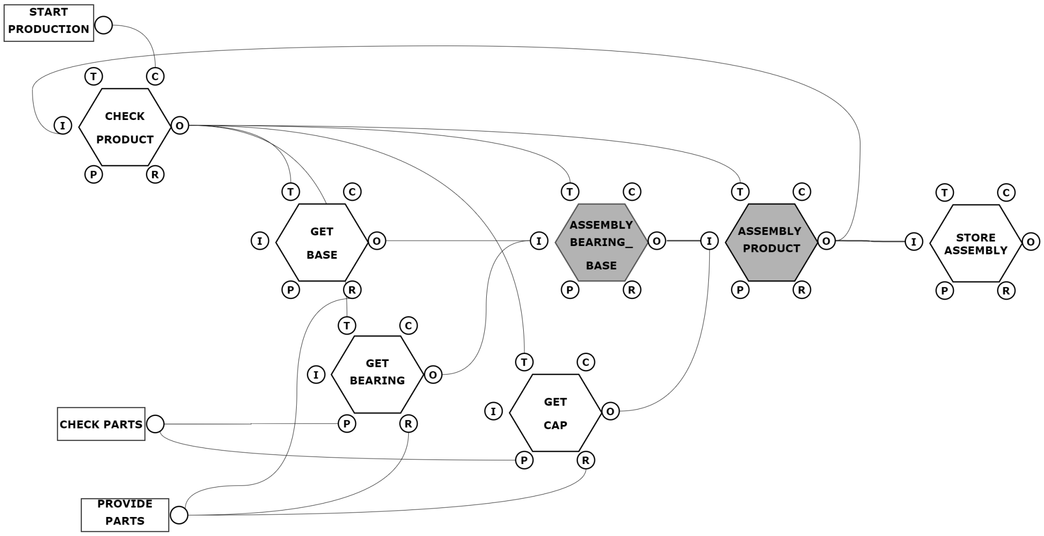


Figure 3.8: The assembly task as an instance of the model FRAM.

Scenario 1. Fully manual task

In this scenario the functions will be executed by a single operator, within the work shift, who performs assemblies according to the production orders that arrive at the workstation. For the execution of the functions a new function is added to the basic model, called `<OPERATORS>`, which oversight resource operator, as shown in Table 3.6.

Table 3.6: Function `<OPERATORS>`.

Name of Function	`<OPERATORS>`
Description	Oversight resource operator
Function Type	Human
Aspect	**Description of Aspect**
Input	Assembly Process
Output	OPERATOR
Control	Work Permit

According to the FRAM methodology the functions executed by the operator are 'Human' type. Therefore the Function Type characteristic initially labelled as 'Not described initially' now changes according to those options shown in Table 3.7.

Table 3.7: Function Type defined as 'Human' for all the activities in the manual assembly task.

Function	Function Type
`<ASSEMBLY PRODUCT>`	Human
`<ASSEMBLY BEARING_BASE>`	Human
`<GET BASE>`	Human
`<GET BEARING>`	Human
`<GET CAP>`	Human
`<OPERATORS>`	Human
`<CHECK PRODUCT>`	Human

Scenario 2. Fully automated task with a robot

In this scenario functions are executed by a single robot, within the work shift, which performs the amount of assemblies possible according to the production orders. For the execution, the function called `<OPERATORS>` is redefined as shown in Table 3.8.

Table 3.8: Function `<OPERATORS>`.

Name of Function	`<OPERATORS>`
Description	Oversight resource operator
Function Type	Human
Aspect	**Description of Aspect**
Input	Assembly Process
Output	Robot
Control	Work Permit

Now the functions executed by the Robot are of the Technological type, and the 'Function type' characteristic changes according to those shown in Table 3.9.

Table 3.9: Function Type defined as 'Technological' for all the activities in the Scenario 2.

Function	Function Type
`<ASSEMBLY PRODUCT>`	Technological
`<ASSEMBLY BEARING_BASE>`	Technological
`<GET BASE>`	Technological
`<GET BEARING>`	Technological
`<GET CAP>`	Technological
`<OPERATORS>`	Human
`<CHECK PRODUCT>`	Technological

Scenario 3. The process is executed in a collaborative manner, Human-Robot shared task

In this scenario, the functions will be executed collaboratively by either an operator or a robot, within the work shift, performing assemblies according to the production orders. For the execution, the function `<OPERATORS>` is in charge of changing the type of function within the model, according to the strategy established by a human agent or by a technological agent. As result, now the functions executed by the robot are

‘Technological’ type, and the functions executed by the operator are ‘Human’ type. The characteristic changes according to those shown in Table 3.10.

The choice between ‘Technological’ and ‘Human’ for this scenario has been determined in order to mix both types for Assembly functions and Get functions, for illustrative purposes. It has been assumed that the base-bearing assembly is a delicate one, from a decorative perspective. Hence, introducing dexterous human abilities will improve final quality of the product from a decorative/customer perspective that the robot is not able to perform always with the current sensor setting or programming.

Table 3.10: Function Type defined as ‘Human’ or ‘Technological’ depending on the activities to be performed in the Scenario 3.

Function	Function Type
`<ASSEMBLY PRODUCT>`	Technological
`<ASSEMBLY BEARING_BASE>`	Human
`<GET BASE>`	Human
`<GET BEARING>`	Human
`<GET CAP>`	Technological
`<OPERATORS>`	Human
`<CHECK PRODUCT>`	Technological

3.3.6 Identifying variability

For the identification of the variability, the type of function defined in the model is considered. The objective of the study is to determine the variability according to the type of agent used to perform the functions. Based on the FRAM methodology, to check the variability of the performance of the output of the functions, the characteristics *Time* and *Quality* are selected.

The measurement of the output characteristics will be performed through the ‘Time to Task’ and ‘High Quality Product Percentage’ KPIs, as it can be seen in Table 3.11.

Table 3.11: KPI quantitative variables definition

Characteristic	**KPI**	Description
Time	`Time to Task`	Time to complete a product (total assembly)
Quality	`High Quality Product Percentage`	Ratio of high quality products to total production expressed as a percentage

Based on the definitions, Equation 3.1 and Equation 3.2 show how they are calculated, respectively,

$$\texttt{Time to Task} = \sum_{i=1}^{5} T_{A_i} \tag{3.1}$$

with T_{A_i} being the time to complete activities `<GET BASE>`, `<GET BEARING>`, `<ASSEMBLY BEARING_BASE>`, `<GET CAP>`, and `<ASSEMBLY PRODUCT>`, for $i = 1, \ldots, 5$, respectively, and

$$\texttt{High Quality Product Percentage} = \frac{N_{HighProduct}}{N_{TotalProducts}} \cdot 100 \tag{3.2}$$

As a general concept, for each planned scenario, the characteristics of the operator are considered as sources of *Time* variability. Reversely, *Quality* of the final product will vary and be reduced when robots are considered into the process. All the products have, at least, Standard quality, but most of them are High quality in some sense for the customer, not affecting functioning but, for instance, decorative issues. For example, the parts for the assembly arrive at the process without any orientation, the process assembly its products with high efficacy and typical quality, but if the operator aligns them by changing their orientation, the customer perceives a better quality of the product. This alignment is an easy task of decision for the human operator, while for the robot it would require the use of extra sensors, for example artificial vision.

Scenario 1. Fully manual task.

In this scenario the variability is considered to depend on the type of operator performing the process, defined as Expert, Standard or Novice. Based on the FRAM methodology, Table 3.12 and Table 3.13 show the characteristics considered.

Table 3.12: Potential output variability for *Time* in Scenario 1.

Function	Type Operator	Output
`<ASSEMBLY PRODUCT>`	Expert	Too early: Time to Task down and keep regular in time
	Standard	On Time: Time to Task is according to design
	Novice	Too Late: Time to Task increases with irregular variations

Table 3.13: Potential output variability for *Quality* in Scenario 1.

Function	Type Operator	Output
`<ASSEMBLY PRODUCT>`	Expert	High Quality Product Percentage value is high
	Standard	High Quality Product Percentage value is typical
	Novice	High Quality Product Percentage value is low

Scenario 2. Fully automated task with a robot

Based on the FRAM methodology, Table 3.14 and Table 3.15 show the characteristics considered. The 'Type Operator' is a cobot than can be considered in a Basic version or an Optimized one, which is faster processing parts.

Table 3.14: Potential output variability for *Time* in Scenario 2.

Function	Type Operator	Output
`<ASSEMBLY PRODUCT>`	Optimized	Too early: Time to Task down
	Basic	On Time: Time to Task is the same all the time
		Too late: Not possible, except in case of complete breakdown

Table 3.15: Potential output variability for *Quality* in Scenario 2.

Function	Type Operator	Output
`<ASSEMBLY PRODUCT>`	Optimized	High Quality Product Percentage value is high
	Basic	High Quality Product Percentage value is typical

Scenario 3. The process is executed in a collaborative manner, Human-Robot shared task

In this scenario the variability will be the result of the multiple possible combinations of the variability of the human-type functions and the technological functions; the result depends on the strategy of assignment of the activities. In this first version, the MABA-MABA (Men-Are-Better-At/Machines-Are-Better-At) method is considered [19] see Table 3.16, for which it is assumed that the human operator better develops the function `<ASSEMBLY BEARING_BASE>`, and the robot for the function `<ASSEMBLY PRODUCT>`. Table 3.17 and Table 3.18 show the characteristics considered, for the different activities.

3.3.7 Human-Robot Collaborative Workspace

Kruger [64] defined a collaborative robot as a mechanical device enabling human–machine cooperation through direct physical interaction with fellow humans. The area where

Table 3.16: MABA-MABA strategy human-cobot.

Human is better than the cobot	**Cobot is better than the Human**
Ability to improvise and use flexible procedures	Ability to respond quickly to control signals, and to apply great force smoothly and precisely.
Ability to reason inductively.	Ability to perform repetitive, routine tasks.
Ability to detect changes in part quality	Ability to maintain on-time
Ability to replanning time	Ability to maintain precision

Table 3.17: Potential output variability for *Time* in Scenario 3.

Function	Type Operator	Output
`<ASSEMBLY`	Expert	Too early: Time to Task down and keep regular in time
`BEARING_BASE>`	Standard	On Time: Time to Task is according to design
	Novice	Too Late: Time to Task increases with irregular variations
`<ASSEMBLY PRODUCT>`	Optimized	Too early: Time to Task down
	Basic	On Time: Time to Task is the same all the time

Table 3.18: Potential Output variability for *Quality* in Scenario 3.

Function	Type Operator	Output
`<ASSEMBLY BEARING_BASE>`	Expert	High Quality Product Percentage value is high
	Standard	High Quality Product Percentage value is typical
	Novice	High Quality Product Percentage value is low
`<ASSEMBLY PRODUCT>`	Optimized	High Quality Product Percentage value is high
	Basic	High Quality Product Percentage value is typical

human and robot work and can co-exist is the workspace Figure3.12. While each robot and human has a space where they can move during performance of job which is called zone. Within each work zones there can be additional zones depending on the interaction type.

According to the Architecture model for human-robot collaboration shown in Figure3.12 the HRCWE can be described in the three dimensions as:

- HRC team composition = 1 Human and 1 Robot: A robot is assisting a human in accomplishing the tasks.
- HRC interaction levels = Cooperation: Human and robot both have shared tasks in the shared workspace but they do not work on the same component. Human and robot have a common shared workspace and they are present in the workspace at the same time. However, each of them are working on a separate workpiece. This done in a sequence.
- HRC Safety implications = Power ‘I&’ force limiting: This follows the safety limitations based human–robot interactions as described in ISO 15066 standard, for HRCWE the cobot establish Power and force limiting.

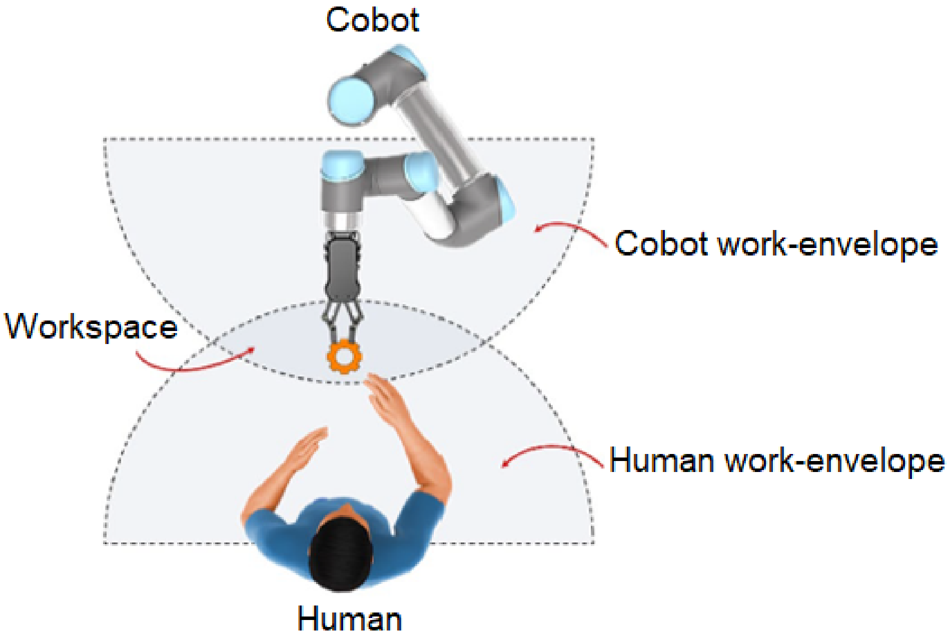


Figure 3.9: Human robot collaboration [71]

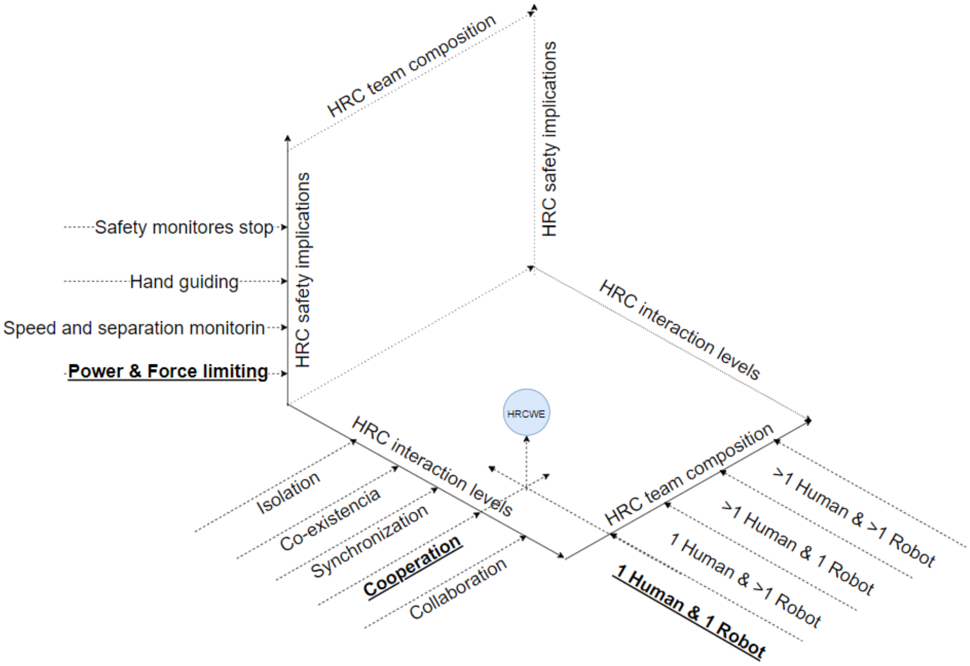


Figure 3.10: Architecture model for human-robot collaboration adapted [71]

Task in HRCWE. the Task 2, the assembly can be performed according to the combination of components to produce 3 different products, without changing the robot programming, the possibilities are shown in the Figure 3.11, the activities shown have been initially distributed according to the grasping conditions of the objects.

