UNIVERSITY OF KRAGUJEVAC
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NEUROERGONOMIC ASSESSMENT OF MENTAL WORKLOAD IN ADAPTIVE INDUSTRIAL HUMAN-ROBOT COLLABORATION

Doctoral Dissertation

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UNIVERZITET U KRAGUJEVCU
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NEUROERGONOMSKA PROCENA MENTALNOG OPTEREĆENJA U ADAPTIVNOJ INDUSTRIJSKOJ SARADNJI ČOVEK-ROBOT

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ABSTRACT

The fifth industrial revolution, known as Industry 5.0 (IR5.0), is on its way to of integrating humans at the centre of production processes, resulting in creative industrial collaborative workplace designs. Collaborative robots, or cobots, enable enterprises to improve their social sustainability while maintaining efficiency. The deployment of these devices pave the way for human-robot collaboration (HRC), which combines the benefits of automation, such as efficiency and precision, with the versatility and soft skills of humans. Psychophysiological measurements in HRC, through the deployment of non-invasive, compact, and versatile sensors, can be used to identify and analyse the human's physiological responses, like the mental workload (MWL), to the robot engagement. In this sense, Neuroergonomics enables a more accurate estimation of the workload of the operator executing a task. MWL reflects the amount of mental effort required by an employee to complete a task.

The PhD work presents a comparative analysis of three laboratory experimental scenarios: in the first, the participant assembles a component without the intervention of the robot (Standard Scenario); in the second scenario, the participant performs the same activity in collaboration with the robot (Collaborative Scenario); in the third scenario, the participant gets fully guided task in collaboration with the robot (Collaborative Guided Scenario). EEG analysis was applied to objectively and real-time assess mental workload. To decrease noise and artefacts, the data were pre-processed using several procedures such as Independent Component Analysis (ICA). The mental workload was calculated using a formula that correlated the most intense waves from the scalp during the analysis. The analysis was connected with questionnaires and observational data to evaluate the effectiveness of the task completed by the participant in the three different scenarios, as well as the impact of the cobot on the workforce.

The goal of this analysis is to show the different responses of participants while working or not alongside the robot in terms of mental workload, efficiency, and productivity of the task.

Key words: *Collaborative Robotics, Neuroergonomics, Industry 5.0, Human-Robot Collaboration, Mental Workload, Lean Manufacturing*

REZIME

Peta industrijska revolucija, poznata kao Industrija 5.0 (IR5.0), je na putu da integriše ljude u centar proizvodnih procesa, što rezultira kreativnim industrijskim kolaborativnom organizacijom radnog mesta. Kolaborativni roboti ili koboti, omogućavaju kompanijama da poboljšaju svoju društvenu održivost uz održavanje efikasnosti. Primena ove opreme otvara put saradnji čoveka i robota (HRC), koja kombinuje prednosti automatizacije, kao što su efikasnost i preciznost, sa svestranošću i mekim veštinama ljudi. Psihofiziološka merenja u saradnji čoveka i robota, kroz primenu neinvazivnih, kompaktnih i raznovrsnih senzora, mogu se koristiti za identifikaciju i analizu ljudskih fizioloških odgovora, poput mentalnog opterećenja (MWL), na zajednički rad sa robotom. U tom smislu, neuroergonomija omogućava tačniju procenu opterećenja operatera koji izvršava zadatak. MWL odražava količinu mentalnog napora potrebnog od strane zaposlenog da završi zadatak.

Doktorska disertacija predstavlja komparativnu analizu tri laboratorijska eksperimentalna scenarija: u prvom, učesnik sprovodi proces montaže komponente bez intervencije robota (standardni scenario); u drugom scenariju, učesnik obavlja istu aktivnost u saradnji sa robotom (kolaborativni scenario); u trećem scenariju, učesnik dobija potpuno vođen zadatak u saradnji sa robotom (vođen kolaborativni scenario). EEG analiza je primenjena za objektivnu procenu mentalnog opterećenja u realnom vremenu. Da bi se smanjila buka i artefakti, podaci su prethodno obrađeni korišćenjem nekoliko procedura kao što je analiza nezavisnih komponenti (ICA). Mentalno opterećenje je izračunato korišćenjem formule koja je povezivala najintenzivnije talase sa kože glave tokom analize. Analiza je povezana sa upitnicima i opservacionim podacima kako bi se procenila efikasnost zadatka koji je učesnik obavio u tri različita scenarija, kao i uticaj kobota na radnu snagu.

Cilj ove analize je da pokaže različite odgovore učesnika dok rade ili ne zajedno sa robotom u smislu mentalnog opterećenja, efikasnosti i produktivnosti zadatka.

.

Ključne reči: *Kolaborativna Robotika, Neuroergonomija, Industrija 5.0, Saradnja čovek-robot, Mentalno opterećenje, Lean proizvodnja*

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1. INTRODUCTION

1.1 CONTEXT AND MOTIVATION

The fifth industrial revolution, or Industry 5.0 (IR5.0), considers humans as the core of production processes, designing new industrial collaborative workspaces. In contrast to the previous four industrial revolutions, which aimed to marginalise the human role in manufacturing activities, the IR5.0 emphasises how technology should be used for the benefit of individuals, by focusing on the personalised demands and requirements of customers.

Sustainability is one of the most significant aspects of IR5.0. Sustainable businesses take into account environmental, social, and economic factors to provide a higher standard of production, quality, and efficiency. In this regard, sustainable products are the outcome of processes that decrease environmental consequences and respect safety and ergonomics standards for employee welfare.

Occupational Health and Safety (OHS), well-being, and satisfaction are necessary to industrial sustainability procedures that aim to improve operator safety, physical, and mental health. As a result, industrial organisations should view the human element as a valuable resource, enhancing working conditions and establishing human-centered production methods. Collaborative robots, or cobots, represent a potential and concrete way to increase social sustainability without sacrificing production efficiency, allowing enterprises to achieve social sustainability while maintaining productivity. The deployment of these technologies opens the door to human-robot cooperation, or HRC, which combines the benefits of automation, such as accuracy and repeatability, with the flexibility and cognitive soft-skills of humans.

HRC allows a sophisticated approach to collaborative interaction between humans and robots in industrial sectors. It ensures that the machine provides proper support or engagement with the operator in stressful, repetitive, and complex operations where the physical and mental effort may be increased. HRC's success is owed in part to the groundbreaking use of cobots. These innovative robotic arms are more intuitive than their predecessors and allow for closer connection with the operator in a fenceless environment.

The adoption of cobots has altered the human role in real-world manufacturing scenarios due to automation technology disruption. As assembly tasks are increasingly monitored by the agent for potential system failures, ergonomic assessment is critical for an HRC activity.

Manufacturing assembly activities are competing to be one of the most intriguing and promising applications in collaborative settings, accounting for about half of the typical workload in the real manufacturing process. Recent research investigations have developed many case scenarios of assembly tasks portrayed in laboratory situations using HRC activities. In this regard, ergonomics considerations are of crucial importance for designing these collaborative activities.

There are three types of ergonomics: physical, cognitive, and organisational ergonomics. Physical and cognitive ergonomics are critical components of effective and efficient human resource management. Physical ergonomics is concerned with human physical activity, namely its limitations and capabilities. Cognitive ergonomics studies how humans' mental processes are influenced by other systems in their surroundings..

With the disruption of sensors applied in HRC environments, psychophysiological measures can be used to identify and evaluate the human partner's responses to the interaction with the robot.

Different physiological metrics in HRC applications have been proposed as markers of the operator's mental effort. In this sense, Neuroergonomics, as a branch of Neuroscience applied to Ergonomics, enables a more accurate estimation of the workload of the operator executing a task. Mental workload (MWL) is the amount of mental labour needed to complete an activity.

The analysis of MWL is defined through indirect and direct methods. These last methods are possible through unobtrusive and portable devices such as the innovative electroencephaloghram (EEG) cap that paves the way to a new methodology of objective ergonomic assessment, monitoring, and evaluation of parameters in the field of HRC. EEG provides an online, objective, real-time, and quantitative direct measure of the neuronal activity to further analysis the mental stress or engagement of the operator while performing tedious, repetitive and stressful activities.

The PhD work sets out a comparative evaluation of three laboratory experimental conditions: in the first, the participant assembles a component without the intervention of the robot (Standard Scenario); in the second scenario, the participant performs the same activity in collaboration with the robot (Collaborative Scenario); in the third scenario, the participant gets fully guided task in collaboration with the robot (Collaborative Guided Scenario) through poka-yoke or lean principles.

The purpose of this analysis is to demonstrate the different responses of participants in terms of mental workload, efficiency, and productivity in the three settings. Furthermore, the research used observational measurements to calculate the productivity index in terms of accurately assembled components across the three scenarios. EEG sensors are put on the applicant to collect quantitative data for comparison analysis and to assess the operator's mental workload during the task in the two different scenarios. The quantitative and objective EEG study of the mental effort is backed up by observational measurements of the corrected components constructed to correlate the mental workload with production rate. Following these measurements, a qualitative analysis, using questionnaires, is useful to assess the user experience while working with the robot in the collaborative scenario.

1.2 BASIC HYPHOTHESES

H1 - The implementation of collaborative robot solutions can reduce the level of mental workload (MWL) during work activities.

H2 - Reducing the level of mental workload improves the efficiency, effectiveness, and quality of work activities.

H3 - It is possible to define mental workload through objective sensorial devices and measurement.

H4 - The use and implementation of collaborative robots has subjective positive impact on workers during work activities.

1.3 STRUCTURE OF THE WORK

The **second chapter** will deal with the analysis of relevant literature that will be used in the doctoral dissertation emphasizing the importance of the following areas: (1) the advantages of Human-Robot Collaboration (HRC) tasks in manufacturing activities (2) Design and optimization of HRC in laboratory activities (3) The effect of mental workload of operators in a HRC activity. The literature analysis will follow the outline content of the dissertation.

In the **third chapter**, the research methodology is explained.

The tests were carried out in a modular industrial assembly workstation built for neuroergonomic research and located at the Faculty of Engineering laboratory at the University of Kragujevac in Serbia, in collaboration with the Mbraintrain firm in Belgrade.