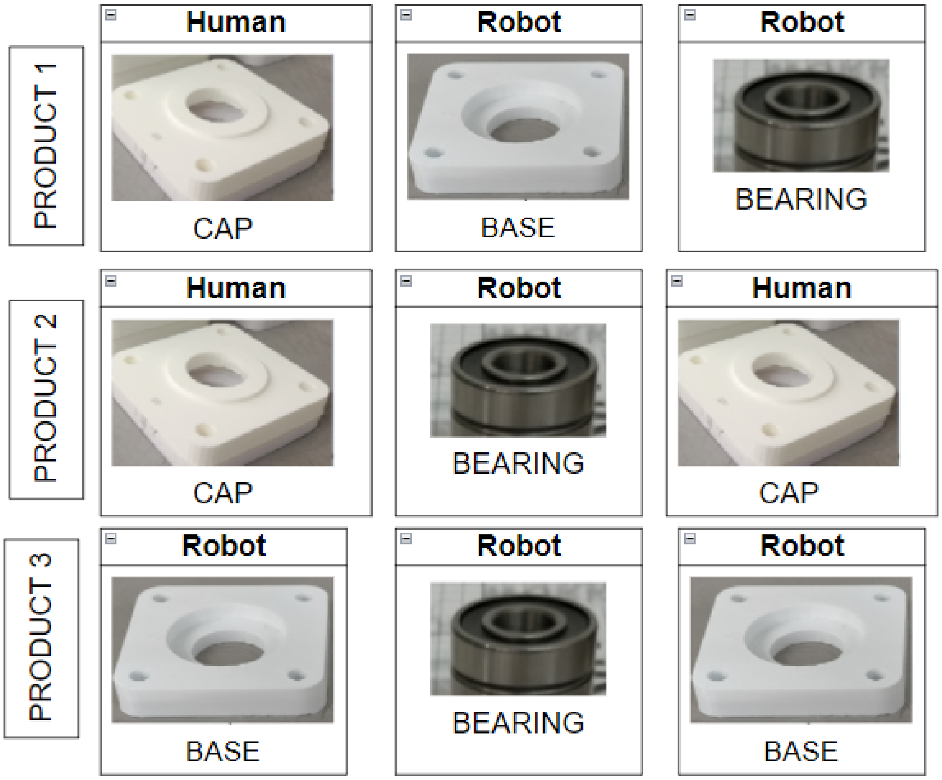


Figure 3.11: Products in HRWCE

The experimental study of this work is developed in the laboratory scenario shown in Figure 3.12. A laboratory scenario has great adaptability for the identification of human-robot solutions, development of new methodologies, application of algorithms and evaluation of collaborative human–robot workstations [32].

The human supervisor plans the activities with one or more human operators, with one or more collaborative robots, tuning the task allocation between human and robot, giving visual feedback of the robot behavior to the human (using visual color lights) and information using pop up windows into the robot teach pendant.

Figure 3.12: Laboratory resources: the main task developed on a tablet and the secondary collaborative task of assembly with the robot on the left in the background

Figure 3.13 shows the workspace, which is divided into two areas. Area1 is where the operator executes the Tower of Hanoi game with five disks (TOH5). It is considered the Task 1, the main task for the operator. Area 2 is where the operator executes the Collaborative Assembly (CA) with the robot of the product. It is named Task 2, the secondary one. In the Area 1 the human is in the loop. The information processing system allows to the participant the visual feedback of the task developed. The participant can plan strategies and make decisions. The participant executes physical actions in a touch screen.

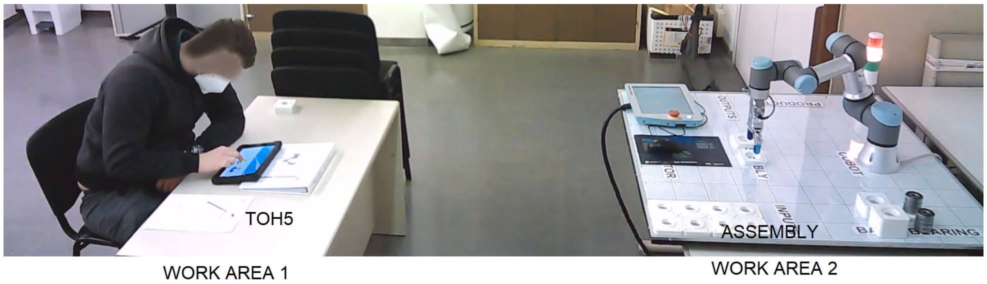


Figure 3.13: Human-robot collaborative workspace: Area 1 is on the left, with the primary task, demanding cognitive skills. Area 2 is on the right, a collaborative assembly task with low demanding cognitive and physical skills

If the participant pays attention to the Area 2, in this case the human is in the loop. The visual color lights alert to the participant if a human collaborative task is required. The participant can decide whether to leave Area 1 momentarily to go to Area 2. In this case the human is in the loop attending the assembly station.

Inside the Area 1 it is possible the design of cognitive tasks regarded with human capabilities. The Tower of Hanoi with 5 disks (TOH5) task is an example of problem solving (high-level reasoning capabilities) where people use mental skills and learning ability to achieve a successful solution [37, 34]. While the collaborative assembly task in Area 2 is a good example of pick and place task in industrial environment. It shows the eye-hand human coordination to achieve a successful solution. Hence, this work illustrates the idea that a human-robot collaborative task must include physical and cognitive aspects together.

Task 1. Tower of Hanoi (TOH5)

The objective of the task is to move the tower of disks from the first support to another support, see Figure 3.19, with the help of an intermediate support. The tower is segmented into disks, which are the ones that actually are moved to rebuild it again in the final position. This task must be performed in as few movements as possible and with as few errors as possible. Disk movements are conditioned by two constraints:

- It is not allowed to place a larger disk on top of a smaller one.
- You can only move the disks in the order in which they are placed in the tower, starting with the one at the top first.

In this study, the Tower of Hanoi is performed only by the human, using a digital version of this problem, available at Google Play HANOI 3D. This software allows the manipulation of the disks and records the number of moves and total time in seconds required to complete the task. It is proved that there is no experimental cognitive variation if either wood pieces or a digital version are used in experimental sessions [34]. Following the workload level evaluation scale in [28], this task is classified as appreciated mental workload because a human without a previous expertise in this game must develop plan and effective strategies. In fact, as a first contact with the Tower of Hanoi problem, the case with 3 disks is a challenge for many users. The difficulty of this task was previously tuned according to several early participants and a medium level of difficulty with 5 disks was decided.

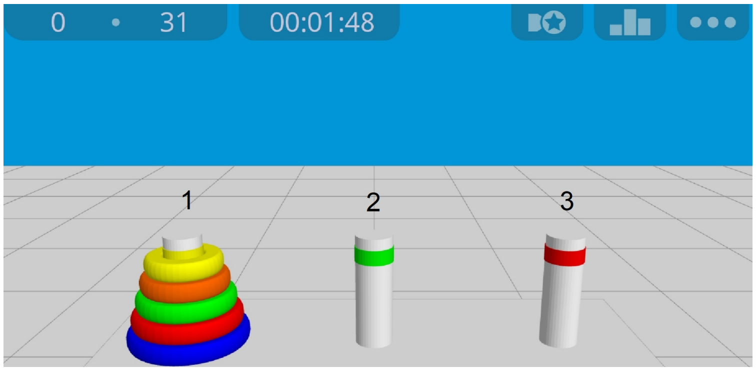


Figure 3.14: Digital version of the Tower of Hanoi with five disks (TOH5) task

For the solution of the TOH task, the minimum number of moves is given by the formula 2^{n-1}, where n is the number of disks on tower number 1 at the beginning of the test [109]. Hence the TOH5 task can be optimally solved with 31 moves.

Task 2. Collaborative Assembly (CA)

The assembly area (Area 2) is where robotic work takes place in the process. Humans and robots should cooperate in order to simplify the job and make the overall system more efficient and productive [23]. The objective of this task is to collaborate in the assembly of a product composed of 3 components: a base, a bearing and a cap, as shown in Figure 3.20. The task is a priori classified as a low mental workload, from a human-centred perspective, because eye-hand coordinated skills are the more relevant in this task. The collaborative assembly task shows a low level of risk for the human and no action is required to decrease this risk.

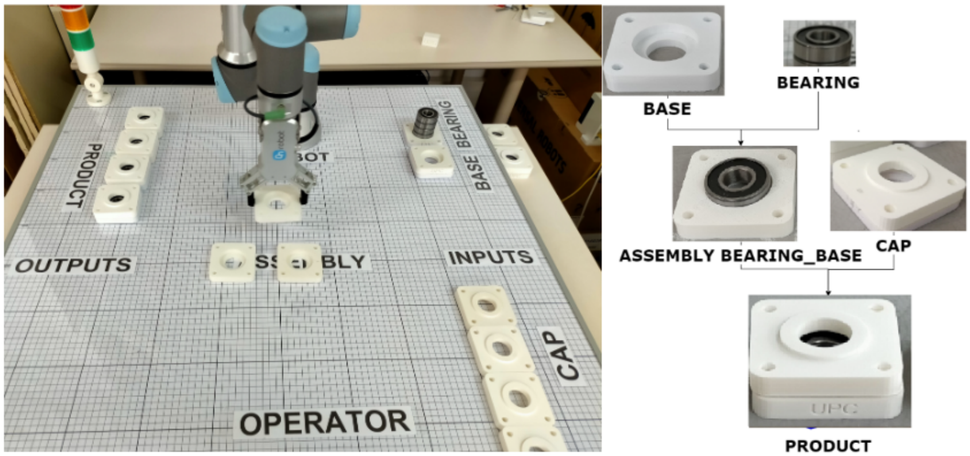


Figure 3.15: Assembly process: on the left, the working area; on the right, the parts to be assembled into the product

Figure 3.20 shows the implementation of the assembly process using a collaborative robot from the company Universal Robots, model UR3. The difficulty of the programmed robot task was previously tuned experimenting with early participants and a medium level of difficulty for robot velocity was decided. The purpose is to allow the participant to approach the station and be able to intervene physically without compromising safety and performance.

Cycle of Work

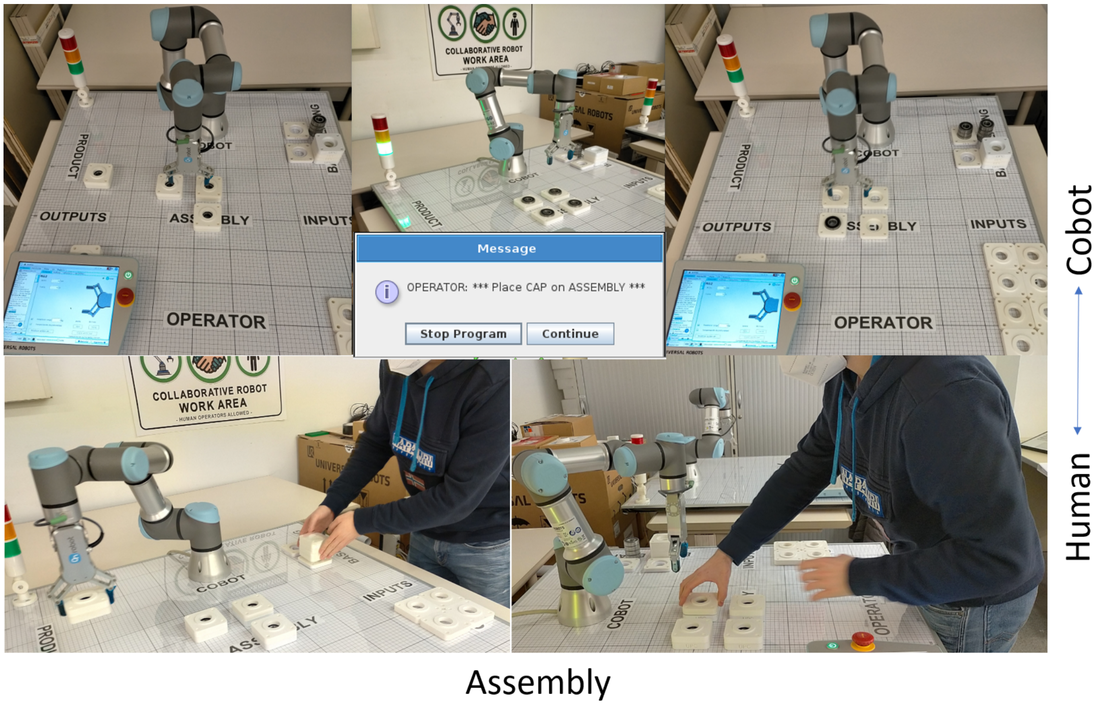
In the workspace, the distribution of activities between the human operator and the collaborative robot (cobot) is shown in Table 3.19. Figure 3.16 shows an instance of the cycle of work for a participant.

Safety conditions

In the Human-Robot Collaborative Workplace, safe conditions are considered, different from traditional industrial robots. These specific safety requirements are:

Table 3.19: Tasks and activities allocation in the human-robot collaborative workspace's experiment.

Task	**Activity**	**Operator**
Task 1	Solve problem TOH5	Human
Task 2	Get base	Cobot
Task 2	Get bearing	Cobot
Task 2	Get cap	Human
Task 2	Reload storage	Human
Task 2	Assembly product	Cobot
Task 2	Palletize product	Cobot



OPERATOR: *** Place CAP on ASSEMBLY ***

Figure 3.16: Cycle of work in the Collaborative Assembly task (CA)

1. Universal Robot's UR3 cobot has been designed to work in direct cooperation with humans within a defined workspace according to the ISO 10218-1: 2011 standard [113].
2. Maximum speeds and torque have been reduced as it can be seen in Table 3.20.
3. Virtual safety planes are defined for the cobot to reduce the workspace.
4. Visual indicators alert the operator of the robot's operating condition.

Table 3.20: Motor operating conditions for the UR3 cobot

Variable	**Normal Mode**	**Maximum**
speed	1500 mm/s	5000 mm/s
torque	150 N	250 N

Authors are not considering in this approach strategies and possibilities of collision between robot and human operator because human operator and robot do not physically coincide in the same spatial location in the case study [101]. In fact, the robot can wait the ending of the human operator activity before starting its work [123].

The different emerging technologies affecting the Operator 4.0 work environment and the very concept of human centrality motivate the need to search for a methodology which considers human values as part of the design process of any human-automation type system.

3.4 Evaluate the design solutions

Periodically, researchers carry out the validity of methodological proposals in human-robot interaction using several measures [108, 80]. According to the increasing presence of collaborative and intelligent robots in industry, standardized metrology for the performance measurement of human-robot (H-R) systems [73] is still needed in the manufacturing environment.

Along with the development of robotic interfaces, there has been an increase in the evaluation of these systems. HRI researchers have employed a variety of evaluation styles in their work; they can evaluate their systems summatively (i.e., after-the-fact) or formatively (i.e., during system development). [16]

3.4.1 Sumative Evaluation

According to Clarkson, [16] the HRI Heuristic Validation is useful to make a summative evaluation, according to which eight heuristics are established.

1. *Sufficient information design*: The interface should be designed to convey "just enough" information: enough so that the human can determine if intervention is needed, and not so much that it causes overload.
2. *Visibility of system status*:The system should always keep users informed about what is going on, through appropriate feedback within reasonable time. The system should convey its world model to the user so that the user has a full understanding of the world as it appears to the system. The system should support the user's situational awareness.
3. *Appropriate information presentation*: The interface should present sensor information that is clear, easily understood, and in the form most useful to the user. The system should utilize the principle of recognition over recall, externalizing memory. The system should support attention management.
4. *Use natural cues*: The language of the interaction between the user and the system should be in terms of words, phrases and concepts familiar to the user, rather than system-oriented terms. Follow real-world conventions, making information appear in a natural and logical order.

5. *Synthesis of system and interface*: The interface and system should blend together so that the interface is an extension of the system, the user and by proxy, the world. The interface should facilitate efficient and effective communication between system and user and vice versa, switching modes automatically when necessary.

6. *Help users recognize, diagnose, and recover from errors*: System malfunctions should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution. The system should present enough information about the task environment so that the user can determine if some aspect of the world has contributed to the problem.

7. *Flexibility of interaction architecture* If the system will be used over a lengthy period of time, the interface should support the evolution of system capabilities, such as sensor and actuator capacity, behavior changes and physical alteration. Sensor and actuator capabilities should be adequate for the system's expected tasks and environment.

8. *Aesthetic and minimalist design* The system should not contain information that is irrelevant or rarely needed. The physical embodiment of the system should be pleasing in its intended setting.

To validate these eight heuristics, the questionnaire show in Table 3.21. is proposed.

3.4.2 Formative Evaluation by HRI Metrics

Regarding HRI metrics, the usual human-centered interaction metrics consider *Effectiveness*, *Efficiency* and *User satisfaction*. Metrics to be considered are, for instance, degree of success in completing a task, total task time, user physical load or mental

Table 3.21: Questionnaire to evaluate heuristics

Heuristic	Question
H1. Sufficient information design	Has the designer considered all tasks and activities in the design?
H2. Visibility of system status	Is the operator informed about the progress of the system with the appropriate response and within an acceptable time?
H3. Appropriate information presentation	Does the system use concepts and language familiar to the operator rather than technical terms?
H4. Use natural cues	Do design elements, such as objects and actions, have the same meaning or effect in different situations?
H5. Synthesis of system and interface	Are the task methods efficient?
H6. Help users recognize, diagnose, and recover from errors	Is appropriate help provided and is the information easy to find and focused on the operator's task?
H7. Flexibility of interaction architecture	Can the operator customize frequent actions or shortcuts?
H8. Aesthetic and minimalist design	Does the dialogue contain irrelevant or rarely used information?

workload. These starting HRI metrics should be increased with metrics associated with the robot behavior, which in the industrial field are known as Key Performance Indicators (KPIs) as percentage of use of the robot, tasks successfully completed by the robot, task time. Some standardized metrics for task effectiveness and task efficiency are listed in Table 3.22.

Table 3.22: Task effectiveness and task efficiency metrics for measuring performance of human-robot interaction.

Metric	**Detail**
Task effectiveness	
TSR	(H, R) Task Success Rate with respect to the total number of tasks in the activity
F	Frequency with which the human requests assistance to complete their tasks
Task efficiency	
CAT	Concurrent Activity Time (H-R): percentage of time that the two agents are active in the same time interval
TT	Time to complete a task (H, R)
IT	Idle Time: percentage of time the agent (H, R) is idle
FD	Functional Delay: percentage of time between tasks when changing the agent (H, R)

Metrics to use in this experiment are show in Table 3.23

Table 3.23: Task effectiveness and task efficiency metrics for measuring performance of human-robot interaction in this experiment.

Metric	**Detail**
Task effectiveness	
TSR	(H, R) Task Success Rate with respect to the total number of tasks in the activity
Task efficiency	
TT	Time to complete a task (H, R)

For measuring user satisfaction in the interaction, qualitative questionnaires is the main approach. In the application of satisfaction questionnaires, the need to adapt existing questionnaires in human-computer interaction to a broader scope should be addressed. As a starting point, a first approach is to adapt questions from questionnaire models, such as the Technology Acceptance Model (TAM) [18], System Usability Scale (SUS) [10], Fluency (Subjective Fluency Metrics) [42] and the Part C questionnaire on comfort in ISO 9241-420 Table D.1 [54]. To facilitate the use of these heuristics, a consensus scale is required. For example, a 5-point Likert scale, where in many of the heuristics the ends of the scale are 'Strongly disagree' and 'Strongly agree'. These cited qualitative metrics for measuring interaction from the user satisfaction perspective are partial since once an H-R task is defined, the synergy between each of the agents involved leads to a broader model that must consider the overall performance and teamwork fluency [43, 38], that is quantitative measures used about effectiveness and efficiency.

Our proposal is defending to quantitatively measure the overall satisfaction of the interaction, that is user satisfaction, but also 'task satisfaction', by using *variability* in the task efficiency metric *Time to Task*, (TT). That is, we propose to move from both, direct quantitative robotics and qualitative human measures to the overall product or process quality evaluation.

3.4.3 Metrics for Product/Process Quality Evaluation: Variability

The product or process quality evaluation aims to investigate if a task or an activity requires improvements in terms of standardization and reduction of process instability or variability [33, 84]. From a manufacturing approach, variability is defined as an inherent process deviation from a nominal value. In [33], process variability is identified as a coefficient of variation CV,

$$CV = \frac{\sigma}{mv} \tag{3.3}$$

where σ is the standard deviation and mv is the mean value of time data or success rate data. As a consequence, variability is a negative situation which requires a more controlled condition to achieve the designed process and product quality values [99]. In order to ensure the product quality and save manufacturing costs, growing attention has been paid to the problem of the stability of the manufacturing process with unknown probability distribution and trend [122].

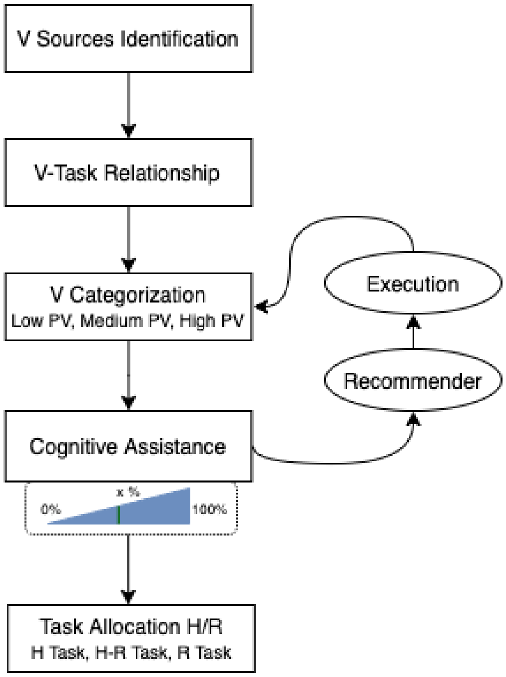


Figure 3.17: Analyzing process variability in human-robot collaborative tasks and task allocation.

The collaboration of workers in automated tasks using cobots improves product quality and process results, but introduces such a kind of unknown/unpredictable variability, specially in time execution for activities. Once all activities are mapped and measured, it is useful to identify a list of them which present a high level of process variability PV (see Figure 3.17). The amount of process variability can be categorized (‘Low PV’, ’Medium PV’, High PV’) according to either, previously registered dispersion in the measures (data-driven), activity modelling in simulation (model driven), or both in the case of digital twins [12]. In case to detect a certain amount of variability, cognitive assistance to the worker can be employed to provide a set of recommendations related with timing, checking accuracy, training for novice workers, modifications in the order. In a qualitative manner, cognitive assistance is related to process variability. After a new execution phase and collected data, variability is again measured and task allocation is reconsidered.

3.4.4 Usability Test Plan

When a new collaborative robot is introduced into production, tasks under development change from the point of view of the human operator. It is necessary to evaluate how these changes affect human operator behavior, measure and analyze human-robot collaboration tasks in detail. With this goal in mind and to take advantage of the experience in the field of human-computer interaction, a Usability evaluation is carried out, following some guidelines for its planning and execution, which have been collected by Norman Nielsen Group in their article “Checklist for Planning Usability Studies” (at https://www.nngroup.com/articles/usability-test-checklist/) The Figure3.18 show this planning.

Define Goals for the Study

The purpose of a usability test is, giving a specific context of use, measure the performance of a system in terms of task effectiveness, efficiency and satisfaction. Thus, the necessary feedback is provided to help decision-making in the redesign of systems. In particular, in this work a collaborative workspace is considered where the operator is developing a main task. It is supposed that the operator have some experience in this main task and the workspace is correctly designed. Next, the operator is required

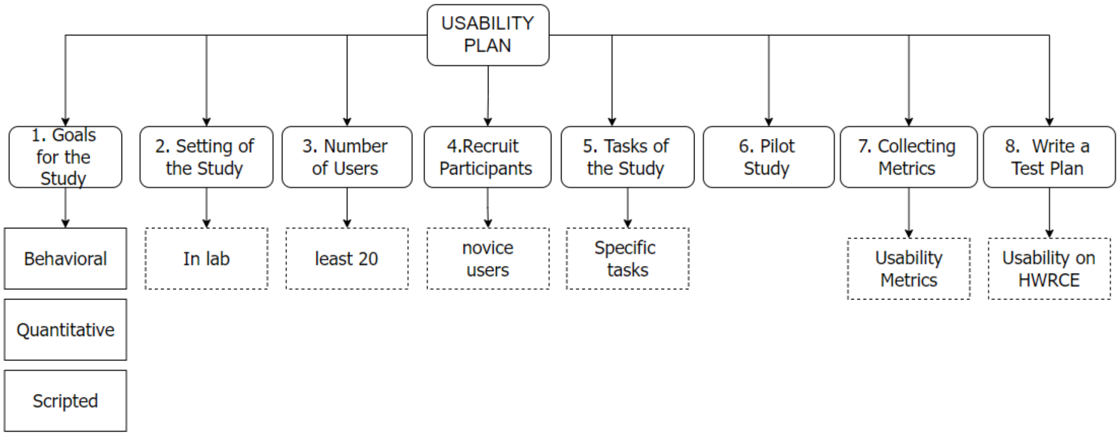


Figure 3.18: Usability Test Plan for HWRCE.

for developing a secondary task, implying collaboration with a robot. The general objective of the usability test in this scenario would be to evaluate the usability of the workspace when a secondary collaborative task with cobots is added to the operator.

The usability of the proposed human-robot collaborative workspace's experience (HRCWE) is evaluated on the basis of the international usability standard ISO 9241-11 [54] which takes into account both, objective and subjective metrics. According to this standard, the effectiveness and efficiency of usability is evaluated through the measurement of *Task to Time*, that is, the time in seconds to complete a task and *Task Completion rate* as the percentage of tasks that users complete correctly , performed by each participant while performing the tasks. In addition to these objective measures, a questionnaire has been developed to evaluate subjective usability using the System Usability Scale (SUS) whose definition is based on psychometric methods [67].

What the usability test is not designed to achieve Our proposed usability test is not oriented to evaluate the design characteristics of the implemented prototype, nor its productive performance. Moreover, this test is focused in early steps of design, and not in final launch of products to the market. Human factors and ergonomics use too the same orientation in early steps of design. The aim is to use the collaborative robot as a partner not as a substitute of human operator. Thus, the context implies the formation of human-robot teams, each contributing with their best skills [110].

Determine the Format and Setting of the Study

Specifying the study's characteristics is the first step in a study of usability, to specify the context of use where the experimental study will be carried out, the description of the process, the type of participants, and the academic purpose of the workspace [59, 76].

Context of use: In this case, the experience is designed in a University laboratory, participants being recruited among students and teaching staff laboring in this environment. The laboratory endows two identical robot stations and a set of computer workplaces. It is designed to introduce students in the managing of collaborative robots in two training steps: the first one is understand the robot and how programming it, and the second step is adopting the role of human operator in a realistic scenario.

The human-robot collaborative workspace experience (HRCWE) is based on a prototype implemented in the laboratory with the aim of developing teaching and research on the relationships between humans and robots. In particular, in collaborative mode, with a focus on the cognitive and mental tasks of the human operator. Certainly, the use of a collaborative robot facilitates physical interaction with humans. However, the cognitive and mental aspects should not be underestimated. The perception of the human regarding the complexity of the task, or the trust that the human places in the robot are also relevant elements.

Location and dates The address of the test facility is: Automatic Control Department , FIB Faculty, Automatic Control Department Laboratory C5-202, Universitat

Politècnica Catalunya Barcelona Tech. Authors plan to test participants according to the schedule shown in Table 3.24.

Table 3.24: Schedule of experiments.

Time	**Monday**	**Wednesday**	**Thursday**
09:00-11:00	Pilot Testing	Participant	Participant
11:00-13:00		Participant	Participant
14:00-16:00		Participant	Participant

Test facilities The experimental equipment under consideration is shown in Table 3.25.

Table 3.25: Experimental equipment.

Name	**Description**	**Use**
Tablet	Android system with digital version of TOH5 (HANOI3D)	Task 1 TOH5
Collaborative Robot	Robot Model UR3 with controller CB3. Manufactured by Universal Robot	Task 2 Collaborative Assembly (CA)
Laptop	Intel Core i5, Windows 10 Operating System	Data collection and logging
Web Cam	External, high definition	Get video of the experiment
Software	Cam video recorder, Visual Components v4.2	Record video of the experiment and record data of the collaborative robot

Determine the Number of Users

This experiment is quantitative, so the number of participants chosen for this usability test is 20 users, who are characterized as novice users.

Recruit the Right Participants

The roles involved in a usability test are as follows. It is worth noting that an individual may play multiple roles and tests may not require all roles.

- Participants: Participants are University's bachelor students and some teaching staff. The participants' responsibilities are attempting to complete a set of representative task scenarios presented to them in as efficient and timely a manner as possible, and to provide feedback regarding the usability and acceptability of the experience. The participants are addressed to provide honest opinions regarding the usability of the application, and to participate in post-session subjective questionnaires. These participants have good skills in engineering methods, computer science and programming. They do not have previous knowledge about collaborative robots and how manage human-robot activities.

  The form *Participants* in Appendix A.1 contains a recruitment form to be used to recruit suitable participants. The more relevant elements in this form are:

  - Participant inclusion questions
  - Participant exclusion questions
  - Participant experience questions

- Main facilitator General facilitator 's responsibilities are to:

  - Write the test plan
  - Organize the recruitment of suitable participants
  - Preserve ethical aspects
  - Prepare the workspace for the development of the experimentation
  - Show the task instructions to the user
  - Record the data of the experiment

  - Analyse usability test data
  - Summarize the results in a usability report

  The facilitator must supervise the ethical and psychological consequences for research participants. Any foreseeable effect on their psychological well-being, health, values or dignity must be considered and, in the case of judging it negative, even to a minimal degree, eliminated [51]. From a robotic perspective, roboethics has as objective the development of technical tools that can be shared by different social groups. These tools aim to promote and encourage the development of robotics and to help preventing its misuse against humankind [115].

  The facilitator must ensure that the test can be carried out effectively. To do this, previously set the level of difficulty for the Tower of Hanoi solution – in this case 5 disks–, adjust the speed of the collaborative robot's movement and program the cobot's task.

Ethics All participants involved with the usability test are required to adhere to the following ethical guidelines:

- The performance of any test participant must not be individually attributable. Individual participant's name should not be used in reference outside the testing session.
- A description of the participant's performance should not be reported to his or her manager.

Considering that this study involves work with humans, the usability plan has been endorsed by the Ethics Committee of the UPC with the identification code 2021-06.

Write Tasks of the Study

To evaluate the effects on the human operator when a collaborative human-robot task is added in the original workspace, a workplace composed of two tasks is defined, in particular with a focus on assembly tasks. The workspace tasks are:

- Task 1: Tower of Hanoi The original task for the human operator is about solving the Tower of Hanoi (TOH5) with five pieces. This problem consists of five perforated disks of increasing radius stacked by inserting them into one of the three posts fixed to a board, as seen in Figure 3.19. The objective is to move one disk from the first pole to another one, making only one move at a time and placing a bigger disk on top of a smaller one. The Tower of Hanoi puzzle, was established as a robotics challenge as a part of EU Robotics coordination action in 2011 and IEEE IROS Conference in 2012 . In our experiment, the Tower of Hanoi is performed only by the human operator.

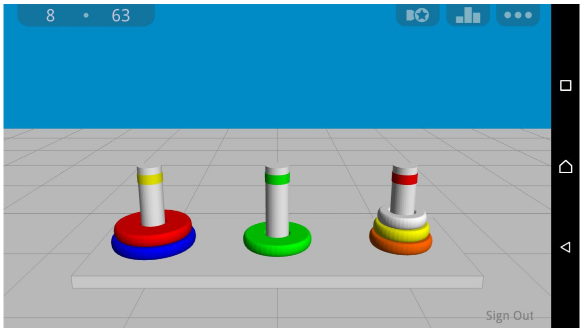


Figure 3.19: Digital version of the Tower of Hanoi problem with five disks, named TOH5.

A digital version of the TOH is used, available at Google Play HANOI 3D. This program allows manipulating the disks and records the number of moves and total time in seconds required to complete the task. No experimental cognitive variation exists if either wood pieces or a digital version is used [34].

- Task 2: Collaborative assembly of a product The introduced secondary task consists of collaborative assembling (CA) of a product composed of 3 components: a base, a bearing and a cap, as shown in Figure 3.20. The task is classified as adding a low cognitive workload, from a human-centred perspective, because eye-hand coordinated skills are the more relevant in this task. Moreover, the assembly task shows a low level of physical risk for the human and no action is necessary to decrease this risk.

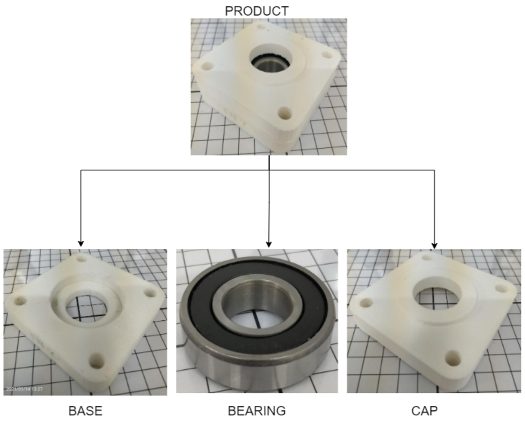


Figure 3.20: Collaborative assembly elements in the secondary process.

Pilot testing:

The purpose of the pilot test is to identify and reduce potential sources of error and fix any technical issue with the recording equipment or with the experiment that might cause delays to the current experiment. It is expected that pilot test take two hours, at maximum. The problems found would be immediately fixed. Observers are not invited due to the nature of the pilot.

3.4.5 Collecting Metrics

In a benchmark test, the usability of products is made measurable and enables a comparison with the competition. Based on different metrics, the usability dimensions, that is effectiveness, efficiency, and user satisfaction [54] are assessed and summarized into a meaningful overall score.