The assessment included successive manual assembly activities. Three case studies were prepared up for the experiments: in the first scenario, the participant achieved the work without any interference in the assembly area; in the second scenario, the robot simply takes the components sequentially to the assembly and provides them to the operator; and in the third scenario robot carries sequentially the components completely prepared to the assembly providing them to the operator. The goal was to conduct a comparative analysis of the mental workload by the EEG real-time acquisition in these three different scenarios. The three experimental scenarios were set in different periods of the year with a time span of minimum 4 months each to reduce the error-bias in the comparative neuroergonomic analysis. Moreover, to reduce the noise due to internal factors that might influence the workload, experiments started in the morning hours of the day, conducted in an isolated environment and at room temperature.

The **fourth chapter** describes the design of EEG neuroergonomic assessment in a HRC task in the modular assembly workstation. The proposed architecture allowed the collaborative robot to be implemented at the workstation without interfering with other systems, as well as conducting an EEG evaluation during the laboratory assembly activities. The purpose of analysing EEG data is to assess mental workload. The mental workload parameter, defined as the power ratio between Beta Waves (stress/engagement index) and Alpha Waves (relaxation index), provides for the evaluation of the participants' mental effort in three scenarios.

In the **fifth chapter**, the analyses of subjective and observational measurements are presented. NASA TLX is an established multidimensional subjective questionnaire that assesses the cognitive effort of participants completing a task. For this study, it is used to correlate the objective analysis from the EEG neuroergonomic assessment in order to further analyse mental workload. A combination of objective and subjective metrics is required to assess the cognitive response of the operator doing the task in the three circumstances. Furthermore, observational measures using a checklist are used to analyse the level of efficiency, effectiveness, and quality of the tasks in the three situations.

In the **sixth chapter**, the analysis of the research results is discussed. The scientific approach is considered, describing how the mental workload of the operator is affected by the cobot activity and how this parameter, from the EEG objective and NASA TLX subjective analyses, is correlated with the productivity and efficiency index of the task from the observational measurements.

In the **seventh chapter**, the conclusions from the conducted research are presented. Also, the limitations of the proposed model and future research are analyzed.

In the **eight chapter**, the references used in the dissertation are given.

1.4 DESIGN OF EXPERIMENTS

In this dissertation, laboratory experiments were conducted for a comparative study of the Mental Workload (MWL) of participants performing manufacturing assembly tasks.

The laboratory trials were carried out at a modular industrial assembly workstation set up at the Faculty of Engineering, University of Kragujevac, Serbia. The workstation was equipped with:

- an industrial computer to monitor and control the performance of various tasks and process visualization.
- a touchscreen PC for task definition and stimulus application.
- lighting LED technology to adjust the light and make soft shadows to put less strain on the eyes of the test participants..
- an audio 5.0 system to simulate the sounds of the industrial environment.
- an adjustable ergonomic work-chair to let the participant seat during the tests.

To conduct the experiment, the participants put together a prototype model of an industrial product. The designed task is similar to the wire harnessing tasks performed in manufacturing environments. This activity, similar to wire harness assembly tasks, was chosen since there are not enough research studies involving the neuroergonomic analysis of these activities with the involvement of collaborative technologies, such as cobots.

The MWL investigation was carried out using real-time EEG recording and analysis. The data were acquired by means of an innovative technology such as the EEG cap, which allows for the unobtrusive acquisition of data from the outer region of the participant's scalp during the task via Bluetooth.

The comparative analysis was set up in three scenarios: in the first, the participant performs the assembly task of the component without the intervention of the robot (Standard Scenario); in the second scenario, the participant performs the task in collaboration with the robot (Collaborative Scenario); in the third scenario, the participant gets fully guided task in collaboration with the robot (Collaborative Guided Scenario).

The data were pre-processed through different steps like the Indipendent Component Analysis in order to reduce the noise and artifacts.

The MWL was extracted from a function correlating the most intensive waves from the scalp during the analysis.

Finally, the analysis was correlated with questionnaires and observational measurements to evaluate the efficiency of the task performed by the participant in the three different scenarios and the evaluation of the cobot’s impact on the workers.

1.5 EXPECTED RESULTS

For the comparative analysis, the participants accomplished three different types of experiments, which include standard scenario, in which the participant performed the task without any intervention and support; collaborative scenario, in which the participant performed the task interacting with the robot (supporting activity) in the workplace;

collaborative guided scenario, where the participants performed the task in collaboration with the robot and guided by Poka-Yoke aspects taken into account.

The realization of the set goals within this doctoral dissertation is expected to develop a method to design HRC activities through the real-time acquisition of EEG data. In this sense, the following results are expected, which represent the contribution of this work:

- Efficient Real-time acquisition of physiological data such as EEG.
- Development of an extended stage Best-Worst model for determining the relative importance of RFs' impact on each denoted KPI
- Analysis of cognitive workload of the operator while performing assembly tasks in HRC scenarios.
- Evaluation of productivity in a HRC activity.
- Lower level of mental workload in the collaborative scenarios.

1.6 THE LIST OF PUBLISHED WORKS

International journals (M22):

1. **Caiazzo, C**., Savković, M., Pusica, M., Milojevic, D., Leva, M.C., & Djapan, M. (2023). Development of a Neuroergonomic Assessment for the Evaluation of Mental Workload in an Industrial Human–Robot Interaction Assembly Task: A Comparative Case Study. Machines. https://doi.org/10.3390/machines11110995

2. Petrovic, M., Vukicevic, A.M., Djapan, M., Peulic, A., Jovicic, M., Mijailovic, N., Milovanovic, P., Grajic, M., Savkovic, M., **Caiazzo, C.**, Isailovic, V., Macuzic, I., Jovanovic, K. (2022) Experimental Analysis of Handcart Pushing and Pulling Safety in an Industrial Environment by Using IoT Force and EMG Sensors: Relationship with Operators' Psychological Status and Pain Syndromes. Sensors, 22, 7467. https://doi.org/10.3390/s22197467

3. Savkovic, M., **Caiazzo, C.**, Djapan, M., Vukicevic, A.M., Pušica, M., Macuzic, I. (2022) Development of Modular and Adaptive Laboratory Set-Up for Neuroergonomic and Human-Robot Interaction. Research Frontiers in Neurorobotics, Vol. 16, https://doi.org/10.3389/fnbot.2022.863637

International conferences (M33):

1. **Caiazzo, C**., Nestić, S., Savković, M. (2022). A Systematic Classification of Key Performance Indicators in Human-Robot Collaboration. In: Mihić, M., Jednak, S., Savić, G. (eds) Sustainable Business Management and Digital Transformation: Challenges and Opportunities in the Post-COVID Era. SymOrg 2022. Lecture Notes in Networks and Systems, vol 562. Springer, Cham. https://doi.org/10.1007/978-3-031-18645-5_30

2. **Caiazzo, C**., Savković, M., Djapan, M., Macuzic, I. (2022). Framework of modular industrial workstations for neuroergonomics experiments in a collaborative environment. Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022), Edited by Maria Chiara Leva, Edoardo Patelli, Luca Podofillini, and Simon Wilson https://doi.org/10.3850/978-981-18-5183-4_J01-07-285-cd

3. **Caiazzo, C**., Djordjevic, A., Savković, M., Djapan, M., Vukicevic, A. Architecture of human-robot collaboration in manufacturing industries. The 19th International Conference “Man and Working Environment” Occupational and Environmental Safety engineering and Management, pp. 307-314, November 24-25th 2022, Niš, Serbia. https://scidar.kg.ac.rs/handle/123456789/18387

4. Savković, M., Mijailović, N., **Caiazzo, C**., Djapan, M. Advanced physical ergonomics and neuroergonomics research on an assembly workstation. The 19th International Conference “Man and Working Environment” Occupational and Environmental Safety engineering and Management, pp. 351-358, November 24-25th, 2022, Niš, Serbia. https://scidar.kg.ac.rs/handle/123456789/18500

6. **Caiazzo, C.,** Savkovic, M., Pusica, M., Nikolic, N., Milojevic, Dj., Djapan, M. Framework of a Neuroergonomic Assessment in Human-Robot Collaboration. Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023). Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio, pp. 2814-2820, doi: 10.3850/978-981-18-8071-1_P214-cd

7. Pusica, M., **Caiazzo, C.,** Djapan, M., Savkovic, M., Leva, M.C. Visual Mental Workload Assessment from EEG in Manual Assembly Task. Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023). Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio, pp. 2999-3005, doi: 10.3850/978-981-18-8071-1_P667-cd

8. **Caiazzo, C**., Savkovic, M., Pusica, M., Nikolic, N., Macuzic, I., Djapan, M. Comparative Analysis of Mental Workload in Adaptive Human-Robot Collaboration During Assembly Tasks. Proceedings of the 34th European Safety and Reliability Conference (ESREL 2024). – TO BE PUBLISHED

2. LITERATURE REVIEW

2.1. INDUSTRY 5.0 OVERVIEW

Several significant changes in production, technology, and society took place between the 18th and the present day in the methods of production, technology, and society have been referred to as the Industrial Revolution X.0 (IRX.0), Figure 2.1. These industrial revolutions have had a profound impact on economies, societies, and daily life, which has led to significant changes in labour practices, urbanization, global trade, and technology developments. In each phase, change has taken place and reshaped the world as we know it now.

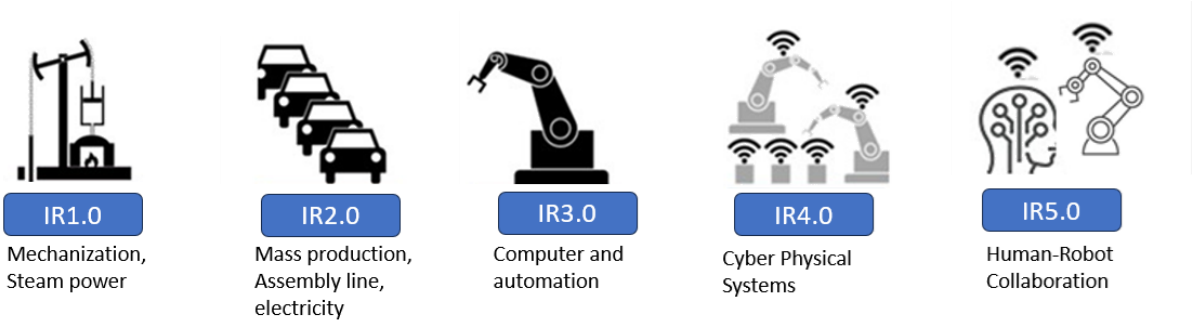


Figure 2.1 – *Industrial Revolution Phases*

The First Industrial Revolution, or IR1.0, (1760-1840) shifted the economy from the agrarian to the industrial one. The deployment of steam power, advancements in iron and steel production, and the introduction of railways were key elements during this time (Mokyr, 2010). In the Second Industrial Revolution, or IR2.0, (1870-1914) more significant technological advancements raised including the proliferation of steel production, the introduction of the telegraph and telephone, widespread use of electricity, the internal combustion engine, and the rise of mass production techniques pioneered by figures like Henry Ford. This period saw rapid industrial growth, urbanization, and the emergence of large corporations and industrial empires (Mokyr and Strotz, 2000). The IR3.0 (1950 - beginning of 2000s), also named Digital Revolution, was characterized by the rise of electronics, telecommunications, computers, and the internet. It introduced automation and digital technologies, transforming the way industries operate, communicate, and produce goods (Teixeira et al., 2019). The IR4.0 (beginning of 2000s – 2020) involved the integration of artificial intelligence (AI), machine learning (ML), robotics, nanotechnology, biotechnology, and the internet of things (IoT) to the digital development of the last industrial revolution. Industry 4.0 introduced a new level of interconnectivity, data-driven decision-making, and the integration of cyber-physical systems (Heat, 2016).

The late Industrial Revolution 5.0 (2020-ongoing), or IR5.0, has been considered a successor or complement to the IR4.0. While IR4.0 highlighted the high level of interconnectedness that crossed the barriers between the physical, digital, and biological spheres, IR5.0 is recommended to emphasise human collaboration and engagement with modern technologies. The European Commission defined the idea of IR5.0 to reflect the need to integrate European priorities in the context of social and environmental concerns, as well as to encourage businesses and industries to evolve and become more sustainable, resilient, and human-centred. (Javaid and Haleem, 2020; Tiwari et al., 2022).

Furthermore, the recent Covid-19 global pandemic underlined the limitations of traditional working methods and approaches. It has worsened our sectors' weaknesses, such as fragile key value chains, and highlighted the necessity of flexible yet durable solutions to these vulnerabilities. Nevertheless, the pandemic has accelerated the deployment of digital technologies and automation across businesses. With lockdowns and limitations affecting traditional workplaces, businesses have increasingly turned to remote labour, automation, and digital solutions to assure business continuity. Thus, the increasing use of technology to sustain operations may have contributed to the advent of IR5.0, emphasising human-machine collaboration (Stovicek, 2023).

According to Ivanov (2022), unlike the other four industrial revolutions, which concentrated on automating processes, IR5.0 attempts to use modern technology to suit customer’s demand highlighting their personalised expectations and requirements. To accomplish this, Demir and colleagues (2019) proposed that humans collaborate with robotic machines in all feasible scenarios and contexts, resulting in the widespread integration of robots into organisations. Despite some writers' criticism that the IR5.0 has not yet begun (Mourtzis et al., 2022), both IR4.0 and, more importantly, I5.0 stress human-robot collaboration (HRC) as a critical feature for the well-being and pleasure of industrial operators. (Nahavandi, 2019).

Many enabling technologies from IR4.0 are expected to be leveraged to help fulfil the societal goals of IR5.0. However, some IR5.0 technologies, such as bio-sensor technologies and the ones for energy efficiency, storage, and renewable energy, deserve special attention. (Gladysz et al., 2023).

However, IR4.0 addresses the challenges of human-centricity, sustainable development, and adaptability with an emphasis on outcomes and a defined technology strategy. Unlike IR4.0, IR5.0 highlights a significant transition from individual technologies to a systematic approach. This method enables the sector to fulfil societal goals other than jobs and growth, and it prioritises the well-being of industrial workers throughout the production process. This may assist to explain why IR5.0 is regarded as distinct from previous Industrial Revolutions (Alves et al., 2023).

IR5.0 is neither a historical continuation of nor an alternative to the IR4.0 paradigm. IR5.0 is the product of a forward-thinking exercise that envisions how industry and developing society trends and requirements will coexist. As a result, Industry 5.0 enhances and expands on the key elements of IR4.0. This may help distinguish IR5.0 as a distinct type of Industrial Revolution from the others, while accepting that the other Industrial Revolutions are a chronological continuation of their predecessors (Raja Santhi and Muthuswamy, 2023).

According to the prediction of Brunetti and colleagues (2022), IR5.0 will be the period of the socially smart factory, or "Social Smart Industry", in which social business networks converge with people for seamless communication, specifically, cyber-physical production systems that are synergistically coupled with the human component (Wang et al., 2022). Furthermore, IR5.0 is a human-centered approach in which humans and technologies operate in tandem. Machines performes labor-intensive or repetitive jobs, while people will handle personalisation and critical thinking (Pizon and Gala, 2023).

Thus, the key concepts of IR5.0 revolve around the concept of "human-centric" design manufacturing, which entails integrating and syncing the capabilities of both humans and machines in order to create more harmonious and cooperative working environments in which humans and robots can collaborate more effectively. Safety, ergonomics and human factors, and efficiency are the pillars for a collaborative automation, as shown in Figure 2.2.

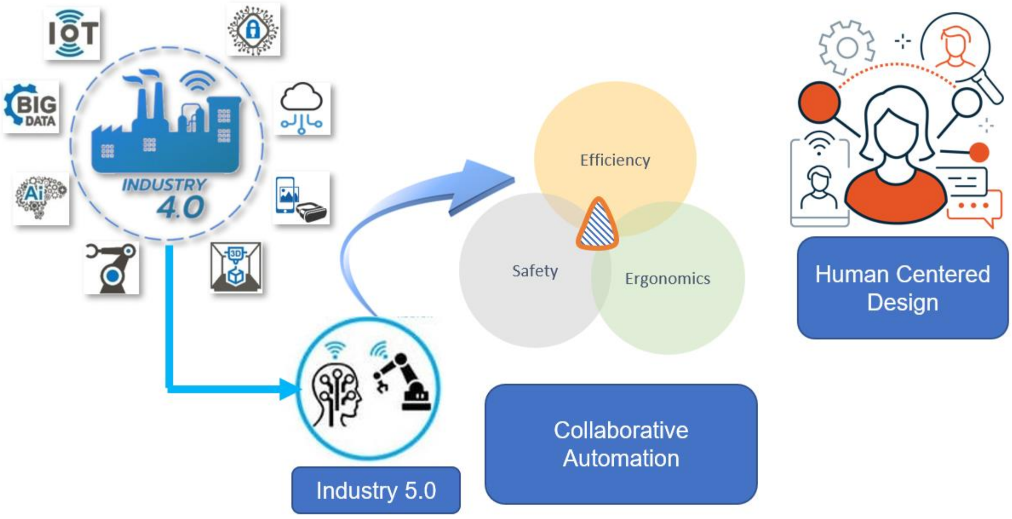


Figure 2.2 – *Key pillars of Industry 5.0*

In this perspective, sustainability is one of the most important features of IR5.0. Sustainable businesses take into account environmental, social, and economic factors to provide a greater level of production, quality, and firm efficiency. Sustainable products are the result of methods that limit environmental consequences while also respecting safety and ergonomics guidelines for employee well-being (Nielsen and Brix, 2023).

Nonetheless, OHS, well-being, and satisfaction are pivotal to these procedures aiming to improve operator safety and wellbeing. Hence, industrial organisations should view the human role as a valuable resource, enhancing working conditions and establishing human-centered production methods (Avila-Gutierrez et al., 2022).

2.2 LEAN MANUFACTURING

Lean manufacturing, noted for its attention on waste reduction and efficiency, has played an important role in the advance of industrial practices, particularly the recent shift to IR5.0 (Nikolic et al., 2023). Lean production, also known as lean manufacturing, consists of a series of strategical methods for reducing waste within a system (manufacturing environment) while maintaining productivity. It is based on the Toyota Production System and aims to preserve value with less work (Hawee and Al-Tai, 2024). Here are its main characteristics:

- Waste Elimination (Muda): Lean production aims to detect and eliminate non-value-adding activities. This can include overproduction, long wait times, wasteful transportation, excess inventory, excess motion, faults, and over-processing.
- Continuous Improvement (Kaizen): Lean production aims to make incremental changes to pursuit higher levels of quality, productivity, and efficiency.
- Just-In-Time Production (JIT): it aims to create and deliver products in the exact quantity and time required. This decreases both inventory and storage costs.
- Flexibility: Lean systems are designed to be adaptable and flexible, allowing them to adjust swiftly to changes in customer demand while avoiding extra inventory and time delays.

- Quality management: it emphasises defect prevention over detection, as a target of obtaining zero defects through continual improvement.
- Employee Involvement: employees are encouraged to be actively involved in the process of identifying inefficiencies and suggesting improvements.
- Value Stream Mapping: this is a process for assessing the current state and developing a future state for a product's life cycle, from conception to customer.

By implementing these principles, lean production aims to create a more efficient, effective, and agile production process that can boost productivity, reduce costs, and improve quality. In this regard, Poka-yoke (or P-Y) is a Japanese phrase that essentially means "mistake-proofing" or "error prevention." It is a concept used in lean manufacturing and quality management to create processes or mechanisms that reduce human error (Lv et al., 2023). Key aspects of P-Y include:

- Error Prevention: designing processes or equipment in a way that makes it impossible or extremely difficult to make mistakes. For example, using shapes that only fit together one way (like USB plugs) so that incorrect assembly is impossible.
- Error Detection: incorporating systems detecting errors when they happen. This can include sensors or alarms that activate when something is done incorrectly, allowing for immediate corrective action.
- Simplicity and Intuitiveness: the solutions should be simple and intuitive, often employing visual cues or easy-to-understand mechanisms that guide the user to perform tasks correctly.
- Reduced Rework and Waste: by preventing errors, P-Y helps reduce the need for rework or correction, thus minimizing waste and improving efficiency.
- Improved Safety and Quality: The system enhances safety for workers by reducing the chance of accidents and ensures higher quality products by preventing defects.
- Employee Control: workers are part of the creation and implementation of P-Y solutions, which empowers them and enhances their role in quality control.

Poka-yoke is a key component of the lean manufacturing concept, and it is widely utilised in a variety of industries to improve product quality, safety, and productivity.

2.2.1 Metrics deployed in Lean Manufacturing

Efficiency, quality, and productivity are fundamental metrics in lean manufacturing, each playing a crucial role in determining the success and competitiveness of a manufacturing process. Understanding and effectively measuring these metrics is key to implementing lean principles and achieving continuous improvement.