Data collection and metrics A dataset with data collected from experiments is organized as shown in Figure 3.21. A set of statistical measures and tests available in the tool Usability Statistics Packages[1] [124] are used for dataset analysis.

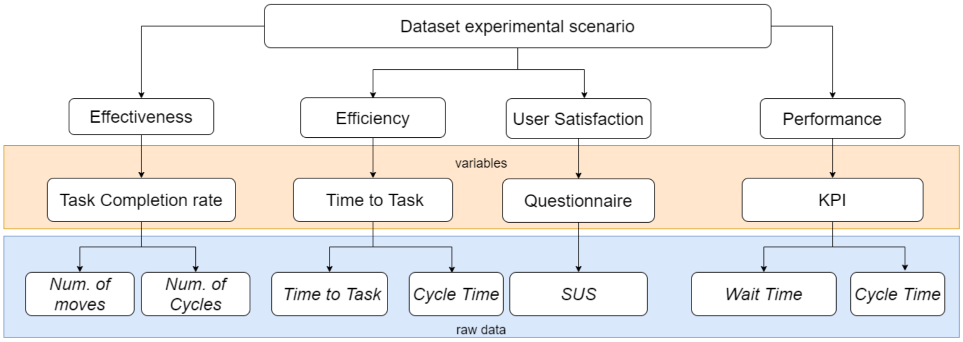


Figure 3.21: Organization of the dataset for the experimental study.

Task effectiveness and efficiency

The quantitative component involves handling of numerical variables and use of statistical techniques to guard against random events. This quantitative component includes information about the statistical significance of the results.

Effectiveness The efficiency is evaluated using the *Task Completion rate* measure. For this binary variable, a maximum error of 10% of the optimal number of moves needed to solve the problem is set. Hence, it is coded with 1 (pass) for participants who solve the task and 0 (fail) for those who do not solve it.

Efficiency To evaluate efficiency, the *Time to Task* measure is obtained from dataset associated to TOH5. Only participants who completed the task are considered and the analysis is made with the mean values obtained from each participation.

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[1] Jeff Sauro's formulation available in http://www.measuringusability.com/products/statsPak

Satisfaction The System Usability Scale (SUS) is used to evaluate the level of user satisfaction. The advantage of using SUS is that it is comparatively quick, easy and inexpensive, whilst still being a reliable way of gauging usability. Moreover, the SUS questionnaire allows to provide us with a measure of people's subjective perceptions of the usability of the experience in the very short time available during evaluation sessions.

However, interpreting SUS scoring can be complex. The participant's scores for each question are converted to a new number, added together and then multiplied by 2.5 to convert the original scores of 0-40 to 0-100. Though the scores are 0-100, these are not percentages and should be considered only in terms of their percentile ranking [5, 100]. A way to interpret SUS score is to convert it into a grade or adjective [5], as shown in Figure 3.22.

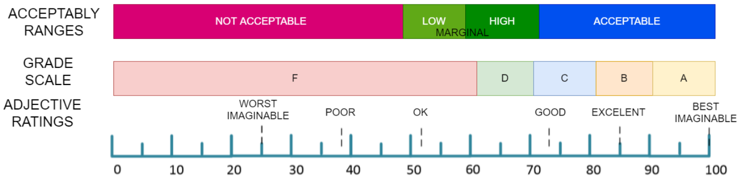


Figure 3.22: Grade rankings of SUS scores adapted from [5].

Key Performance Indicators for cobot To evaluate the CA task, that is the secondary task in the experimental scenario, some Key Performance Indicators (KPIs) have been collected, based in KPIs defined for cobots in [9]. Table 3.26 shows the definitions used in this work.

Table 3.26: KPIs referred to cobots.

KPI	Definition
Cycle Time	Cycle Time measures the duration of one cobot sequence
Cycled Completed	How many cycles have been performed by the cobot in a particular time period
Per Utilization	How long a cobot is being used compared to how long it could
Per Efficiency	It defines the percentage of time that the cobot performs productive work while running a program
Wait Time	The percentage of time that the cobot is waiting while it is running a program

The data gathering procedure to calculate cobot's KPIs has been implemented through a tool for obtaining the values of the variables recorded in the robot through the communication protocol with an external desktop. The values for *Cycle Time*, *Wait Time*, *Products* as the number of assembled products, and *Bases* as the number of bases, are acquired using this tool. It is shown in Figure 3.23 an example employing the Visual Components software so this information is saved as an electronics sheet, for KPI analysis. The *CapTime* in the Figure 3.23 is the operator's time to place the cap. This value will be considered as the idle time of the robot and also the *Human Operator Time*, since the robot is stopped.

Figure 3.23: Time data and raw material sent from cobot UR3.

Video recording Experimental sessions are recorded on video, hence the facilitator can later measure events like: operator travel time from one task to another, how many times the operator check whether the robot has finished, the right development of user actions in the assembly task.

While the user is developing the Tower of Hanoi task, the robot is working placing bases and bearings (red light). The vertical column of lights indicates with a green light when the presence of the user is required. The video recording can show if the user is paying attention to the column of lights or concentrating on the Tower of Hanoi task.

As a further analysis in collaborative human robot stations, video recording allows the observation of repetitive hand and arm movements that allow risk analysis and physical ergonomic assessment of the task.

Usability Sessions

Each participant session will be organized in the same way to facilitate consistency. Users will be interviewed at the end of the tasks.

Introduction: The main facilitator begins by emphasizing that the testing is being carried out by a Ph.D. student. This means that users can be critical of the experience without feeling that they are criticizing the designer. The main facilitator is not asking leading questions. The main facilitator explains that the purpose of the testing is to obtain measures of usability, such as effectiveness, efficiency and user satisfaction, when working with collaborative robots. It is made clear that it is the system, not the user, that is being tested, so that if they have trouble it is the workspace's problem, not theirs.

Pre-test interview At the beginning of the experiment it is explained to the participant, about the experience, which are his/her tasks, how the experiment is developed, Appendix A.3 is used for this, and that at the end of the experiment there is one questionnaire to be answered.

Participants will sign an informed consent that acknowledges: participation is voluntary, participation can cease at any time, and session will be videotaped but their privacy of identification will be safeguarded. The facilitator will ask the participant if they have any questions. The form *Consent form* in Appendix A.2 is used for this aim. The more relevant aspects of this form are:

- Description of objectives in the experiment
- Safety explanation for the participant
- Participant's rights

Next, the facilitator explains that the amount of time taken to complete the test task is measured and that exploratory behavior outside the task flow should not occur until after task completion. Time-on-task measurement begins when the participant starts the task.

The facilitator presents a demonstration to the user according to the guide *Demonstrations* in Appendix A.4. The more relevant aspects of this form are:

- Demonstration of the use of the Tower of Hanoi game on the tablet
- Demonstration of operator involvement in product assembly

After all tasks are attempted, the participant completes the post-test satisfaction questionnaire.

Case Study The experimental scenario is composed of two tasks within the HRWCE. The main task is Task 1 TOH5; a secondary task is added, Task 2 Collaborative Assembly (CA), as an additional human-robot collaboration task (see Figure 3.24). Table 3.27 shows the conditions of performance for the tasks. Time allocated for this scenario is 15 minutes.

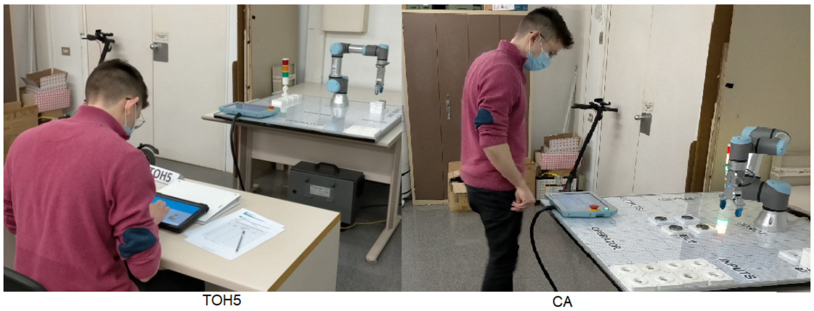


Figure 3.24: Scenario of the experience. Left, the TOH5 task, the main one, is performed. Right, the CA secondary collaborative Assembly task is being developed.

Table 3.27: Experimental scenarios

Task	**Performance**	**Total Time**
TOH5	Maximum number of TOH5 replays with 31 moves	15 minutes
CA	At least 7 work cycles completed	

The objective for the participant in the task TOH5 is to perform as many replays as possible. The secondary task, Collaborative Assembly, is related with responding to requests for collaboration from the cobot, which are indicated by the green light of the beacon in the assembly area. Both, time that human takes to place caps is save as *Wait Time* and *Cycle time* are recorded in a data table as the one shown in Table 3.28, jointly with figures for Task 1 when the operator is in the experimental scenario . In the collaborative assembly task, the activities of the participant, are:

- performing quality control of the assembly process
- place the caps on the sub-assembly zone
- feeding the base and bearing warehouses

Table 3.28: Form to Experimental Scenario (TOH5+CA). Tasks: Solve problem (main) and Collaborate with cobot (secondary).

Operator			**Cobot**		
Replay	**N_moves**	**Time to Task (sec)**	**Cycle**	**Wait Time (sec)**	**Cycle Time (sec)**
1			1		
...			...		

Adapted post-test questionnaire At the end of the experience the participant answers the adapted System Usability Scale (SUS) as the satisfaction questionnaire shown in Table4.14 . As it has been shown [17], SUS can be applied to a wide range of technologies. This feature allows the questionnaire to be adapted to this particular experiment. In the SUS standard questionnaire, the word ‘system’ has been changed to ‘human-robot collaborative workspace’ because it is not a human-computer task but a human-robot task. A medium or low SUS score means that is necessary a discussion and effort redesign the experiment.

3.4.6 Cognitive Interaction

The evaluation of mental workload is a key issue to research and develop for human machine interfaces, as well as to find levels of comfort, satisfaction, efficiency, and security in the workplace [98]. Moreover, some researchers explain in detail how important the cognitive load and the mental workload are in the design of workplaces for assembly tasks [114]. A laboratory scenario in a manufacturing context has been designed to create an environment where humans can work side-by-side with robots in close proximity [117]. The human operator facilitates the assembly task carried out by the robot since it feeds the station with parts, collects the products and attends to any possible malfunction. The variation of the human operator’s mental workload is evaluated when switching from a main task into a secondary task in this human–robot collaboration workspace scenario. The general objective of the test in this scenario is to evaluate the variation of mental workload, when the mental workload of the operator is increased due to regular time-constrained collaborations with a robot. Our hypothesis is that when the operator performs the collaborative task with the robot, the mental workload value is not very far from the mental workload of the main task. Moreover, both values would be in an intermediate comfort zone of mental workload. If tasks are designed in which the perceived mental workload is in an intermediate zone, quality in performance and decision-making in problem solving are guaranteed [107].

Experiment on Cognitive Workload

Experiments took place at the Teaching Laboratory of the Automatic Control Department of the Universitat Politècnica de Catalunya, Barcelona Tech (North Campus, FIB Faculty, Barcelona, Spain).

Following the hypothesis explained at the beginning of this section and the tasks detailed in Table 3.19, two working scenarios are designed:

- Working Scenario 1 (TOH5): The participant only executes Task 1, without distractions, using a tablet for this end, as seen in Figure 3.25.
- Working Scenario 2 (TOH5+CA): The participant executes a combination of the two tasks. The main task is TOH5 and also collaborates with the cobot in activities of Task 2, according to the work cycle in Table 3.19 (see Figure 3.26).

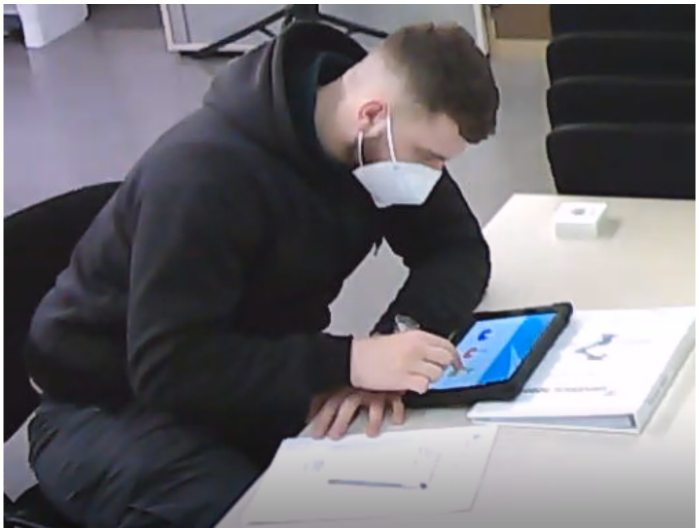


Figure 3.25: Working Scenario 1 (TOH5): the operator works on Task 1 (TOH5) without distractions.

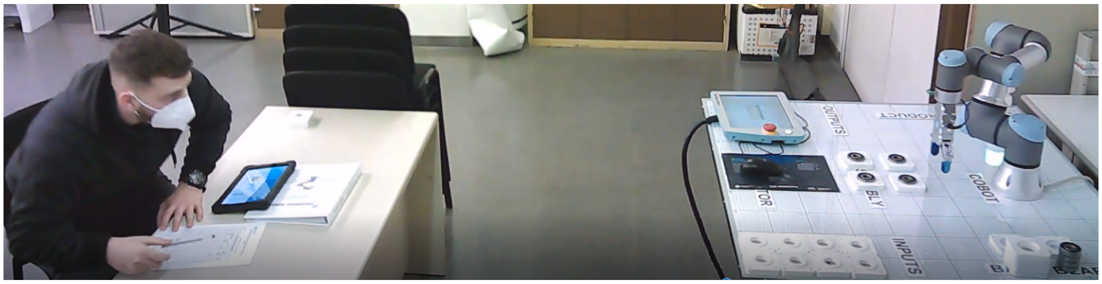


Figure 3.26: Working Scenario 2 (TOH5+CA): the operator works with divided attention on the main task (TOH5) and a secondary task (CA).

Participants

Data in both scenarios were collected from 18 participants. Among the participants there were undergraduate students, vocational students, and teaching staff. Details about them are shown in Table 3.29. Nobody had previous experience working with cobots.

Table 3.29: Participants.

Type	**Number**	**Gender**	**Age (Years)**	**Percent**
2*Undergraduate students	10	male	22–26	55%
	2	female	22–24	11%
Vocational students	2	male	18–20	11 %
Teaching staff	4	male	40–50	23 %
Total	18	-	-	100 %

Procedure

The participant's study is composed of two main steps: demo and test.

- Demo. As a first step, a facilitator provides each participant with a brief demonstration, usually about 2–3 min long, about the main functionalities of the experience.

- Test. For each test, the participant works on the two defined working scenarios.

During the test, both scenarios are considered by the participant: firstly, Scenario 1 for 6 min, then Scenario 2 for 15 min, fulfilling the objectives described in Table 3.30.

Table 3.30: Experimental tasks and activities.

Scenarios	**Task**	**Activities**	**Goals**	**Time**
Scenario 1	TOH5	The participant solves the TOH5 problem	Solve the problem with 31 moves	6 min
Scenario 2	TOH5+CA	The participant solves the TOH5 problem and responds to requests for collaboration from the robot	Solve the problem with 31 moves and complete 9 cycles of work with cobot	15 min

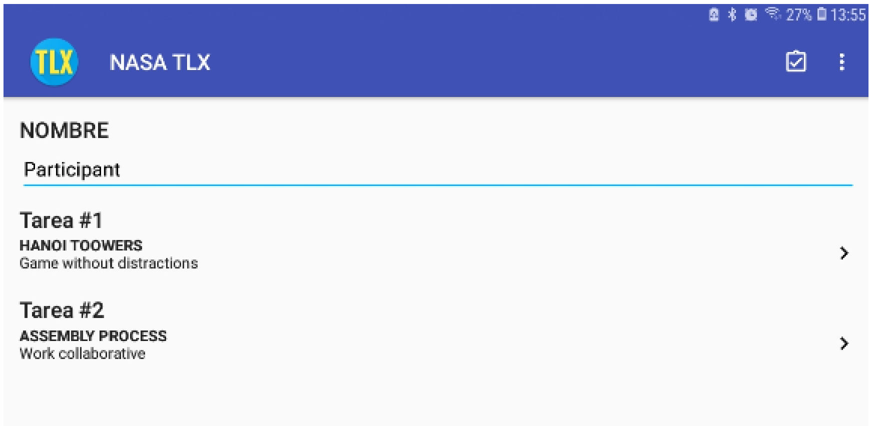
A facilitator supervised the test and took notes about the time expended by the participants during the performance of each task. When tasks were completed, each participant was invited to fill a NASA TLX index questionnaire form about the proposed experience.