Efficiency in lean manufacturing refers to the amount to which time, effort, and resources are employed effectively for the intended task or goal. It is about doing things in the most cost-effective way feasible. Efficiency is commonly quantified by comparing actual production to maximum achievable output, or operational efficiency. Another metric for efficiency is Overall Equipment Effectiveness (OEE), which takes into account the equipment's availability, performance, and quality (Aucasime-Gonzales et al., 2020).

Quality can be determined in a variety of methods, including First Pass Yield (FPY), which determines how many goods are manufactured correctly without rework. Other variables include the quantity of faults per unit, the frequency of returns or complaints, and audit outcomes (Corona et al., 2021).

Productivity in lean manufacturing is about maximizing output with the minimum amount of input. It's a assesses how well production inputs, such as labor and materials, are being turned into outputs. Productivity is often measured as the ratio of output to input. For instance, labor productivity can be calculated by dividing the total output by the total number of labor hours invested in the production (Milosevic et al., 2021).

Each of these metrics are interrelated and critical for lean manufacturing (Kumar et al., 2021).

While both deal with the link between inputs and outputs, efficiency is primarily concerned with process quality (doing things correctly), whereas productivity is concerned with output quantity (doing more with less). Quality and productivity are frequently viewed as trade-offs. Lean manufacturing, viceversa, seeks to enhance both simultaneously. High quality saves rework and waste, resulting in increased production. In terms of quality and efficiency, high-quality operations are typically more efficient. They reduce waste and rework, two essential aspects of lean production. Efficient processes aim to create consistent, high-quality results. In a lean manufacturing context, these metrics are more than simply individual signs; they are part of a comprehensive strategy to continuous improvement. The goal is to optimise all three areas to establish a balanced, efficient, and lean manufacturing system.

Effectiveness is another critical indicator in lean manufacturing that is different yet closely related to efficiency, quality, and productivity. Understanding the role and measurement of efficacy is pivotal for fully analysing and improving manufacturing processes. In the manufacturing setting, effectiveness relates to how successful something is at generating the desired output. It is about doing the proper things to accomplish the desired aims or goals (Kulakov et al., 2023).

While efficiency focuses on how well resources are used, effectiveness is primarily concerned with the outcome or output's alignment with the desired goals. For instance, a process may be efficient (using fewer resources) but ineffective if it fails to accomplish the desired result. A process might be successful but inefficient if it uses more resources than are required to produce the desired output.

Different measurements might be applied to measure the effectiveness of industrial processes, considering specific aims and objectives involved. Customer happiness, market share, product quality, and the success of specific strategic goals such as new market penetration or product development are all common measures. Customer Satisfaction assesses the quality of a product that fulfils or exceeds the customer's expectations. While goal achievement entails establishing explicit, quantifiable objectives (such as production targets or quality benchmarks) and evaluating how efficiently they are reached.

In lean manufacturing, effectiveness is critical to ensuring that waste reduction, efficiency, and productivity improvements are aligned with the organization's overall goals. Not only is it saving resources or speeding up production, but it is also ensuring that these efficiencies help produce the appropriate product, at the right time, and in the correct quality to meet consumer demands (Vukadinovic et al., 2019).

Lean Manufacturing aimes to achieve a balance of efficiency, effectiveness, and quality. It entails developing procedures that not only maximise resource utilisation (efficiency) and provide a high output (productivity), but also guarantee that the output satisfies the required objectives in terms of customer satisfaction and strategic goals.

In summary, while efficiency and productivity concentrate on the "how" of operations (how resources are used, how much is generated), effectiveness is concerned with the "what" (what is accomplished, what the outcomes are). An effective lean manufacturing process not only reduces waste and increases output, but it also guarantees that the output meets customer's expectations (Nounou, 2018).

2.2.2 Measurement of the Lean Manufacturing Parameters

This section shows general metrics used in Lean Manufacturing. These metrics are crucial for ensuring that lean principles are effectively implemented and maintained.

- Cycle Time: this measures the total time taken to complete one cycle of a process. It's essential for identifying bottlenecks and understanding how long it takes to produce a single item (Pinheiro et al., 2023).
- Lead Time: it is the total time from the initiation of a process (like an order) to its completion. The reduction of lead time is one of the crucial goals in lean practices, as it increases the system's responsiveness to customer demand (Rekha et al., 2017).
- Takt Time: it is the rate at which products need to be produced to meet customer demand. It is calculated as the ratio of the available production time over the number of products suiting the customer needs. (Soliman, 2017).
- Overall Equipment Effectiveness (OEE): OEE is a comprehensive metric that measures the efficiency of a manufacturing process by considering capacity, performance, and quality. It contributes to recognising losses, benchmarking progress, and increasing the productivity of equipment and processes. (Shmatkov and Shmatkova, 2021).
- First Pass Yield (FPY): FPY measures the percentage of outputs that are correctly manufactured according to the specifications the first time without requiring rework. High FPY indicates effective manufacturing processes and quality control (Mehta, 2009).
- Value Stream Mapping: while not a metric in the traditional sense, value stream mapping is a lean tool used to visualize and analyze the flow of materials and information through a production process. It contributes to identifying waste and opportunities for improvement (Lian and Landeghem, 2002).
- Inventory Turnover: this metric measures how many times a company's inventory is sold and replaced over a period. High inventory turnover indicates efficient use of inventory, whereas low turnover might suggest overproduction or inefficiencies (Soliman, 2017).
- Work In Process (WIP): WIP refers to the materials and components that are currently being processed. WIP helps ensure production is smooth and inventory levels are not excessive (Corona et al., 2021).
- 8 Wastes/DOWNTIME: it is a checklist of eight types of waste to be eliminated in lean manufacturing: defects, overproduction, waiting, non-utilized talent, transportation, inventory excess, motion waste, and excess processing (Corona et al., 2021).

- 5S Score: 5S is a workplace organization method (sort, set in order, shine, standardize, sustain). The 5S score assesses how well these practices are being implemented (Amrina and Lubis, 2017).

These metrics help in tracking efficiency, identifying non-value-adding activities, and guiding continuous improvement initiatives by applying lean practices. By regularly monitoring and acting on these metrics, organizations can maintain a lean, efficient, and customer-focused production system.

2.2.3 Key Performance Indicators (KPIs)

Key Performance Indicators (KPIs) are quantifiable measures used to evaluate the success of an organization, employee, team, or process in achieving key objectives and goals. KPIs are critical in business and project management, as they highlight a clear way to track progress and performance (Parmenter, 2015).

KPIs in Lean Manufacturing frequently focus on indicators such as production time, waste reduction, quality rates, and customer satisfaction. KPIs are increasingly evolving to encompass measurements other than efficiency and productivity, like innovation, sustainability, customer personalisation, and the effectiveness of human-machine collaboration. The KPIs would set a trade-off between technological performance and human-centric ideals. Indeed, as IR5.0 reintroduces the human role into manufacturing, emphasising creativity, decision-making, and craftsmanship while complementing automated processes, IR5.0 KPIs would measure how effectively human skills are integrated into production processes, influencing product quality and innovation (Sangwa and Sangwan, 2018).

Furthermore, both Lean Manufacturing and IR5.0 emphasize sustainable practices. KPIs would therefore include metrics related to environmental impact, resource efficiency, and sustainable practices. KPIs are pivotal tools in performance management, as they help organizations focus on areas of importance, aligning resources and efforts towards strategic goals.

Below, it is presented some general key aspects of KPIs:

- Specificity: KPIs are specific to the organization’s goals and are deployed to assess performance that is essential to the success of the organization. They should align with strategic objectives.
- Measurable: KPIs must be quantifiable. This allows for clear tracking and assessment of whether goals are being met. Examples include sales revenue, profit margin, customer expectation scores, and turnover.
- Actionable: Effective KPIs can inform decision-making and guide actions to enhance performance.
- Relevant: KPIs should be relevant to the specific goals of the organization.
- Time-Bound: KPIs are set with a specific time frame, for instance, monthly, quarterly, or annually. This helps track progress over time.

KPIs vary depending on the organization, the specific business, its goals, and its strategic focus (Contini and Peruzzini, 2022).

KPIs serve as critical metrics to gauge the success and alignment of Lean Manufacturing principles with the evolving landscape of IR5.0, ensuring that the collaboration between technology and humans in production processes is both efficient and aligned with broader organizational goals like sustainability, innovation, and customer needs. IR5.0’s focus on customization and flexibility aligns with Lean Manufacturing' s emphasis on meeting specific customer needs. So, KPIs would therefore track the efficiency and adaptability of production systems when demands changes and thus, coming up with customized solutions (Chalak et al., 2022).

KPIs are variables used to report on progress towards targets. Furthermore, indicators should be relevant with the company's vision, goals, and plans. KPI assessment is an essential component of Performance Management in successful businesses. However, it is not always clear which KPIs should be utilised and whether they can effectively measure the performance of systems (Stefanovic et al., 2017).

A systematic distinction of KPIs in manufacturing contexts is offered on the base of the relevance of resources regarding the whole business. According to Brown (2005), in a manufacturing environment, KPIs are grouped into three management segments: production management, procurement management, and sales management. Nonetheless, other KPIs were pointed out by Nestic and colleagues (2019) regarding the performance assessment of small-medium enterprises (SMS).

KPIs provide managers the necessary information to identify opportunities for improvement and encourage them to strive for higher performance (Rajkovic et al., 2020). An overview of indicators that are related to the workers’ performance is offered by Bauters and colleagues in their research work (2018).

2.3 HUMAN ROBOT COLLABORATION (HRC)

2.3.1 General Overview

HRC is a working relationship between humans and robots performing activities together in a shared space. This notion represents a substantial departure from traditional robotics, in which robots frequently work independently of humans due to safety concerns. HRC combines the advantages of humans and robots to iimprove efficiency, flexibility, and productivity (Segura et al., 2021).

The ultimate goal of HRC is to develop a synergistic collaboration in which people and robots can collaborate more effectively than they could individually. This relationship has significant promise in a large scale of domains, including manufacturing, healthcare, service industries, and research. HRC can boost productivity, innovation, and worker safety by exploiting the particular qualities of human intelligence as well as robotic precision.

In HRC, robots and humans complement each other's abilities. Robots handle repetitive, high-precision, or heavy tasks, while humans manage tasks requiring judgment, fine motor skills, or adaptability. Furthermore, Safety is the most important component of human resource management. Collaborative robots (cobots) are built with force sensors, soft materials, and rounded edges to work securely alongside humans. These robots are frequently outfitted with advanced sensors that sense human presence and change their behaviour accordingly. This is the reason why in some HRC setups, robots assist humans by reducing ergonomic strain. For instance, a robot might handle heavy lifting or maintain tools in an optimal position, thereby decreasing the physical burden on the human worker (Gualtieri et al., 2020).

HRC involves effective communication. This could include interfaces that make it easy for people to programme and direct robots to allow robots to communicate their intents to human coworkers. Unlike traditional robotic setups, HRC often occurs in flexible and adaptive environments. Robots in these settings can quickly be customized to new activities in the workspace (Hjort and Chrysostomou, 2022).

2.3.2 The Origins of Robots

The first examples of robots, which are mechanical devices designed to mimic human or animal actions, were found back to ancient civilizations. For example, in ancient Greece, myths and traditions concerning mechanical beings created by the gods existed (Fron and Korn, 2019). Historically, the Greek scientist Hero of Alexandria (10-70 AD) invented mechanical devices that can be considered early examples of automated machinery. Automata regained popularity throughout the Renaissance period. Around 1495, Leonardo da Vinci created sketches of a robot with human traits (Iavazzo et al., 2014). This era witnessed the development of many mechanical gadgets intended to entertain or fulfil useful functions, like the concept of robots. In the Modern Era, Figure 2.3, Machines started taking over tasks that were previously done manually, especially in manufacturing (Gasparetto, 2016). The word "robot" was first used in its modern sense in 1921 by the Czech writer Karel Čapek in his play "Rossum's Universal Robots" ("R.U.R."). Specifically, the word 'robot' comes from the Czech word 'robota,' which means forced labour or drudgery. In this play, robots were imagined as artificially created beings that eventually rebel against their human creators (Bay-Cheng, 2015).

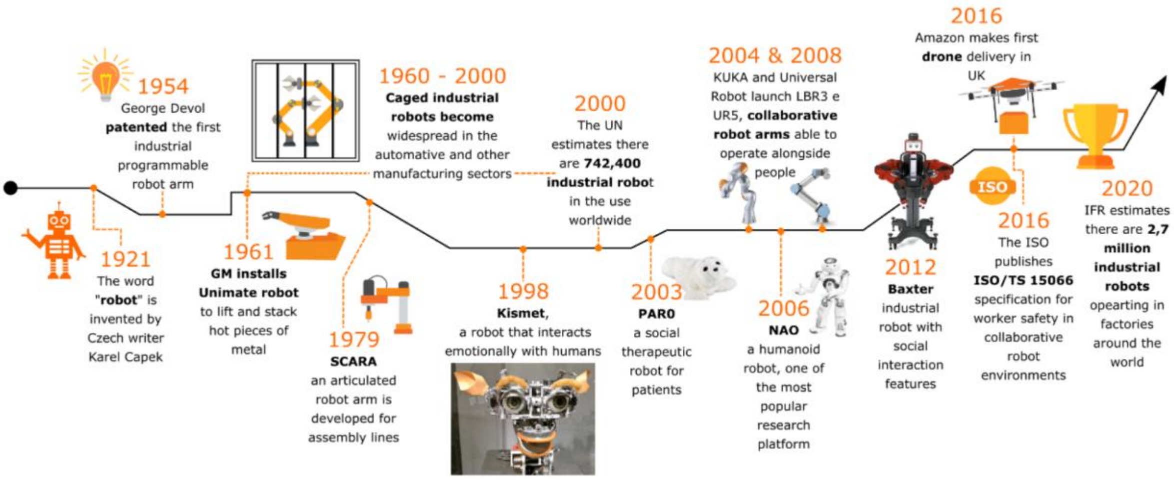


Figure 2.3 – *Map of the robot's evolution in the Modern Era (Villani et al., 2022)*

Always from the field of Arts, the so-called Rules of Robotics were proposed by Isaac Asimov, a science fiction author known for his extensive work on robotics and artificial intelligence. Asimov first introduced these laws in his 1942 short story "Runaround" and they have become a central theme in discussions about the ethics and design of artificial intelligence and robotics. The rules are (Asimov, 1950):

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.

This rule prioritizes human safety above all other directives for a robot.

2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.

This rule establishes the subservience of robots to human commands unless those commands result in harm to humans.

3. A robot must protect its own existence if such protection does not conflict with the First or Second Law.

This rule allows a robot to defend itself and ensure its operational longevity, but not at the expense of human safety or disobeying human commands.

Later, Asimov added a fourth, or "Zeroth" rule, which precedes the original three:

4. A robot may not harm humanity, or, by inaction, allow humanity to come to harm.

This law extends the First Law's protection of individual humans to include humanity as a whole, taking into account the greater impact of a robot's actions on human civilization.

Then, the first true electronic robots were introduced in the 1940s and 1950s. These were simple machines capable of performing automated tasks. A significant development was the creation of Unimate, the first robot deployed in industrial settings, which started work in a General Motors factory in 1961 (Gasparetto and Scalera, 2018).

These principles were more than just narrative devices in Asimov's fiction: they were a genuine proposal for how autonomous robots should be managed to guarantee their safety and benefit to humans. As of my latest update, they were neither legally enforceable nor technically implemented in real-world robotics. However, they continue to impact discussions about the ethical design and usage of AI and robots.

In IR5.0, the combination of human intelligence, adaptability, and problem-solving abilities, as well as robot precision, strength, and endurance, serves as the foundation for efficient and innovative production processes. The aim is to design a harmonic connection between humans and machines to maximise productivity, safety, and overall effectiveness in industrial settings.

2.3.3 The Rise of Collaborative Robots (Cobots)

HRC has become of paramount importance in IR5.0 aiming to human-centered manufacturing and production. Its achievement has made possible through cobots. A cobot is, by definition, a “robot designed for direct potential interaction with humans within a defined collaborative workspace”. This kind of robot is being adopted at unprecedented rates in organizations and it is expected to become the central tool of manufacturing globally, due to its specific characteristics, such as safe interaction with humans (Duarte et al., 2022).

Colgate and colleagues, academics at Northwestern University, were the first to suggest the notion and the word "cobot" coming up with the concept of a cobot in the 90s. The goal was to design robots that could physically interact with humans in a shared workspace. This was a considerable shift from typical robotic systems, which were intended to operate autonomously and frequently required safety barriers to protect human workers (Colgate et al., 1996).

Cobots were first designed without autonomous actuation for task performance. Instead, they were designed to direct and support human movement, making it more efficient, safe, and precise. The assistance was provided by techniques such as power steering, in which the cobot sensed the direction in which a human worker desired to move an object and assisted with the movement, lessening the physical strain on the human worker.

Cobots' definitions and capabilities have expanded over time. Modern cobots are more complex, able to conduct a wide range of activities autonomously or semi-autonomously while ensuring human coworker safety and seamless interactions. They are equipped with safety sensors, advanced control systems to detect collisions allowing them to recognise and act to human presence and activities, making them ideal for collaborative tasks in industries such as manufacturing, healthcare, and services. The introduction of cobots reflects a broader shift in the field towards more interactive, flexible, and adaptable systems. This approach aligns with the principles of IR4.0 and IR5.0, which emphasize automation, data exchange, and human-machine collaboration in industrial settings (Liu et al., 2022; Sahan et al., 2023).

The deployment of cobots in manufacturing environments has allowed to increase productivity in industrial production processes (Wang et al., 2017; Picco et al., 2023). Several measures can be applied for evaluating a manufacturing system's productivity, including the number of units produced every period, the number of resources consumed for a given output, the number of defective products produced, and so on (Michalos et al., 2018; Caiazzo et al., 2023). Productivity is increased by combining the good qualities of robots such as high precision and repeatability, handling heavy loads and operate without performance deterioration even in difficult or dangerous environments with the human's ability of problem solving, awareness and manual dexterity in complex or sensitive tasks (Arai et al., 2010). This brought to a shift from the traditional manual assembly tasks, as shown in Figure 2.4 (Bensch et al., 2017)

Thus, the transition from a manual to a human-robot collaborative activity may provide a decrease in takt time because cobots do some activities and typically complete them faster than humans, increasing productivity. Furthermore, cobots, with their precision and reproducibility, can reduce the ratio of defective items caused by human mistake (Caiazzo et al., 2023b).