Measure

There are several mental workload physiological metrics to be taken into consideration, for instance, heart rate, pupil dilation, respiration rate, skin temperature and fundamental frequency [39, 79]. In the participants' study presented in this paper, the authors used a subjective mental workload measure through the adoption of the NASA TLX index standard questionnaire. It allows deriving the overall workload score based on a weighted average of ratings on six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration level. This questionnaire is an effective tool for the study of the mental workload.

[25]The questionnaire form was derived from the app NASA TLX index v1.8.2 (see Figures 3.27 and 3.28). As shown in Figure 3.27, the participant must fill in the

two questionnaires, one for the working scenario 1 (TOH5) and the other for scenario 2 (TOH5+CA).



NOMBRE

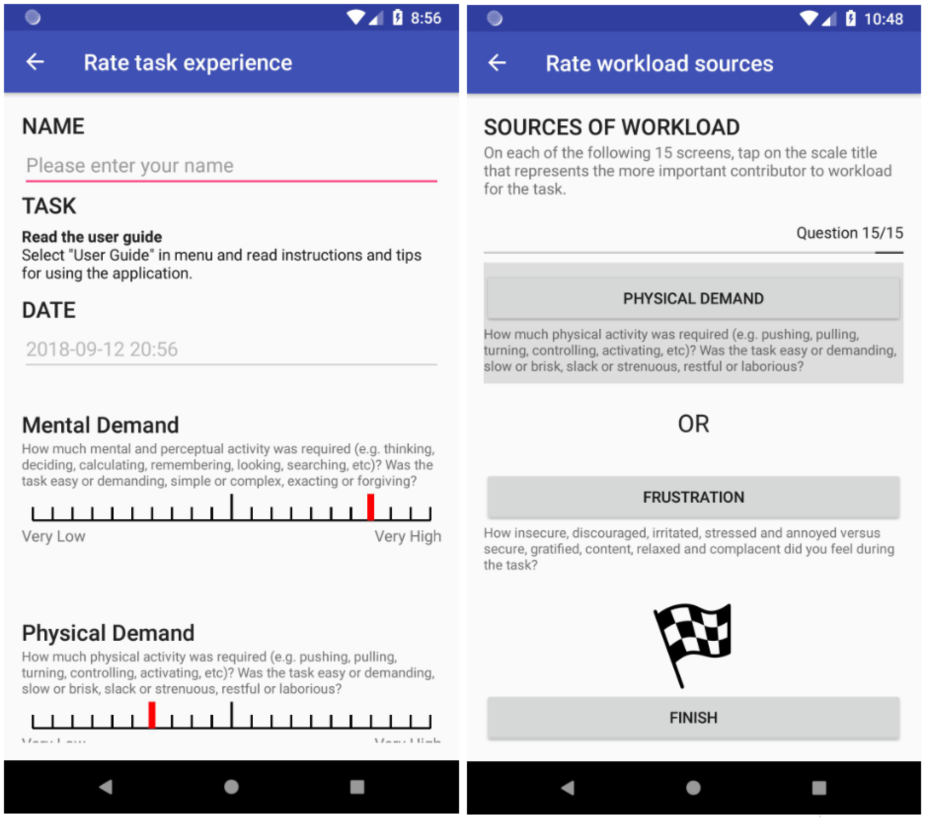
Participant

Tarea #1
HANOI TOOWERS
Game without distractions

Tarea #2
ASSEMBLY PROCESS
Work collaborative

Figure 3.27: NASA TLX index app with the two forms defined.

A description for each of these subscales was provided to help participants answer accurately. They are rated for each task within a 100-point range with 5-point steps. These ratings are then combined with the task workload index. These scales and descriptions are shown in Table 3.31.



NAME

Please enter your name

TASK

Read the user guide
Select "User Guide" in menu and read instructions and tips for using the application.

DATE

2018-09-12 20:56

Mental Demand

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

Physical Demand

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

SOURCES OF WORKLOAD

On each of the following 15 screens, tap on the scale title that represents the more important contributor to workload for the task.

Question 15/15

How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

OR

How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Figure 3.28: Example NASA TLX index app. On the right, the range of sub-scales, and on the left, the weight of the pair of sub-scales.

Table 3.31: Rating scale definitions for the NASA TLX index standard questionnaire.

Subscale	**Endpoints**	**Descriptions**
Mental Demand	Low/High	How much mental and perceptual activity was required? Was the task easy or demanding, simple or complex?
Physical Demand	Low/High	How much physical activity was required? Was the task easy or demanding, slack or strenuous?
Temporal Demand	Low/High	How much time pressure did you feel due to the pace at which the tasks or task elements occurred? Was the pace slow or rapid?
Overall Performance	Low/High	How successful were you in performing the task? How satisfied were you with your performance?
Effort	Low/High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Frustration Level	Low/High	How irritated, stressed, and annoyed versus content, relaxed, and complacent did you feel during the task?

Chapter 4

Results of Experimentation

This chapter presents the results obtained, firstly those obtained through simulation, and then those of the real case in the HRCWE prototype.

4.1 Results from simulated experiment

This section shows the results obtained through the simulation of the three scenarios.

- Fully manual task
- Fully automated task with a robot
- Collaborative task Human and robot

4.1.1 Execution in a Simulated Environment

Experimentation in the Manual Assembly task is performed as described according to the associated activities. Variability for process *Time* and product *Quality* is evaluated. Using the FRAM approach, the task is simulated (in a Flexsim software scenario) under several contexts of use. Some distribution functions for variability will be used to perform a realistic simulation of an industry assembly task.

Before starting the simulation a virtual basic version of the process has been created using the RoboDK simulation software to obtain realistic completion times for each activity, these will be considered as references for the process. Results are shown in Table 4.1.

Table 4.1: `Time to Task` values obtained from the RoboDK virtual model.

Function	Time
`<ASSEMBLY PRODUCT>`	3.3 s
`<ASSEMBLY BEARING_BASE>`	1.0 s
`<GET BASE>`	1.9 s
`<GET BEARING>`	2.0 s
`<GET CAP>`	2.3 s
`Time to Task`, mv_t	10.6 s

Using the FRAM methodology, two variation characteristics are considered in a straightforward form, *Time*, expressed as for Time to Task (in seconds) and *Quality*, defined as the Percentage of High-quality Products Completed (in %).

For the simulation, two types of distribution functions are used. The operator takes different time periods to perform operations about take and place the different parts for the assembly. Time for these operations tends to be greater than the average value for robot, thus affecting downstream in the assembly process and increasing the total production time of the parts. Following the recommendations of experts in manufacturing modelling [91], a *lognormal* distribution is used for this type of cases (see Table 4.2). The Mean variation value ($\Delta mv = 0s$), that is how much time, in mean, is used for the different kind of operators for each activity, is not modified. Hence, there is not difference in how fast are operators completing activities. However, standard deviation increases when expertness operator decreases. In this form, for the study, only variability is affecting *Time* process.

Table 4.2: Values used in distribution functions for *Time*, the same for all the functions.

Function	Type Operator	Value
Log-Normal()	Expert	$\Delta mv = 0s,\ \sigma = 3s$
	Standard	$\Delta mv = 0s,\ \sigma = 4s$
	Novice	$\Delta mv = 0s,\ \sigma = 5s$

Variations in the assembly process affect product Quality, in this case between High quality and Typical quality values. For this case, according to [91], a Bernoulli distribution function is used (see Table 4.3). It is considered that 98% of products are High quality when activities are performed by an expert operator. This percentage decreases to 90% and 80% for the case of standard and novice operators, respectively.

Table 4.3: Values used in distribution functions for *Quality*, the same for all the functions.

Function	Type Operator	Output
Bernoulli()	Expert	98 % High Quality products
	Standard	90 % High Quality products
	Novice	80 % High Quality products

For the simulation the Flexsim software has been configured with a working time of $3600s$, that is one hour, and a total of 30 replicates per experiment, to avoid bias from the probability distribution.

4.1.2 Results on Task Indicators

In this section the results for task indicators (Time to Task and Percentage of products finished with high quality) are shown using simple statistics (mean and standard deviation).

Scenario 1. Fully manual task

For the first scenario it is considered that only one operator develop activities. It can be observed how mean time mv_t and its standard deviation σ_t for completing the task increases as the level of expertise decreases (see Table 4.4). It should be noted that it was supposed that all the operators are identically fast performing activities ($\Delta mv = 0$). Thus, variability introduces delays in the task performance from 11.87 seconds to complete a task, in the case of an expert operator, to 13.77 and 15.20 seconds, for the other two cases. In this form, an expert operator is able to complete 173 products in one hour, a standard one is completing 152 products and a novice operator is only completing 138 products.

Table 4.4: Scenario 1: Results for *Time* (mv_t, σ_t) and *Quality* (mv_Q, σ_Q).

Type Operator	$mv_t(s)$	$\sigma_t(s)$	$mv_Q(\%)$	$\sigma_Q(\%)$
Expert	11.87	0.43	98%	3.01
Standard	13.77	0.57	90%	3.79
Novice	15.20	0.81	80%	4.03

As it could be expected, mean quality mv_Q is similar to the default percentages assigned for each type of operator (see Table 4.3). However, it is worth to note how standard deviation for high product quality σ_Q gets significantly high values for all the type of operators, showing clearly how time variability impacts on final product *Quality*.

Scenario 2. Fully automated task with a robot

For this fully automated scenario, it is considered for the cobot that starting from the typical/normal condition, an optimization upgrade allows increase its speed by 20%, and so is the result for mv_t, as displayed in Table 4.5. Besides, no time deviation is considered, as it is the usual high precision case in industrial robotics, therefore σ_t gets a null value as result.

Table 4.5: Scenario 2: Results for *Time* (mv_t, σ_t) and *Quality* (mv_Q, σ_Q).

Type Operator	$mv_t(s)$	$\sigma_t(s)$	$mv_Q(\%)$	$\sigma_Q(\%)$
Optimized	10.0	0.0	79%	3.14
Basic	11.0	0.0	79%	3.50

Our hypothesis is that the cobot is not well prepared for this new task, because some decorative specifications are asked for the user that the robot is not able so sense. This is the reason why human operators are helping in the assembly process. Consequently, the mean value used in the distribution function for high quality products is 79%, below novice operator. Consequently, a similar mv_Q is obtained as result for both type of cobots. It is worth to note that standard deviation value is higher for the basic operator than for the upgraded (faster) one. Hence, high quality is not downgraded because faster processing.

Scenario 3. The process is executed in a collaborative manner, human-robot shared task

The implementation of the MABA-MABA (Men-Are-Better-At/Machines-Are-Better-At) strategy has been carried out in this scenario, as a result of which there are 6 possible cases, as observed in Table 4.6. For the implementation of the cases the

ETTO [45] (Efficiency-Thoroughness Trade-Off) principle has been maintained.

Table 4.6: Scenario 3: Results for *Time* (mv_t, σ_t) and *Quality* (mv_Q, σ_Q).

Operator (R)	**Operator (H)**	$mv_t(s)$	$\sigma_t(s)$	$mv_Q(\%)$	$\sigma_Q(\%)$
Basic	**Expert**	11.03	0.18	98%	2.96
	Standard	11.93	0.25	89%	2.99
	Novice	12.43	0.50	79%	3.39
Optimized	**Expert**	10.93	0.25	98%	3.07
	Standard	11.03	0.18	90%	3.04
	Novice	11.80	0.41	79%	3.43

For this collaborative scenario, mv_t values are ever higher than the ones for the fully automated scenario. No significant time increase is observed for the Basic cobot, hence humans are not delaying too much the product completion. However, this is the case for the optimised cobot case, for all the type of human operators. As a first conclusion, optimise cobots are not worthy for the collaborative scenario in this assembly task. The standard deviation is reduced from the totally manual scenario, as it is expected because cobots are not inserting variability.

For the measure of *Quality*, it is important to highlight how percentages of high quality products mv_Q in this collaborative scenario are very similar to the ones in the totally manual scenario. That is, the human-robot shared task allows to outperform the low percentage due to the use of only cobots due to the dexterous expertise of the human operators.

In Figure 4.1 the boxplot for the variation of the Time to Task for 30 replicates is shown in a workspace composed of a Human Operator (Expert, Standard, Novice) and the Robot Operator set Basic, in this image you can see a greater variability in the novice operator. A similar boxplot figure is displayed in Figure 4.2 for the percentage of high quality products. For this scenario, quality is more related to the characteristics that the operator imposes on the process, which is why there is greater variability for each case.

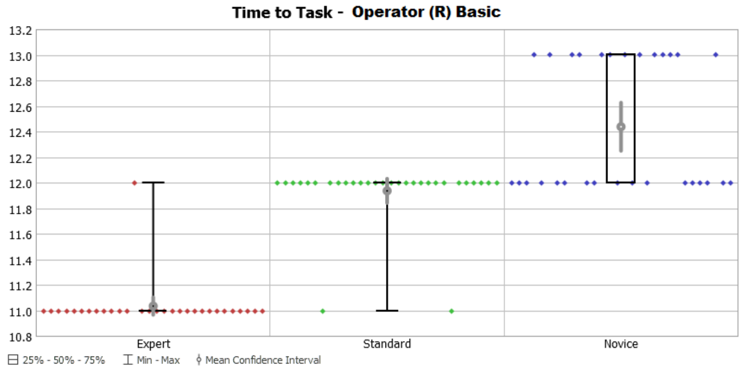


Figure 4.1: *Time* variation with Operator Robotic Basic in Scenario 3

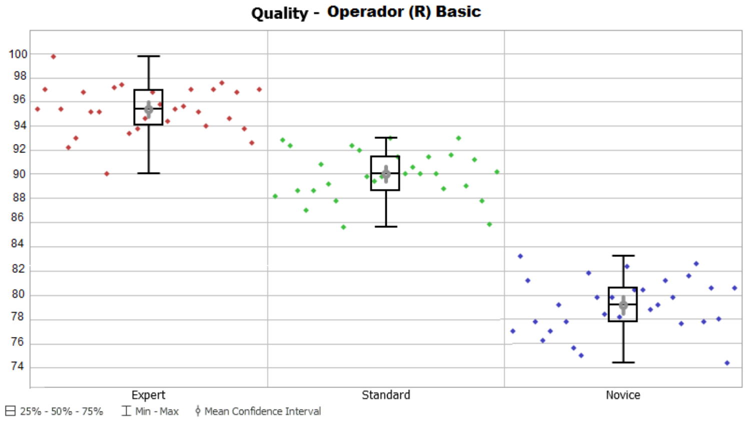


Figure 4.2: *Quality* variation with Operator Human Standard in Scenario 3

4.2 Results from Heuristics Evaluation on HRCWE

Prior to the implementation of the HCRWE the evaluation of the preliminary design is carried out, through the questionnaire show in Table 4.7

With these results we have a validated design to start working with.

Table 4.7: Questionnaire to evaluate heuristics

Heuristic	Question	Answer
H1. Sufficient information design	Has the designer considered all tasks and activities in the design?	All task are analyzed and all activities review
H2. Visibility of system status	Is the operator informed about the progress of the system with the appropriate response and within an acceptable time?	Feedback is send to operator by LED's tower and tech-pendant on robot
H3. Appropriate information presentation	Does the system use concepts and language familiar to the operator rather than technical terms?	The name of piece and name of activities is standard
H4. Use natural cues	Do design elements, such as objects and actions, have the same meaning or effect in different situations?	Pick and Place is defined in same manner for all activities.
H5. Synthesis of system and interface	Are the task methods efficient?	The activities has low workload for operator
H6. Help users recognize, diagnose, and recover from errors	Is appropriate help provided and is the information easy to find and focused on the operator's task?	The errors are minimal and easy to recover from error
H7. Flexibility of interaction architecture	Can the operator customize frequent actions or shortcuts?	the operator is free to decide to who activities can do it.
H8. Aesthetic and minimalist design	Does the dialogue contain irrelevant or rarely used information?	The minimal intervention additional is necessary.

4.3 Results from Real Experimentation on HRCWE

The results are presented according to the planned methodology, Figure 4.3, shows the organization of results, for usability the results of the usability plan are presented, then the results of the cognitive workload will be presented, to finish with metrics of the robot and the human-robot team.