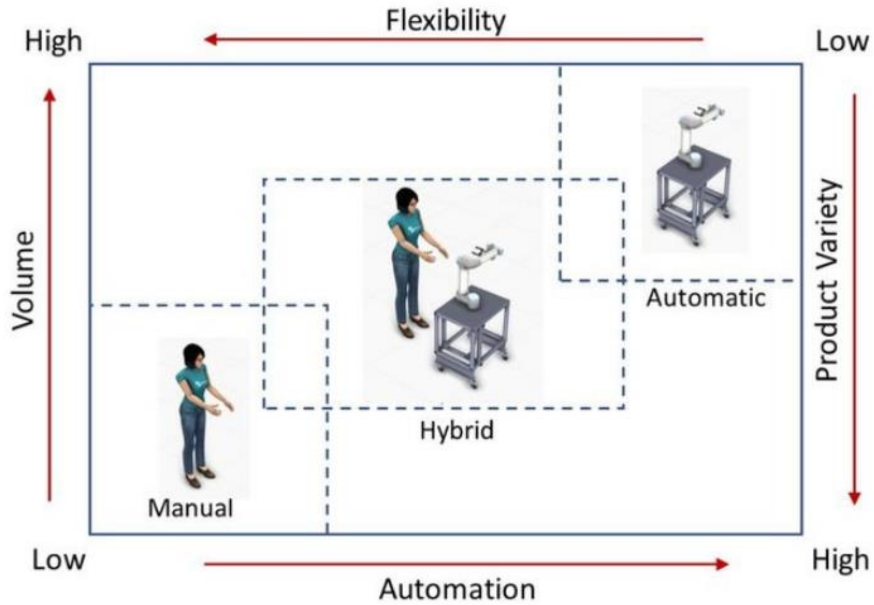


Figure 2.4 – *The benefits of a hybrid (collaborative) scenario*

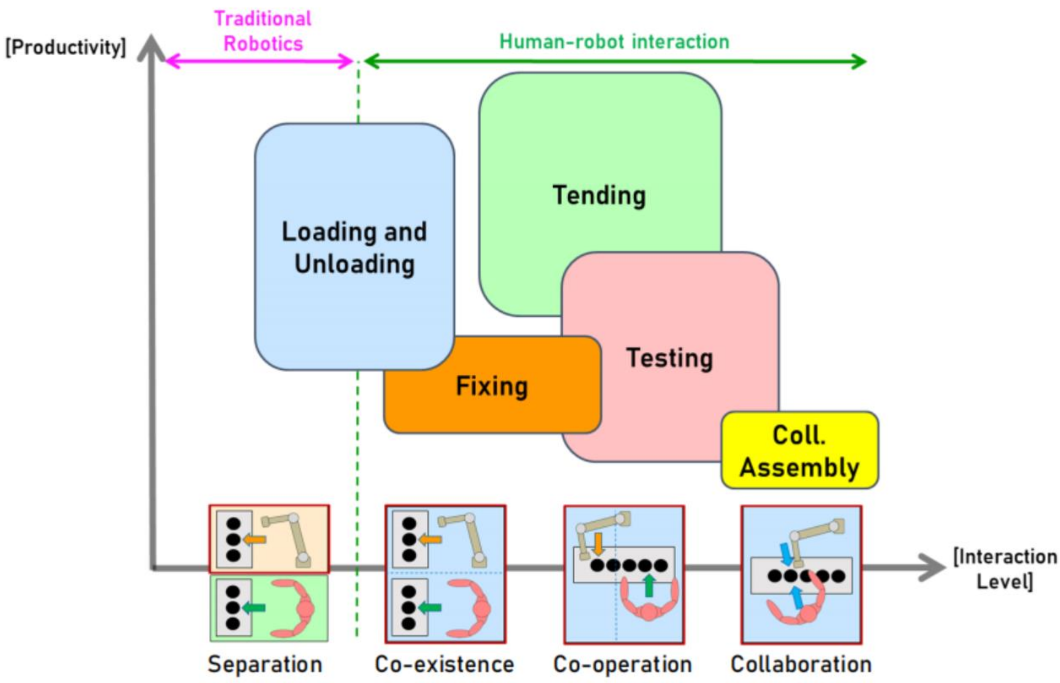


Figure 2.5 – *Overview of HRC applications and the connection between the grade of interaction and productivity index level (Vicentini, 2017)*

The Figure 2.5 describes the potential applications of cobots in different tasks. Cobots are commonly employed in manufacturing to perform tasks such as part assembly, machine tending, packaging, and quality inspection. They can handle repetitive jobs while humans concentrate on more complicated parts of the assembling process. As technology progresses, the range of applications for cobots expands, creating new room for HRC across industries (Colim et al., 2021).

EU has made a substantial contribution to the effort in this field by recognising cobots as a technology with the potential to positively impact the economy and society. (Nielsen and Brix, 2023).

Industries are enthusiastic about cobots and automation. They can see the substantial benefits that robots may provide, like higher productivity and job happiness. A study found that robots produce more jobs. Following the report of Word Robotics (2023), companies that implemented robots had an overall boost in recruiting and production. In contrast, those companies that avoided automation lost productivity and were more likely to lay off workers (Maddikunta et al., 2021).

HRC has allowed a more agile manufacturing processes that can quickly adapt to changes in product design, production volumes, or customizations, without requiring significant reprogramming or reconfiguration. Thus, cobots can contribute to cost savings by improving efficiency, reducing errors, and optimizing processes. While the initial investment in robotics may be significant, the long-term benefits in terms of increased productivity and reduced operational costs can be substantial (Picco et al., 2021; Adel, 2022).

Cobots can handle physically demanding or hazardous tasks, freeing humans from such labour-intensive activities. This shift can lead to a better work environment, reducing worker fatigue, stress, and exposure to potentially dangerous conditions (Alojaiman, 2023).

2.3.4 Mechanical Design of Cobots

First, the mechanical design of cobots must focus on safety, efficiency, and flexibility of the machine while working with humans. An overview of their mechanical design aspects is offered below (Villani et al., 2018; Rodriguez-Guerra et al., 2021; Patil et al., 2023):

- Lightweight Structure: cobots are designed with lightweight materials like aluminium and advanced composites to reduce inertia and make them safer for human interaction.
- Reduced Moving Parts: unlike conventional industrial robots, cobots often have fewer moving parts, reducing maintenance needs and increasing reliability.
- Joint Flexibility: cobots typically feature multiple joints that mimic human arm movement, allowing for greater flexibility and range of motion. These joints are often powered by servo motors with advanced control systems for smooth operation.
- Force and Torque Sensors: to guarantee safe operations, cobots are equipped with force and torque sensors in their joints and end effectors. These sensors allow the cobot to detect unexpected collisions and respond appropriately by stopping or altering their path.
- Soft and Rounded Surfaces: the mechanical design often includes soft and rounded surfaces to minimize injury risk in case of accidental contact with humans.
- End-of-Arm Tooling (EOAT): the EOAT system must be designed to be easily interchangeable and often includes grippers, screwdrivers, or other tools. This flexibility allows cobots to perform a different task.
- Integrated Cable Routing: to avoid the risk of entanglement and improve safety, cobots often have cables and hoses integrated within their body, maintaining a clean and uncluttered design.
- Safety-Compliant Materials: materials used in cobots are chosen not only for their strength and durability but also for compliance with safety standards, which might include being non-toxic and shatter-resistant.
- Advanced Gripping Mechanisms: the gripping mechanisms are conceived to be versatile and sensitive, allowing cobots to handle different objects with different shapes.

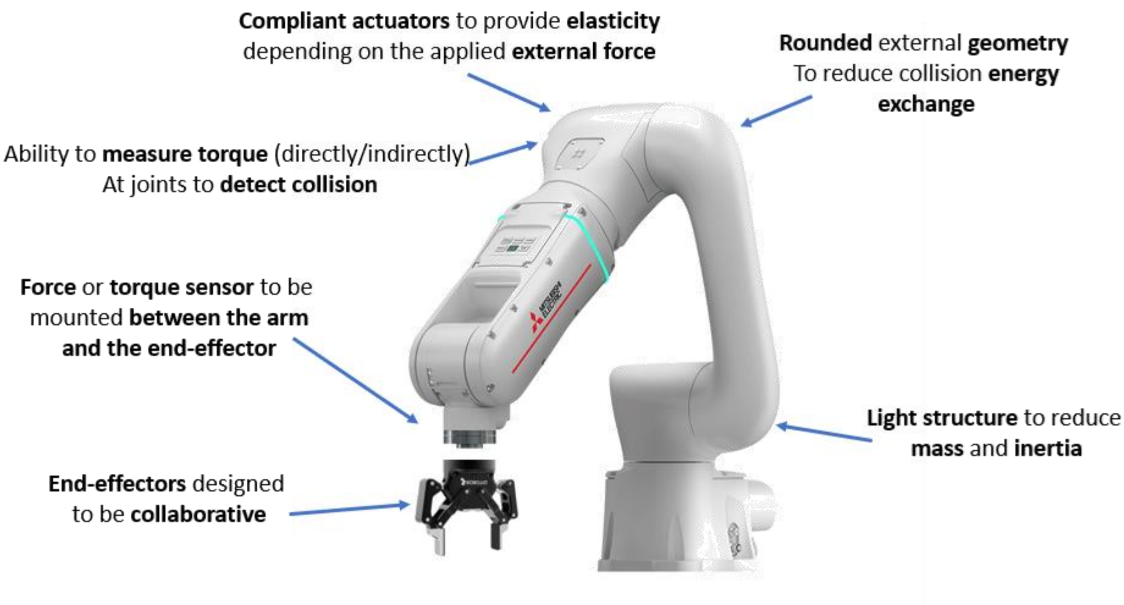


Figure 2.6 – *Overview of the Mechanical Design of Cobots*

The Figure 2.6. also shows a summary of the main mechanical components and aspects to consider in the design of cobots.

2.3.5 Degrees of Freedom (DOFs) of Cobots

DoFs in cobots indicate the number of independent movements or axes of motion they have. Each degree of freedom corresponds to a joint in the robot, which allows it to move in a specific manner. The number of degrees of freedom influences the robot's flexibility and versatility while doing complex tasks. Here are some popular setups for degrees of freedom in cobots.

With 4 DOFs, cobots have four independent axes of motion. While somewhat limited in their range of motion compared to higher DoF cobots, they are still useful for simple, straightforward tasks (Sasane, 2014).

In 5 DoFs, these cobots can perform more complex tasks. However, they may still have limitations in certain orientations or positions (Pisetskiy and Kermani, 2023).

The traditional configuration for cobots is 6 DoFs. With six axes of motion, these robots can replicate most of the movements of a human arm, allowing them to approach an object from virtually any angle. This level of flexibility is suitable for a wide range of applications, including assembly, painting, and welding (Fu and Zhang, 2018).

Finally, in other configurations with 7 DoFs, cobots offer even greater flexibility, closely mimicking the range of motion of a human arm. The additional degree of freedom allows the robot to manoeuvre in tight or complex spaces more easily. This configuration is applied in those applications where positioning and orientation of the tool are critical, and space is constrained (Doliwa, 2020).

Some advanced cobots may have more than 7 DoFs, which can be useful in highly specialized applications. However, the increased complexity can make programming and control more challenging (Dahmouche et al., 2020).

The choice of DoFs for a cobot depends on its intended application. More DoFs allow greater flexibility and versatility, but also add to the complexity, cost, and sometimes the size of the machine. For many standard industrial and collaborative tasks, 6-DoF cobots are the most popular solutions for a balance between flexibility and ease of use (Akkar and A-Amir, 2016).

2.3.6 Difference between Industrial Traditional Robots and Industrial Cobots

Traditional industrial robots were designed to do certain jobs and were frequently distinguished by great speed, precision, and power. They were often deployed in production environments to conduct repeated operations with high precision. These robots were often huge, fixed-location machines that operate in fenced-off or restricted areas to protect human workers from potential threats. In contrast, cobots are designed to interact and work with people in shared workspaces. They are designed to be naturally safe for direct interaction with humans. Cobots contain safety features such as force-limiting mechanisms, sensitive skins, and safety-rated sensors, which enable them to recognise human presence and respond appropriately to guarantee a safe collaboration (Sahan et al., 2023).

In terms of safety, Figure 2.7, traditional industrial robots often operate independently from humans or in enclosed environments to avoid unintentional contact that could cause injury. Because of their size, speed, and power, they necessitate safety precautions such as physical barriers or safety zones to protect workers. Cobots, on the other hand, are meant to function safely alongside humans, eliminating the need for physical separation. They have safety systems that let them to stop or lessen their speed when they detect human presence or contact, facilitating safe collaboration in shared environments.