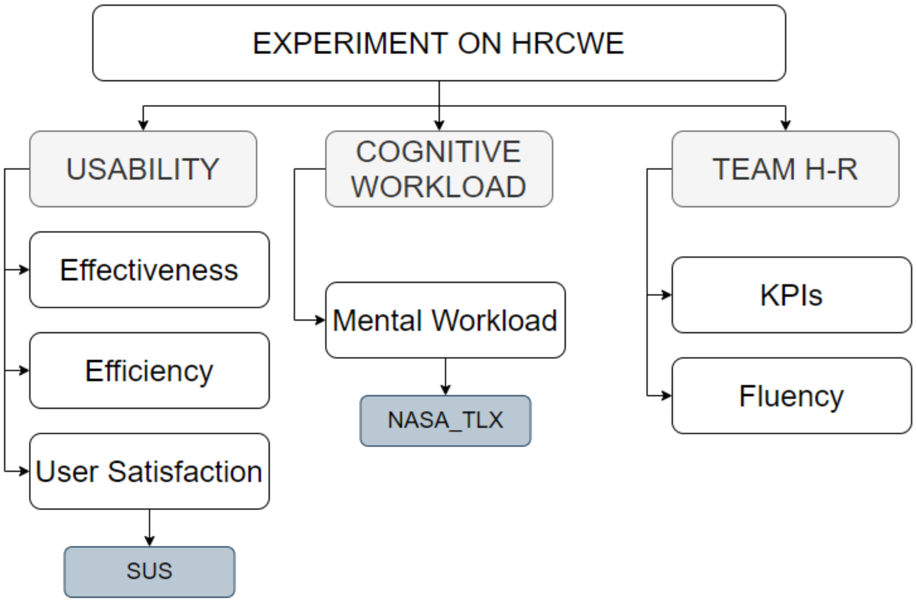


Figure 4.3: Organization of results presented

4.3.1 Usability Results in the HCRWE

Out of the seventeen participants, three are discarded as they have not correctly completed the proposed questionnaires A.1. For this reason, results on fourteen participants are presented (n=14). For the analysis the following values are configured, the statistical significance level set at $p < 0.05$, and confidence level is 95%.

Effectiveness The next 'pass and fail' histograms show the results in solving the tasks within the HRCWE: the histogram in Figure 4.4 shows 11 participants solving Task 1 (TOH5) and the histogram in Figure 4.5 shows the results of the human-robot

(H-R) team in solving task 2. Values for *Task Completion rate* are calculated using the equation

$$Task\,Completion\,rate = \frac{\text{Number of participants with successfully task}}{\text{Total number of participants undertaken}} \tag{4.1}$$

according to experimental results shown in Table 4.8.

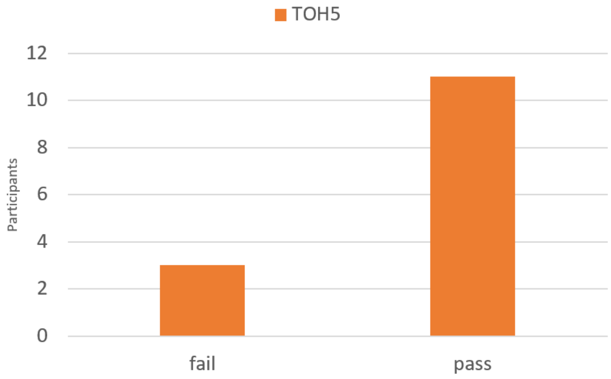


Figure 4.4: Histogram of fail and pass for tasks TOH5.

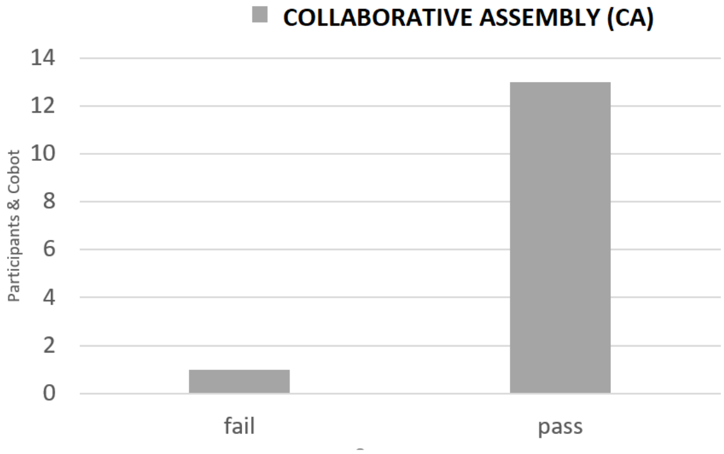


Figure 4.5: Histogram of fail and pass for tasks CA (Collaborative Assembly)

Table 4.8: Statistics *Task Completion rate*

	TOH5		**CA**	
Success	11		13	
n	14		14	
Task Completion rate	78.6 %		92.9%	
Confidence Interval	Low	High	Low	High
	51.70%	93.2%	66.5%	100%
Benchmark	56%			
p-value	0.044		0.002	

Sauro and Lewis experience states that a *Task Completion r ate* lower than 56% could indicate a very low level of trustness for this variable. Results show a a superior level in both tasks ($p - value = 0.044$ and 0.002).

Results for the *Task Completion rate* level for TOH5 have a mean value of 78.6%. Based on benchmark with percentile Jeff Sauro, locate this value at percentile 50, this value is acceptable as it is a first experience of the participant, however for a continuous work it is necessary to improve this value. The *Task Completion rate* level for the CA on 70% could be considered standard given the characteristics of human participation in the human-robot task.

Efficiency To evaluate the efficiency, the *Time to Task* variable is analysed. Firstly, with all the data obtained from experiment a percentile scale is generated with five ranges for the variable defined as shown in Table 4.9, according to the time spent in solving it.

Table 4.9: Percentiles in Time to Task to resolve TOH5 and CA

Percentile	**Time to Task (sec)**	
	TOH5	**CA**
10	23	102
50	44	107
75	66	113
90	93	116
98	¿94	¿120

Task 1 (TOH5) is firstly analyzed. Statistical results for *Time to Task* are shown in Table reftab:Efficiency Scoring, with a mean value of 56.2 sec bring above the percentile 50%. This table also shows values of the coefficient of variation (CV) (see Eq. 4.2), for the *Time to Task*. Task 1 (TOH5), with a value of 0.42 represents a high level of variation, as a result of solving the task only with human participation.

$$CV = \frac{\text{standard deviation}}{\text{mean value}} \tag{4.2}$$

Table 4.10: Statistics of *Time to Task* for Task 1.

	TOH5	
Mean Value	56.2 (sec)	
sd	25.9	
n	14	
Confidence Interval	Low	High
	43.34	72.89
CV	0.42	

For Task 2, *Time to Task* is defined as the result of the team human-robot, as shown in Eq. 4.3. This time is composed of the human's time (t_H) and the cobot's time (t_C).

$$Time\ to\ Task = t_H + t_C \tag{4.3}$$

Figure 4.6 shows the results obtained by each participant. It can be observed the time composition of the task.

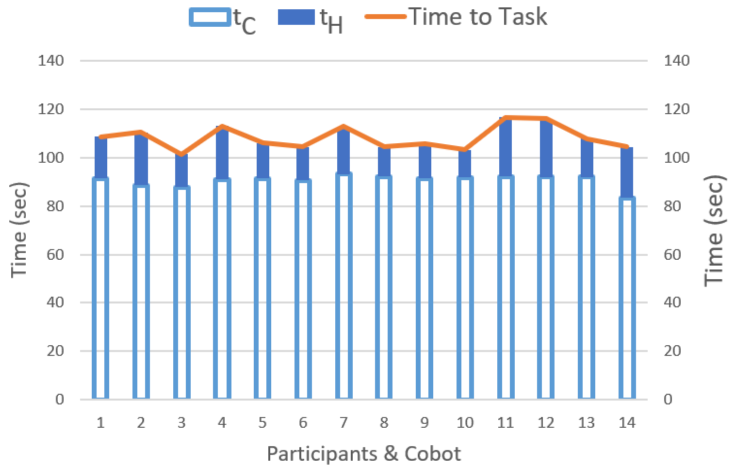


Figure 4.6: *Time to Task* for Task 2.

For the statistical analysis we consider *Time to Task* equal to *Cycle Time* for the cobot, and t_H equal to *Wait time*, obtained directly from the cobot controller.

Table 4.11: Statistics times in Task2

	Time to Task sec	t_H sec	t_R sec
mean value	108.9	17.05	90.58
standard deviation	4.8	4.5	2.5
n	14	14	14
Confidence Interval			
Low	105.36	14.7	89.10
High	110.89	19.79	92.08
CV	0.04	0.25	0.027

Results in table Table 4.11 show a *Time to Task* of 108.9 sec as mean value. This corresponds to a percentile of 50%. CV value is 0.04, equivalent to 4% of variation. This is considered a low variation. For t_H the mean value is 17.05 sec, with CV 0.25 equivalent to 25%. In this case, this is considered a high variation , typical for human tasks. Finally, for t_C the mean value is 90.58 sec and CV is down to 0.027, equivalent to 2.7%, that is a minimum variation, as expected considering the high stability of the cobot.

System Usability Scale score results

Table 4.12 provides an overview of mean values, standard deviations, incomplete questionnaires and checking the coding of the questionnaires as well as reliability indices values (Cronbach's α) for the obtained measures.

Table 4.12: Statistics SUS scoring and reliability test.

Mean SUS Score	81.1		
sd	13.3		
Non-Blank	14	**Coding Check**	Values appear to be coded correctly from 1 to 5
Cronbach Alpha	0.814	**Internal Reliability**	Good

Table 4.13 shows results about SUS, the interpretation in percentiles and a descriptive adjective of its value. The value of 81.1 qualifies the HRCWE as *Excellent* and the degree of acceptability as *Acceptable*.

Considering HRCWE as a hardware system, following the Sauro and Lewis classification, the benchmark of experience with hardware shows that a raw SUS score of 81.1 has a higher SUS score than 88.14% for Hardware.

The main value from SUS is providing the single total score. However, it is

Table 4.13: SUS results interpretation

Raw SUS score	81.1	**Percentil Rank**	88.1%
SUS Benchmark	Hardware	**Adjective**	Excellent
		Grade (Bangor)	B
		Grade (Sauro&Lewis)	A-
		Acceptability	Acceptable

still necessary to look into detail the individual score for each statement [5]. This information in presented in Table 4.14. Caglarca [118] suggested taking into account individual evaluation by verifying the shape of a "five-pointed star" visualization. Hence, raw scores from Table 4.14 have been transformed into a radial chart, as shown in Figure 4.7. Caglarca also concluded that the more the five-pointed star looks, the more positive the usability will get. Although it tends to be a subjective assessment, it is worth noting that the five-pointed star shape is almost in perfect form as in this study.

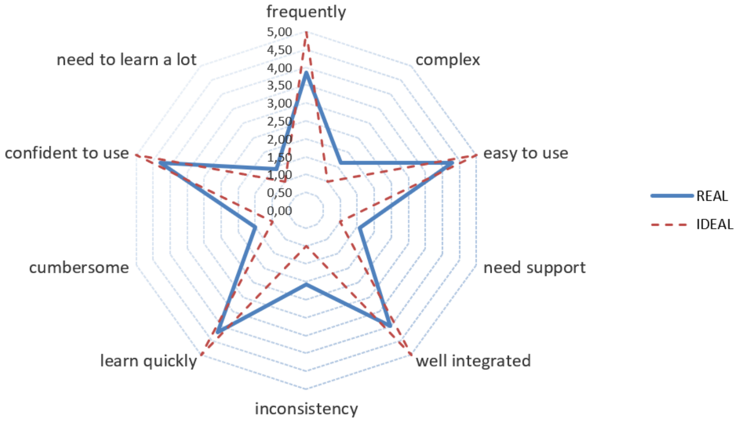


Figure 4.7: Evaluation of the five-pointed star

Table 4.14: Responses to individual statements of the SUS

	Statements	Raw Score
1	I think that I would like to use Workspace Collab (HRCWE) frequently.	3.86
2	I found Workspace Human-Robot Collab (HRCWE) unnecessarily complex.	1.64
3	I thought Workspace Human-Robot Collab (HRCWE) was easy to use.	4.29
4	I think that I would need the support of a technical person to be able to use Workspace Human-Robot Collab (HRCWE).	1.57
5	I found the various functions in Workspace Human-Robot Collab (HRCWE) were well integrated.	4.0
6	I thought there was too much inconsistency in Workspace Human-Robot Collab (HRCWE).	2.07
7	I would imagine that most people would learn to use Workspace Human- Robot Collab (HRCWE) very quickly.	4.21
8	I found Workspace Human-Robot Collab (HRCWE) very cumbersome (awkward) to use.	1.50
9	I felt very confident using Workspace Human-Robot Collab (HRCWE).	4.29
10	I needed to learn a lot of things before I could get going with Workspace Human-Robot Collab (HRCWE).	1.43

Performance of cobot

To finalize the experiment, with the data of *Cycle Time* and *Wait Time*, the KPIs of Per Efficiency and Per Utilization of the cobot are obtained to evaluate the performance of the Cobot in HWRCE. The Per Utilization is calculated as,

$$Per\,Utilizacion(participant) = \frac{\overline{Cycle\,Time} - \overline{Wait\,Time}}{\overline{Cycle\,Time}} * 100 \tag{4.4}$$

The statistical analysis in Table 4.15, with a mean value of 83%, shows an Per Utilization greater than 80% in the use of cobot for task collaborative assembly.

Table 4.15: Statistics of *Per_Utilization* for the cobot in HWRCE.

Mean Value	83%		
sd	0.03		
n	14		
Confidence Interval	Low	High	
	81%	85%	
Benchmark	80%	p-value	0.008

The percentage value of the efficiency (Per Efficiency) is calculated considering the total time of a work cycle, in this case it was set at 900 sec.

$$Per\,Efficiency = \overline{NumberCyclesCompleted} * \frac{\overline{Cycle\,Time}}{900} * 100 \tag{4.5}$$

The statistical analysis of the Per Efficiency in Table 4.16 shows with a mean value of 84% an Per Efficiency higher than the 75% ($p - value = 0.03$) established as a reference in this experiment.

Table 4.16: Statistics *Per Efficiency* of cobot in HWRCE.

Mean Value	84%		
sd	0.13		
n	14		
Confidence Interval	Low	High	
	74%	96%	
Benchmark	75%	p-value	0.03

4.3.2 Workload in HRCWE

As a result of the NASA-TLX questionnaire, the results shown in the following table are obtained Table 4.17 this shows the used markers with adjectives that qualify the mental workload (MWL) [36], where np TOH5 and np TOH5+CA are the number of participants versus the observed qualitative mental workload.

Table 4.17: The interpretation % score for the NASA TLX index.

Mental Workload Range	**Value**	**np TOH5**	**np TOH5+CA**
Low	0–9	0	0
Medium	10–29	0	1
Somewhat High	30–49	5	2
High	50–79	12	13
Very High	80–100 1	2	

4.3.3 Mental Workload Results

Descriptive statistics, *t*-test, and analysis of variance tests were used to analyze the effects of the experience. The statistical significance level was set at $p < 0.05$, and in all the cases, the confidence level is 5%. Data collected from both scenarios were gathered and are presented in the histogram in Figure 4.8

The distribution of the data obtained is not symmetric and they tend to accumulate in the areas with high mental workload. Six out of twelve participants perceived that the mental workload of the task TOH5 was high. Eight of twelve participants perceived that the mental workload of the main and secondary tasks TOH5+CA was high. Table 4.18 shows the obtained score for each scenario in terms of mean value and standard deviation. The mean values of the NASA TLX index score for both scenarios are very close, 59.11% and 60.17%, respectively. These scores are at the end of the first third of the range (High).

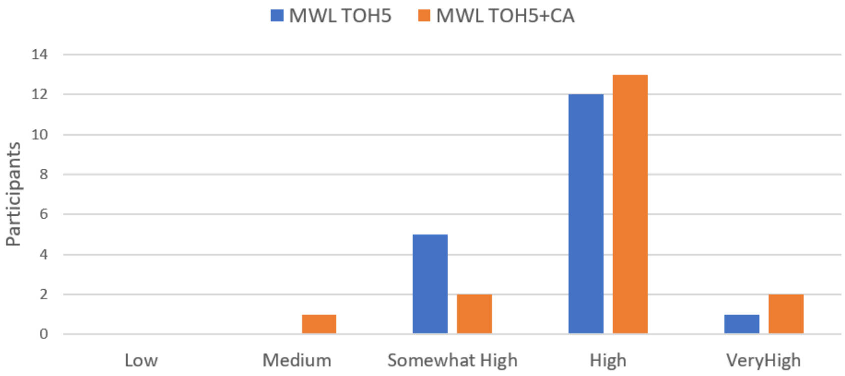


Figure 4.8: Histogram of participants' mental workload (MWL) for both scenarios.

Table 4.18: Results of NASA TLX Index Score.