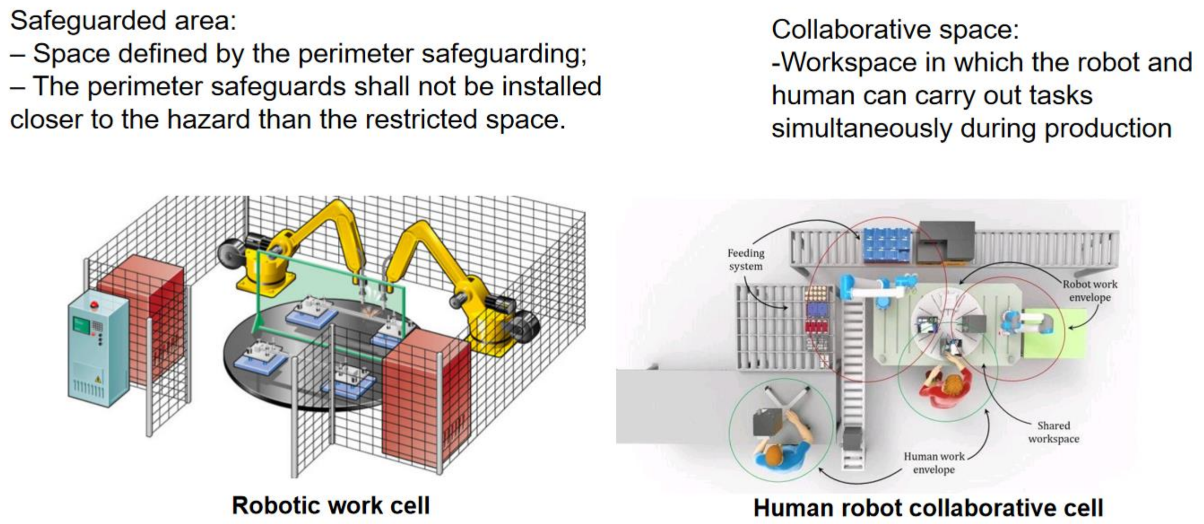


Figure 2.7. – *Robotic workplace differences (EN ISO 10218-2 / ISO/TS 15066)*

In terms of size, conventional industrial robots are often larger, heavier, and have solid structures tailored to certain jobs. They lack the agility and versatility needed for close human connection. Cobots, on the other hand, are typically smaller, lighter, and constructed with rounded edges or softer exteriors to reduce the danger of injury if they come into touch with humans. They frequently have user-friendly interfaces, straightforward programming, and training methods that allow non-experts to quickly programme or instruct them on a variety of tasks.

Furthermore, they are designed with user-friendly interfaces to reduce the physical and mental strain on human workers performing tasks. Additionally, sensors and software are deployed for direct human-robot interaction, allowing robots to interact safely with humans, be operated intuitively, and perform jobs without the risk of physical contact or accident. As they become increasingly widespread in the manufacturing business, HRC has offered itself as a viable approach for firms to increase output and worker safety while relieving them of some of their workload. (Villani et al., 2022).

In summary, the formal scientific distinction between traditional industrial robots and cobots regards their design and application for human-robot interaction (HRI). Scientific standards and research literature emphasize the development and implementation of safety features in cobots to ensure their safe collaboration with humans, see Figure 2.8.

Figure 2.8 – *Cobots vs Industrial Robots*

2.3.7 Cobots' Market Growth

The presence of cobots in various fields has seen a significant increase in recent years, Figure 2.9. Cobot market is experiencing rapid growth. In 2017, the market was valued at less than $400 million but grew by more than 60% in 2018 to almost $600 million. It is projected to reach around $7.5 billion by 2025. By then, it's estimated that nearly 35% of all industrial robots in the market will be cobots (Nikolaev, 2023).

According to the International Federation of Robotics, there has been a rapid growth of the presence of industrial robots worldwide:

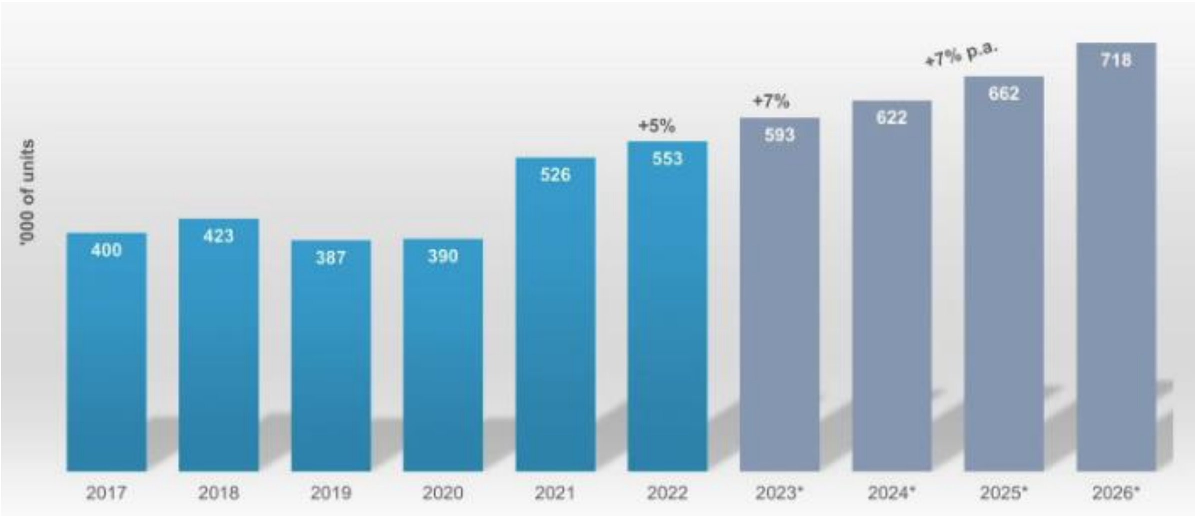


Figure 2.9 – *Estimated annual worldwide supply of industrial robots (Nikolaev, 2023)*

In accordance with the International Federation of Robotics (IFR), cobot technology could be useful in two separate situations. It could be employed in SMS enterprises to automate certain aspects of the production line while leaving others untouched, resulting in greater productivity and quality. It could also help people do assembly duties, which frequently result in physical injuries, in organisations that already have automated processes (for example, the automobile industry). According to industry data, the professional service robotics sector surged by 32% in 2019 (from $8.5 billion to $11.2 billion) (Executive Summary World Robotics, 2020), with cobot sales volume outpacing traditional ones (IFR Press Conference, 2020).

Furthermore, the pandemic appeared to strengthen the market for robotic components used in warehouses, factories, and home deliveries, as well as because the technology fosters social separation.

As shown in Figure 2.10, the increase of traditional robots was estimated from 368.000 to 478.000 units while the increase of cobots was estimated from 26.000 to 39.000 units. Cobots applications represent still nearly the 10% of the conventional industrial robot applications, though their rapid rise in industrial applications.

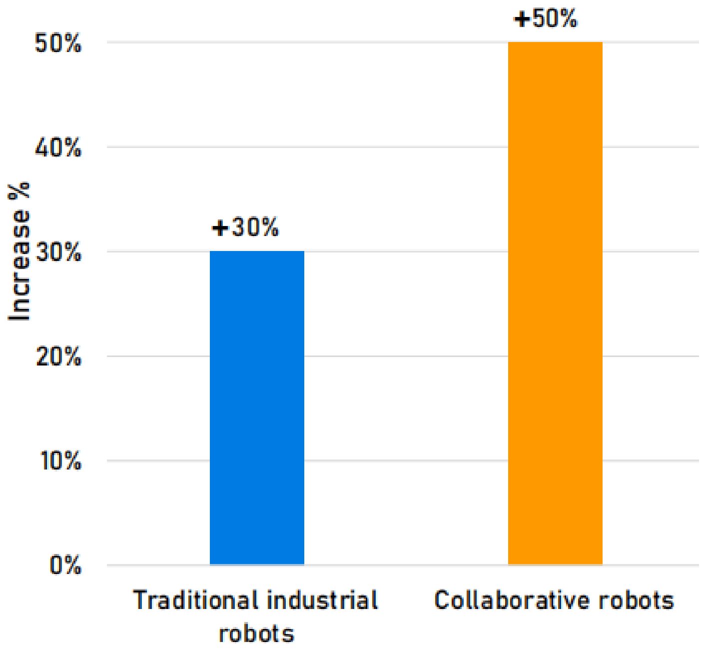


Figure 2.10 – *Annual Installation Growth of traditional robots and cobots from 2021 to 2022 (World Robotics, 2022)*

Europe is currently leading the global cobots market, with significant growth expected in the automotive sector. As shown in Figure 2.11, the European cobot market is estimated to reach USD 5.62 billion by the end of 2024. Meanwhile, the Asia-Pacific region, including China, Japan, and India, predict to see the most growth in the coming years as the demand for automation expands in these countries (Nielsen and Brix, 2023).

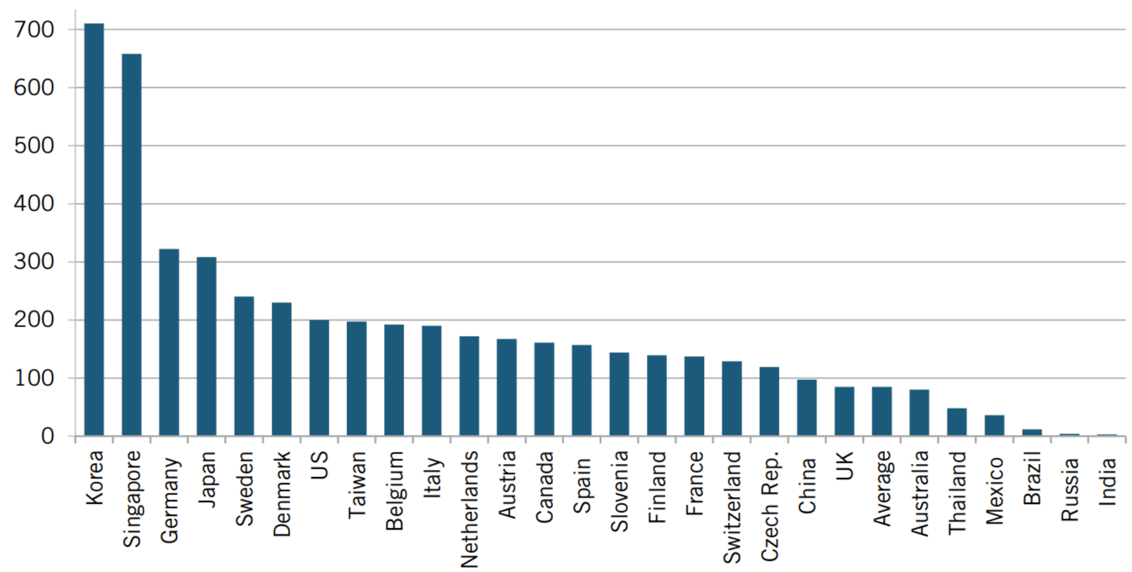


Figure 2.11 – *Estimated number of industrial robots per '000 units in the countries worldwide (World Robotics, 2022)*

In summary, the application of cobots in various fields is not only increasing but also diversifying. The growth in their market size, technological advancements, and expanding regional markets all indicate a significant upward trend in cobot applications across industries.