Statistics	**TOH5**	**TOH5+CA**
Mean value	59.11	60.17
sd	12.20	17.41
Non-Blank	18	18
Interpretation Score	High	High

The hypothesis in this study is that when the operator performs the collaborative task with the robot (TOH5+CA, second scenario), the mental workload value is not very far from the mental workload of the main task (TOH5, first scenario). That is, a very little increment δ is expected,

$$MWL_{TOH5+CA} \sim MWL_{TOH5} + \delta \tag{4.6}$$

Moreover, both values would be in an intermediate comfort zone of mental workload; hence, they are not saturating the mental workload.

To test this hypothesis, a paired t-test was performed on the results obtained. The results in Table 4.19 show that there exists a p-value ¡ 0.02 associated with the probability that the difference is greater than 10, so the null hypothesis is rejected, $\delta < 10$, and the alternative hypothesis is corroborated: certainly, there is only a small increase in MWL when the operator is moving from only one task to a dual task with a collaborative robot.

Table 4.19: Paired t-test.

Confidence Level	**95**		
Null Hypothesis	Diff> 10		
Descriptive Statistics	-	Average Difference	1.06
Mean Difference value	-1.10	Confidence Interval Low	-9.72
Median Difference value	-8.00	Confidence Interval High	7.61
sd	17.43	Margin Error	8.70
n (sample size)	18	p-value	0.02

The interpretation scores shown in Table 4.18 for the associated mental workload are in the low range of the label ”High” (59.11 and 60.17) for both scenarios using the scale in Table 4.17. According to the cumulative frequency distributions of TLX Global Workload Scores by Task by Grier [30] (see Table 4.20), a common experimental mental workload score is related to cognitive tasks with a value of 64.90 as the maximum and 54.66 as within 75% of the results obtained in experiments with the TLX-Index. Hence, the results for scenarios TOH5 and TOH5+AC are in this range, indicating that the proposed tasks are actually high cognitive tasks, but they are not saturating the regular experiments on cognitive tasks.

Table 4.20: Cumulative frequency distributions of mental workload scores by task.

	Min	**25%**	**50%**	**75%**	**Max**
Cognitive Tasks	13.08	38.00	46.00	54.66	64.90

Figure 4.9 shows the distribution of the mean values of MWL for the different subscales. The mental demand is the subscale with the highest values for both scenarios, which is in accordance with the working conditions established for this study.

The results obtained for the subscales studied using the NASA TLX index are

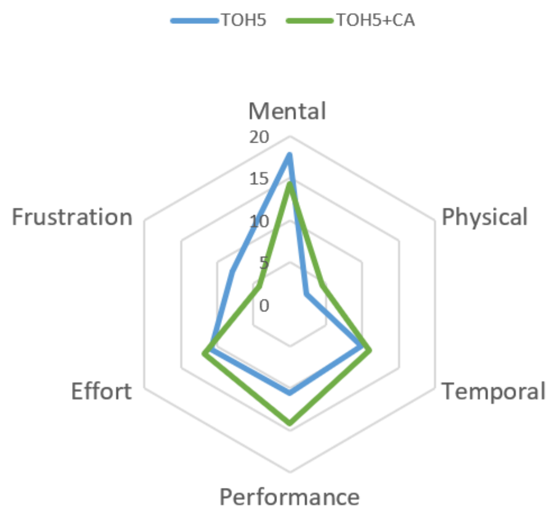


Figure 4.9: Mean values of subscales in the NASA TLX index on the experiment.

shown in Table 4.21. The physical subscale shows a *p*-value ¡ 0.05, i.e., it is the only one showing significant statistical differences between both scenarios, while the other subscales do not. This is consistent with our hypothesis.

Table 4.21: Paired samples test for subscales of the NASA TLX index, TOH5 and TOH5+CA.

Subscale	**Mean**	**Standard Dev.**	***p*-Value**
Mental	3.39	10.01	0.172
Physical	−2.11	2.66	**0.004**
Temporal	−1.15	10.03	0.633
Performance	−3.72	7.00	0.038
Effort	−1.07	8.39	0.594
Frustration	3.61	7.26	0.050

4.3.4 Task Performance Human-Robot Team

To consider the performance of the work performed by the human-robot team, the result of the task is presented through the *Effectiveness* and the *Fluency*

Effectiveness

This subsection shows the results for the effectiveness of the tasks developed in the Human–Robot Collaborative Workplace. The variable *Task Completion Rate* (TCR) is considered,

$$TCR = \frac{N_{sucsess}}{N_{replay}}\% \tag{4.7}$$

Table 4.22 shows the results for TCR when task TOH5 is solved in both scenarios. For Scenario 1, a low effectiveness is obtained (TCR = 44.44 %), while for Scenario 2, there is a 22 % of percent increase (TCR = 66.67 %) as a result of the experience obtained from Scenario 1.

Table 4.22: TCR results for TOH5 in both scenarios.

	Scenario 1 (TOH5)	**Scenario 2 (TOH5+A)**
Nsuccess	8	12
Nreplay	18	18
TCR	44.44 %	66.67%
Difference	22.22%	

Table 4.23 shows the results for the effectiveness in the resolution of the TOH5 problem as well as in the collaboration in the CA assembly. The results show that the collaboration is carried out effectively, TCR = 94.44 %.

Table 4.23: TCR results for TOH5 and CA in Scenario 2.

	TOH5	**CA**
Nsuccess	12	17
Nreplay	18	18
TCR	66.67 %	94.44%
Difference	27.77%	

Fluency

A measure able to evaluate the team's work is fluency. According to [42], fluency evaluation allows determining the performance as a team that the human–robot pair has. These metrics are percentage of concurrent activity (C-ACT), human's idle time (H-IDLE), robot's functional delay (F-DEL), and robot's idle time (R-IDLE). To calculate fluency, parameters shown in Table 4.24 were measured from the robot side. Values obtained are summarized in Table 4.25 in the form of mean values.

Table 4.24: Time parameters from robot.

Parameter	**Description**
Idle_Time	Sum Robot wait time
Cycle_Time	Sum Robot work time
Shared_Time	Sum Shared Time to resolve task

Table 4.25: Mean values of times from robot.

Statistics	**Cycle_Time**	**Idle_Time**	**Shared_Time**
Mean value	626	117	34
sd	176	38	8
n	18	-	-

The fluency values are calculated as follows:

$$Time\ to\ Task \quad = \quad Cycle\_Time + Idle\_Time \tag{4.8}$$

$$H - IDLE \quad = \quad \frac{Cycle\_Time}{Time\ to\ Task} \tag{4.9}$$

$$R - IDLE \quad = \quad \frac{Idle\_Time}{Time\ to\ Task} \tag{4.10}$$

$$C - ACT \quad = \quad \frac{Shared\_Time}{Time\ to\ Task} \tag{4.11}$$

Figure 4.10 allows to visualize the results from the calculation. It can be seen that the value for H-IDLE is much higher than the one for R-IDLE. Moreover, C-ACT gets a low value.

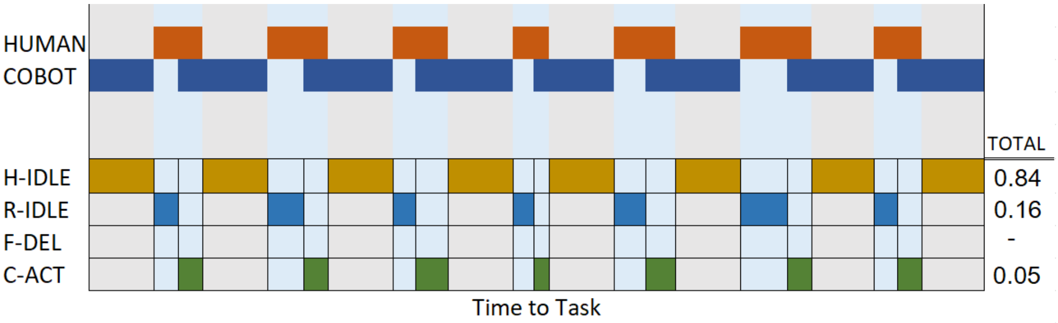


Figure 4.10: Objective fluency metrics in the Human-Collaborative Robot Workplace.

Chapter 5

Discussion

In this discussion we discuss the results obtained in the different stages of the research, we will first present the design using the FRAM methodology and the simulation, in the part of experimentation in the HRCWE, we will discuss about the usability, the cognitive load and the performance of the human-robot team.

5.1 Methodology for assistant

To start this discussion, the structure of the methodology resulting from the conception, design and evaluation of a 4.0 cognitive operator assistance system in a product assembly process is presented in Figure 5.1

This methodology basically consists of five steps,the most relevant features of which are presented in this discussion.

5.2 FRAM design and simulation

From the FRAM methodology (model, scenarios and identification of variability) and the simulation of the model (distribution function, discrete event simulation) it has been quantitatively checked that variability in the output of the system is directly

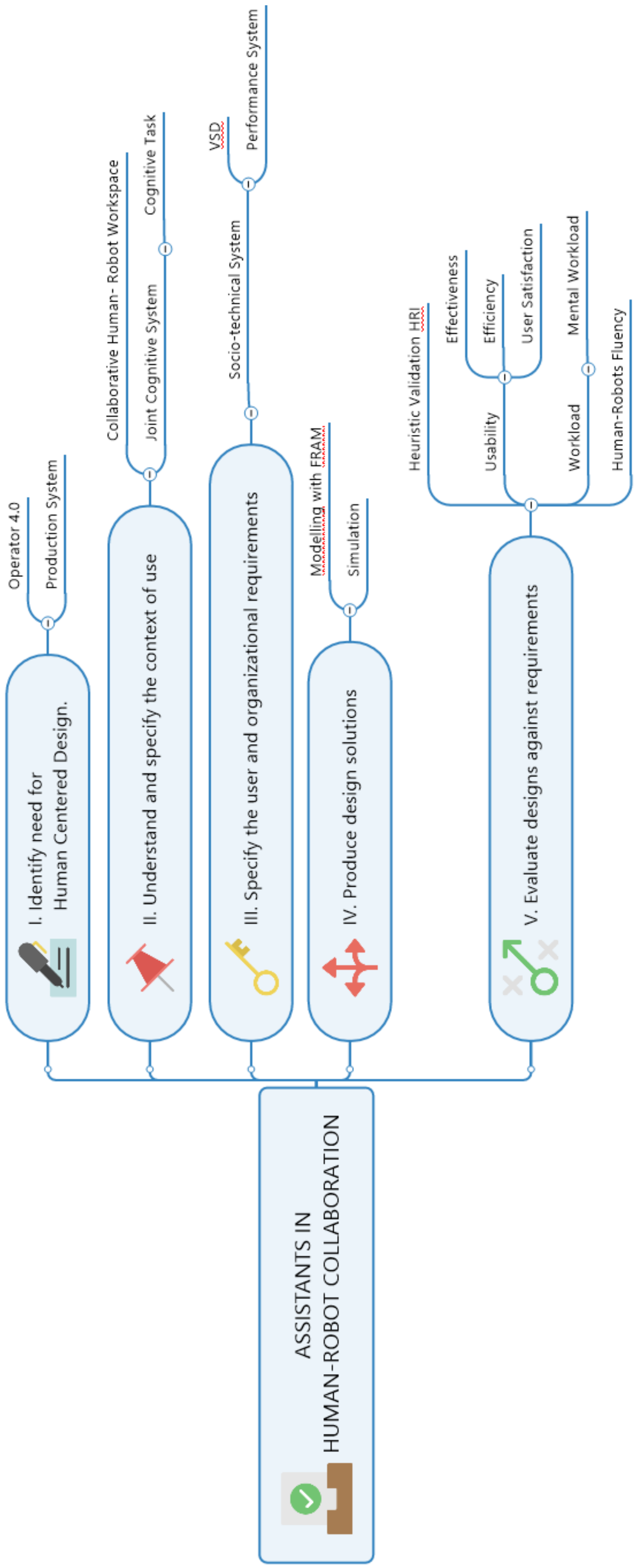


Figure 5.1: Methodology to follow in development to assistant in Human Robot Collaboration

related to the performance of the type of operator in the workplace. Now is time to convert these results into cognitive information, so the operator can organize her/his shift time, the supervisor can organize production. Eventually, According to this research, the robot could be equipped with an assistant-type module that could be used as an assistant to recommend some strategy to the operator or the supervisor in case some deviation in the actual production specifications is happening.

For this analysis the coefficients of variation defined in Equation 3.3 as the ratio between standard deviation and mean expressed as a percentage, are used for the operator human, the one introducing variability in time. Hence, CV_{TA} is calculated and displayed in Table 5.1 in reference to the time in activities (5) to complete the product, as the mean value, $CV_{TA} = \overline{\sigma_t}/\overline{mv_t}$.

Table 5.1: Results for the overall activity (Manual Assembly). Values are the mean for each the activities related for the task

Operator (H)	$\overline{mv_t}(s)$	$\overline{\sigma_t}(s)$	CV_{TA}
Expert	2.34	0.07	2.99
Standard	2.70	0.09	3.33
Novice	2.99	0.10	3.34

In Table 5.2, CV_{TT} represents the resulting variation in time for the assembly of the product. Values for mean and standard deviation are obtained from Table 4.4.

Table 5.2: Results for the overall tasks (Manual Assembly). Values are the mean for all the task

Operator (H)	$mv_t(s)$	$\sigma_t(s)$	CV_{TT}
Expert	11.87	0.43	3.62
Standard	13.77	0.57	4.14
Novice	15.20	0.81	5.33

Next, for the *Time* variable the percentage of variation from mean time in task and time in activity is obtained,

$$\%Var_t = \frac{CV_{TT}}{CV_{TA}} \tag{5.1}$$

It is shown in Table 5.3 the results obtained for variability at each scenario.

A similar percentage of variation is calculated for *Quality*, also shown in Table 5.3. In this case, it is assumed that parts are introduced into the system with the same distribution, independently from the operator in the activities. The coefficient of quality in input, CV_{QI} has the same value for all the cases, and the quality total of output is CV_{QT}, hence $\%Var_Q = CV_{QT}/CV_{QI}$.

Table 5.3: Relation of Coefficient of Variation for *Time* and *Quality*

Scenario	**Operator (H)**	**Operator (R)**	CV_{TA}	CV_{TT}	$\%Var_t$	CV_{QI}	CV_{QT}	$\%Var_Q$
1	**Expert**		2.99	3.62	121.12	4.3	3.07	71.43
	Standard		3.33	4.14	124.18	4.3	3.79	97.93
	Novice		3.34	5.33	159.36	4.3	5.04	117.15
2		**Optimized**	0.0	0.0	0.0	4.3	3.97	92.43
		Basic	0.0	0.0	0.0	4.3	4.43	103.03
3	**Expert**	**Optimized**	2.99	2.28	76.46	4.3	3.13	72.85
	Standard		3.33	1.63	48.96	4.3	3.38	78.55
	Novice		3.34	3.47	103.92	4.3	4.34	100.97
3	**Expert**	**Basic**	2.99	1.63	54.56	4.3	3.02	70.24
	Standard		3.33	2.09	62.89	4.3	3.36	78.13
	Novice		3.34	4.02	120.31	4.3	4.29	99.79

5.2.1 General Remarks

As it can be see in Table 5.3, input variations are amplified through the system. Novice operators insert the greatest variation and therefore there is the greatest amplification. On the other hand, if the system activities are only executed by the robot, quality variability changes when moving from an optimized robot to a basic one, but not so much.

The Human-Robot collaborative system presents less variability for time and quality with respect to a human only system. Moreover, this scenario increases the production. The assignment of activities can be optimized based on the information of the activity times employed and the functions performed, so dynamic assignment of functions is possible. For the assignment of activities, a strategy is employed based on system operating conditions that are favorable to the operator and that maintain acceptable levels of efficiency within the work shift. The activity assigner could consider transitioning from a novice operator to an expert operator and modify the assignment to achieve maximum efficiency of the HRC system.

5.2.2 Cognitive Agent Recommendation

Let's suppose our customer is asking for a batch of products such that at least 85% are high quality. According to the variability study performed, a fully manual task (Scenario 1) with Expert or Standard operators is providing for sure this result. It is impossible to get it for the Scenario 2, only considering a fully automated task. Finally, in the collaborative Scenario 3, again Expert or Standard operators should be considered. Hence, a first recommendation message is not to consider novice operators for this case. However, they could be considered in the case that the asked high quality percentage were 75%. A fully automated scenario could be also considered.

Looking at the percentage of variation for *Quality*, $\%Var_Q$ is not spreading in the Scenario 1 for Expert and Standard operator, so a Standard one can be considered without risks. In the case that the percentage of high quality products can be reduced to 75% a novice operator is not a good choice for the Scenario 1 because variation is increased to 117.15%. However, it can be considered in case that Scenario 3 is selected. If a cognitive assistance module were to be implemented a recommendation from this module would be, in case only novice operators are available in this moment for this task, to work in a collaborative Scenario 3. In this case, for example supervisor can provide autonomy to the novice operator selecting the basic or the optimized version of the cobot because percentage of high quality products will be similar and variation is also similar.

A similar study could be performed on the *Time* specification, depending on the customer specifications as well as the plant organization, in order to improve task effectiveness and productivity.

5.3 Usability on Human-Robot

From usability experimentation the feasibility of extrapolating the usability experience in HCI towards HRI is clearly defined along with this study: the context of use, requirements, workspace design, task allocation between human and robot, experimental testing, and validation steps.

In this study, with a *Task Completion rate* value of 78.6 in the effectiveness of the task 1, it can be considered that the human operator can effectively solve Task 1 in the HRCWE. To increase the effectiveness in this task, a first alternative is the incorporation of a training stage, and a second alternative could be the use of an assistant that considers assisting the operator when the real-time value of the *Task Completion rate* is lower than a minimum set value. For the second task, the value of the *Task Completion rate* shows that the human-robot team effectively solves the Task 2. However, a redesign of the physical architecture of HRWCE, in which the human operator is closer to the work area, could improve the efficiency of the work team.

The efficiency in Task 1, measured through the *Time to Task* with mean values of 56.2 seconds for Task 1 and 108.09 seconds for Task 2, places the efficiency between the low and standard level, with a higher accumulation towards the standard level. Hence, it can be considered that the human operator is able to efficiently solve the tasks in the HRCWE.

The SUS score shows that the collaborative workspace is perceived as acceptable for working with humans, and the star chart proves that the performance of its components is balanced, as expected.

The evaluation carried out about HWRCE, through the KPIs, corroborate the capacity of the team human-robot, with values higher than 80% of Per Utilization and higher than 75% of Per Efficiency, and a value of *Task Completion rate* over 80%. The variability analysis show that the system is able to absorb the variability introduced by the human operator.

In order to improve the results obtained in the efficiency and effectiveness of the tasks within the HWRCE, adding the real-time variable *Difficulty Task*, which considers the variables *Task Completion rate* and *Time to Task*, could be used to work with an assistant to guide a strategy for solving the tasks.

Overall, the usability benchmark additionally demonstrates the flexibility of the human operator to work in conjunction with a cobot operator in collaborative assembly tasks within the HRCWE.

5.4 Cognitive workload

The use of the NASA TLX-index protocol has allowed us to perform a multidimensional assessment of the variation of the mental workload on the participant, in this case in the role of human operator/collaborative robot As established in the hypothesis of the study, it has been shown that there are no significant differences between the mental workload in the solution of the TOH5 problem and its solution when a collaborative task with a robot is added in the same workspace. Moreover, as the results show, the level of mental workload found in both scenarios is high without overloading the operator. In the results, it can be observed that no participant has indicated a level of underload in the mental workload, and according to the experience found with other experiments, the level of mental workload can be considered normal in cognitive tasks, such as the TOH5 of this study. It could be that a high level of mental workload is necessary to be alert and make decisions in time.

The NASA TLX-index considers that the first three subscales (mental, physical and temporal) correspond to the demands imposed on the operator. In this aspect, the results show that the mental demand is the largest subscale of the mental workload. However, as the results show, no significant differences were found between the scenarios. The physical subscale is the least contributing subscale; however, the results show that there are significant differences in both scenarios, which is consistent with the differences in the physical characteristics of the scenarios. The next three subscales (effort, frustration and performance) refer to the interaction of the participant with the workspace. In this aspect, the results show that there are significant differences in performance between the scenarios, which is a result of the demand of attention that the cobot imposes on the participant. The frustration subscale, according to the results, does not show significant differences; however, it is an important subscale in the resolution of the problem when the operator begins his experience in the experiment. The use of descriptive adjectives and multidimensional graphs allows stakeholders to have a representative perspective of the results obtained.

5.5 Task Performance of the Human-Cobot team

In relation to the performance of the tasks, the results show that human operators can solve the task TOH5 effectively (TCR = 66.67%). Additionally, the human–robot team working in the collaborative assembly task is also able of effectively solving the task (TCR = 94.44%).

Following the results of the objective metrics and based on [42], some considerations can be presented. The measure H-IDLE relates the subjective perception of the human operator while waiting for the robot, e.g., wasting time or being bored. In this study, H-IDLE value remains at the same level, as shown in Figure 4.10, when the human operator develops Task 1 while waiting for the robot's request for collaboration; hence, it could be said that the human operator is taking advantage of his/her time.

Moreover, Hoffman relates the R-IDLE measure with fluency, establishing two possible conditions; either the robot is physically inactive but is doing internal work on its processor, or it is inactive while waiting for an intervention from the human operator. In our use case, the second condition is present, the robot starts its idle time by sending a message to the operators waiting for their collaboration and remains in this state until an operator informs it about the end of the collaboration. This collaboration time of the human operator is variable. In the subjective sense, this could be seen as either an inefficient use of the robot or an imbalance in the distribution of the task. In this study, the R-IDLE value is much lower than the H-IDLE value (see Figure 4.10), indicating that there is an efficient use of the robot. However, it could also indicate an imbalance in the distribution of the task.

Regarding C-ACT, Hoffman describes that a high value for this measure could indicate a subjective feeling of fluency when considering that the teams are well synchronized and that there is a similarity in the team members, perhaps a fair balance of work. In this study, the value for C-ACT is low from a physical point of view (see Figure 4.10). It could be considered an imbalance in the work. However, when considering a complete vision of the work capacities for each member, the distribution is fair in the sense that each member does what it does the best, i.e., the human operator undertakes more of the cognitive activity and the robot operator more of the physical activity.

For the measure F-DEL, it is established that a low level is related to the subjective perception of human–robot fluency since it indicates an efficient use of the time of the team members. In this study, it can be seen that such F-DEL is not present (see Figure 4.10). The human operator's sensation would be of efficient work; however, it should be taken into account that for this task, the level of collaboration is also low.

Chapter 6

Conclusions

6.1 Conclusions

Today, synergy combinations are required to support the development of smart and cognitive solutions. Understanding of HCPS from socio-technical systems with the perspective of joint cognitive systems (JCS) shows in the first place the current ability to provide the operator with functions and tools that allow him to amplify his abilities, in particular the cognitive ones for which it can be seen that there are different cognitive tools , thanks to which cognitive solutions are capable of being applied.

The underlying idea is to combine the strengths of robots and humans: the physical strength, precision, and endurance of robots with human problem-solving skills and the ability to cope with new and unexpected situations, this combination together with a cognitive assistant brings in the symbiotic relationship between human operators and technological operators. The assistance systems are developed to be integrated into manufacturing processes so that production is more efficient, safer and more reliable.

The integration of the different technologies of operator assistance 4.0, require the operator to develop greater cognitive skills, so a cognitive assistant must first of all collaborate with the development of human values in the workplace, it must be integrated as an extension of the user, of the system, even of the industry itself, the functions of the operator.

As Sheridan [105] suggests there is a positive relationship between the predictability of the system and the amount of mental work exerted on the user. One of the incentives of developing such an assistance system is to reduce the mental workload of the worker in the workplace; this goal is difficult to achieve if the system has high variability, or the user may often have to guess "What is the automation doing now?". The identification of sources of variability presented in this work, associated with performance metrics, are a first step in the design of a system that assists human in tasks allocation (human operator, collaborative robot), identification of optimal production scenarios and gap reduction in the connectivity between plant and manufacturing execution systems, where it is important to analyze economical costs of possible production scenarios. The Discussion section explain in detail the relationship between different human operators (expert, standard, novice) and the percentage of variation (time to task, quality) in an assembly system (manual task, fully automated task, H-R collaborative task).

Next the assembly task was modeled taking into account that it may be subject to variations in quality and fluctuations in productivity due to working styles, and robot and operator expertise. The FRAM methodology was employed in this article as a first approach in this context.

The human-robot interaction, and in particular with a cobot, has the advantage of a high flexibility inherent in the human part and a high efficiency inherent in the technical part. In later stages this mixed flexibility could be considered through indicators to reach an improved symbiosis within the human-robot collaborative system. In this symbiosis, an advanced topic is to add a principle of failure analysis. In the FRAM methodology this study means to analyze how to maintain the same level of production when one part (human or robot) is working in abnormal situation and it is necessary to increase the workload of the other part. Finally, it would be also possible to add another module inside the cognitive agent with recommendations in safety critical systems.

This research introduces a methodological and systematic guide for experimenting and evaluating experiments related to human-robot interaction in assembly task workspace. Taking advantage of human center design (HFE), value sensitive design (VSD), usability in human-computer interaction, this experience has been expanded and adapted to the field of collaborative human-robot interaction to have a solid and well-founded basis for evaluating the collaborative workspace, where the human operator shares tasks with a robot. Reviewing and incorporating best practices from relations area, can reduce the number of testing iterations required and save time and money developing and evaluating a process or system.

In industry 4.0 real scenarios, the operator may be subject to task changes, task difficulty, task shared with a robot, and interruptions (for instance, noise) [13, 8]. In these cases, understanding the cognitive load types (intrinsic, extraneous, germane) and the relationship with mental workload could be useful for the improvement of the human information processing system, human performance and the effectiveness of the overall system [26, 86].

Understanding this human cognitive load will allow the design of smart assistant systems to help and support human operators in future cognitive manufacturing systems. Moreover, the vision of the performance of the human–robot team through fluency could be considered an additional component to improve the design of a help support system from the perspective of the human–robot team.

To ensure a high usability and performance, the assist system also needs to be designed in accordance to human factor engineering principles, value sensitive design, human design centered to ensure the well-being of the 4.0 operator. The participants in the experimental session show that it is possible to keep the mental workload under control while they are developing primary and secondary tasks. This feature could consider flexibility as an important parameter in the operator's condition.

In general, an operator's mental workload increases when he has to process the information presented in the workspace and make decisions based on it. Low complexity, highly integrated assistance systems could minimize operator distractions, i.e., the mental workload for the driver.

6.2 Future lines

The application and use of assistants alongside workers in the manufacturing industry can be an important and efficient strategy for companies to create added value in manufacturing and provide better employee welfare, assistants can also be used by companies to increase the attractiveness of jobs in manufacturing production and thus become a socially sustainable factory. The field of worker assistance systems is therefore a research sector that can have a positive impact on the company itself and, above all, on the indispensable operator in manufacturing.

Modern workplaces are located within production systems, in which communication between different levels of the company is mandatory. In this research work, the workplace has been analyzed as an isolated system. As a future work, communication with manufacturing execution system (MES type management systems) should be considered, towards a complete socio-technical system. Moreover, by transforming the information obtained from data in a real-world process into knowledge, it is possible to change the strategy of assignment of activities. An assistant could handle these strategies.

Further research is needed on how to design and evaluate system performance, usability and user experience in the industrial environment due to its specific requirements. Criteria need to be developed for these new human-robot team contexts in production where safety and performance criteria are adapted. This is a problem that will have to be solved in the future, once production assistance systems are more consolidated.

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Appendix A

Appendix

A.1 Participants Selection

We need 30 participants in total. Each session lasts ¡25¿ minutes. We must have a candidate's completed screener at least one day in advance of the session, so we know which experimental group to assign him or her to.

- Introduction:

  This experiment is part of a research project related to Human Robot Interaction (HRI), the basic objective is to determine the variation of mental load on the operator when a collaborative task with a robot is added.

- Selection questions:

  1. The participant is familiar with information and communication technologies.
  2. The participant is interested in the use of robotics and its applications.
  3. Participant feels confident working with a moving robot.
  4. Participant would like to help in this research.

- Exclusion questions:

    1. The participant is of legal age
    2. The participant feels insecure working with automatic machines.

- Experience Questions
    1. Do you have experience in programming or using robots?
    2. Have you participated in projects related to mind uploading?
    3. Do you have experience playing the towers of Hanoi, in real physical format or in its digital version?

A.2 Statement of informed consent. Consent form

TITLE: Usability Test in the Human Robot Collaborative Workspace

PROTOCOL DIRECTOR: Phd. student Alejandro Chacón.

DESCRIPTION: You have been invited to participate in a study that aims to improve the tasks performed by operators and cobots in workspaces within factories.

The facilitator gives you the instruction (Development of the game Hanoi's Tower and the collaboration with the robot in the assembly of the product)

TIME INVOLVEMENT: Your participation will take approximately 15 minutes

RISKS AND BENEFITS: There aren't risks in this study. The benefits are only for academic purposes. Your decision whether or not to participate in this study will not affect your grades in school.

PAYMENTS: You will not receive anything as payment for your participation. In fact, you will receive feedback about the experimental session.

SUBJECT'S RIGHTS: If you have read this form and have decided to participate in this project, please understand your participation is voluntary and you have the right to withdraw your consent or discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled. The alternative is not to participate. You have the right to refuse to answer particular questions. Your individual privacy will be maintained in all published and written data resulting from the study.

CONTACT INFORMATION:

Questions: If you have any questions, concerns or complaints about this research, its procedures, risks and benefits, contact the Protocol Director, Alejandro Chacón, luis.alejandro.chacon@upc.edu.

I give consent for my identity to be revealed in written materials resulting from this study only inside the class with my teacher and colleagues:

Please initial: _Yes _ No

The extra copy of this consent form is for you to keep.

SIGNATURE DATE

A.3 Case Study

Two different task are defined on these scenario, with different conditions and operating characteristics, as shown in Table A.1. Each participant participates in two tasks, being always the task1 the first one. One iteration of scenario is performed for each operator for 15'.

The objective for the participant in the TOH5 throuble is to perform as many repetitions as possible. The number of movements and the time of each repetition are recorded by the participant in a data table as A.2

The second task, Assembly is related with responding to requests for collaboration from the robot, which are indicated by the green light of the beacon in the area of assembly. Both, time that human takes to place caps defined as Wait Time and

Table A.1: Experimental scenario

	Task	Performance	Time
1	TOH5	Maximum number of TOH5 game replays with 31 moves	
2	CA	At least 7 Cycles Work completed	15 minutes

Cycle time are recorded in a data table as A.2, jointly with figures for Task 1 when the operator is in the scenario 2. In the assembly task, the activities of the participant, are:

- performing quality control of the assembly process
- place the caps on the sub-assembly zone
- refill the base and bearing warehouses

Table A.2: Scenario . Task 1 & Task 2: Resolve TOH5 & Collaborate with cobot (CA)

Operator		**Cobot**		
ReplayN_moves	**Time to Task (sec)**	**Cycle**	**Wait Time (sec)**	**Cycle Time (sec)**
1		1		
...		...		

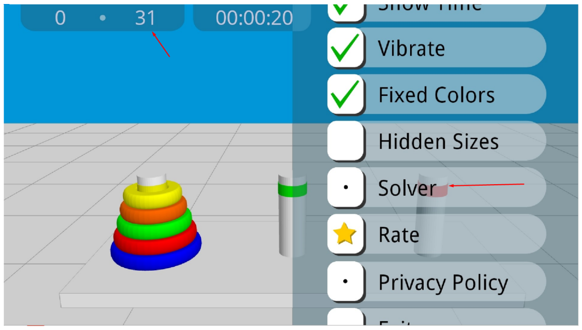
At the end of the experiment the participant answers, the System Usability Scale (SUS) as a satisfaction questionnaire

A.4 Demonstrations

The main facilitator shows the participant the two areas and how the tasks are performed, in particular highlighting the activities that the operator must perform.

A.4.1 TOH5

By using the app's own functions, the facilitator shows once how to solve the game with the least number of moves, see Figure A.1.



☑ Vibrate
☑ Fixed Colors
☐ Hidden Sizes
Solver
Rate
Privacy Policy

Figure A.1: TOH5 - Solver

A.4.2 Assembly

The facilitator shows a complete work cycle, indicating the activities that the operator must perform: place the caps, click on the teach pendant, and reload stores, as well as the meaning of the lights on the indicator tower, see Figure A.2.

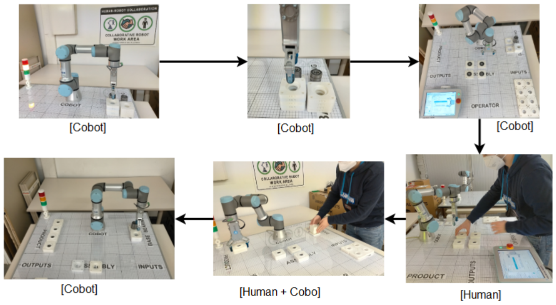


Figure A.2: Demonstration Assembly Cycle Work Human-Robot