2.3.8 Safety in Human-Robot Collaboration

Collaborative systems enable and demand job sharing in a fenceless workspace where the primary danger category is mechanical. The presence of both humans and robots in a shared workspace may result in non-functional physical interaction between the operator and the machine's mobile parts, particularly the robot arm and other types of end-effectors. Unexpected and unintentional collisions can cause a variety of accidents and crushes if the mechanical risks are not appropriately detected, predicted, and handled.

Collaboration is the shared activity of people and robots in a shared workspace to complete a set of specific working tasks. It often requires all parties to engage in either synchronised, synchronous, or sequential activities (Wang et al., 2017), with physical contact permitted. Thus, safety considerations must be made to avoid dangers and potential sources of damage. The impact of collaborative work can result in injury to the operators. Depending on the application, potential hazards are associated with the procedures to be carried out in collaborative activities. These include mechanical, electrical, thermal, noise, vibrations, radiation, material/substance, work-environment, and combination risks.

The most typical risks are mechanical in nature. Typical mechanical risks include crushing, shearing, cutting, tangling, trapping, impact, stabbing, and abrasion. Nonetheless, hazard situations such as entrapment between components of the robot system and workplace (e.g., equipment, fixtures, guards, etc.), entrapment between parts of the robotic system itself (cables, manipulator, end-effector, etc.), unexpected or unwanted contact with moving parts, effects related to the loss of the workpiece during handling and processing, and effects related to the specific loss (screwing, glueing, etc.) can be harmful.

Based on these circumstances, the official guidelines (ISO 10218, ISO/TS 15066) recommend four safety modes Figure 2.12.

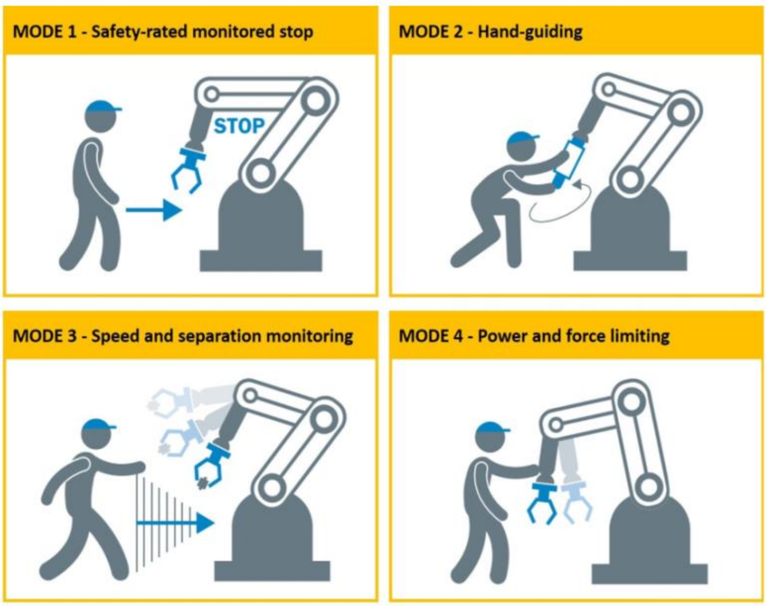


Figure 2.12 – *4 modes of HRI (ISO/TS 15066:2016 Robots and robotic devices, 2016)*

Safety-Rated Monitored Stop (SRMS) is an active functional measure implemented as an operation in which the robot remains powered, but the robot and operator do not interact in the shared workspace at the same time: in this mode, the robot is stopped while interacting with the operator in the collaborative workplace. Before the person reaches the shared workspace, the robot must have safely stopped. It is also possible to schedule an automatic restart when the operator leaves the workplace. Thus, human-robot collisions are impossible. (Amiucci et al., 2022).

Hand-Guided operation (HG) is a mode with zero-gravity control, that is, control without actuation beyond gravity compensation, guided exclusively by an operator: the safety of the HRC is assured by the robot being guided manually and controlled at an appropriately reduced speed (Arai et al., 2010). Hand guidance requires the robot to be in a compliant state, with control exerted by the operator through physical manipulation. In this controlled mode, no hazards may arise because of the transition between manual control and any other form of operation. Thus, collisions between human and the robot are not possible (Ogura et al., 2012).

Speed and Separation Monitoring (SSM) is an active functional measure in which speed is constantly adjusted to the distance between the robot and the operator: both the robot's speed and motion path (i.e., trajectory) are tracked and adjusted based on the operator's position and speed in the collaborative workplace. In this technique, cobots and humans can work together in a collaborative environment. Safety devices, such as sensors, measure the distance between the two agents. Thus, the collision is avoided by stopping the robot immediately (Nandeshwar et al., 2022).

A general formula to calculate the minimum distance between the human and the robot is:

$$S = (K \times T) + C \tag{1}$$

Where:

S = minimum distance between human and robot (mm).

K = parameter derived from data regarding the approach speed of the body (mm/s).

T = overall system stopping performance.

C = intrusion distance.

Another formula regarding the protective separation distance for HRC applications considers the relative speed between the human and the robot:

$$S_p(T_0) = S_h + S_r + S_s + C + Z_d + Z_r \tag{2}$$

This calculation contains the following additional parameters:

- Robot' system reaction time and stopping distance (S_r, S_s) at T_0.
- Position uncertainty of the operator and the robot system (Z_d, Z_r).

To sum up, in this collaboration mode, the human has access to the collaborative workplace while the robot is moving. The safety is based on distance and collisions are not possible as short distances trigger safe stops.

Finally, Power and Force Limiting (PFL) is an approach in which the robot's impact on the human body is reduced, and the robot's power and applied forces are limited: physical contact between the robot system (including the workplace) and the human operator can occur intentionally or unintentionally. In this mode, a robot should not impact a human with more than a predetermined force, with allowable forces determined for various impact sites on the body. Risk minimization is achieved due to the robot's intrinsic safety design and functions. There are two sorts of collisions: quasi-static and transitory. This last mode is the most recent novel sort of human-robot collaboration, yet it remains the least prevalent in industrial manufacturing situations (Aivaliotis et al., 2019).

Different authors use a combination of these modes. A discrete-event controller, as proposed by Heinzmann and Zelinsky (2003), is a mode that is always active during collaborative activities. Long et al. (2017) present a distance-triggered system for switching between nominal (maximum velocity), reduced (speed limiting), and passive (hand-guided) operating modes. Kaiser et al. (2018) and Villani et al. (2018) define and integrate these modes into work arrangements.

In another research studies, authors present some scenarios of HRI. The collaboration between an operator and a cobot can be categorized into several modes, each characterized by the level of interaction and the type of tasks performed, as shown in Figure 2.13.

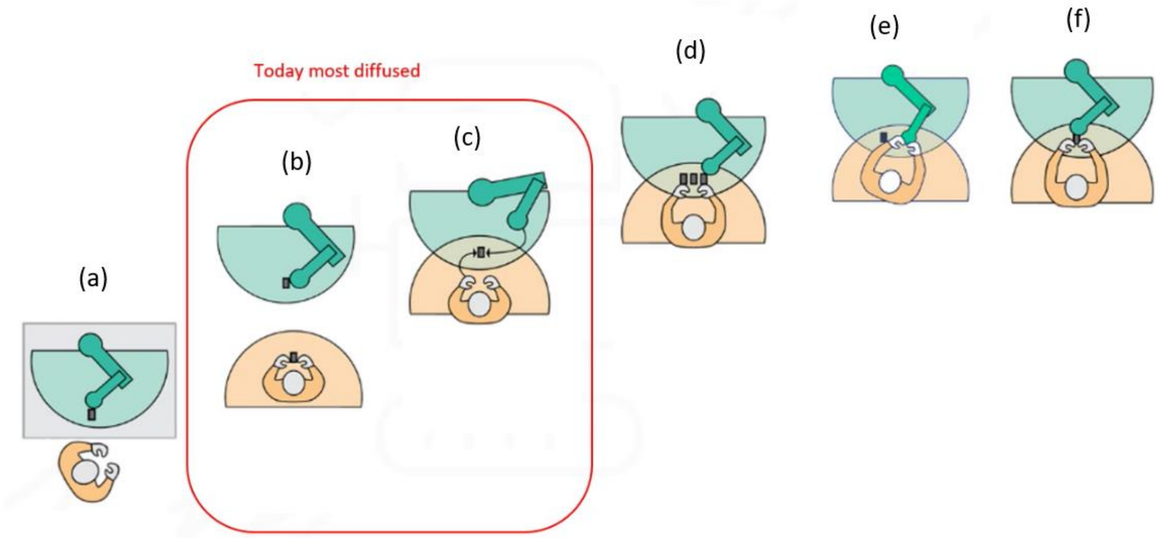


Figure 2.13 – *Different degrees of HRI (International Federation of Robotics, 2020)*

These modes are designed to leverage the strengths of both humans and robots, ensuring safety, efficiency, and productivity.

a) Encapsulation in a fenced robot workspace. In this scenario, the full automation may increase productivity, but it is expensive and does not have the flexibility required to adapt to frequent variable productions. Therefore, in the past, robot automation was mainly employed in a mass production context (Lee et al., 2020). Furthermore, the human operator supervises and monitors the cobot while it performs tasks autonomously. The human may intervene as needed, for example, to handle exceptions or adjust (Banerjee et al., 2015).

b) Co-existence without fencing but separation of human and robot workspace. In this mode, humans and cobots share the same workspace but do not interact directly with each other. The tasks are performed independently, but the presence of safety features allows them to operate in proximity without physical barriers (Hande et al., 2022).

c) Sequential collaboration where operators and robots work in the same workspace but with sequential movements. Here, humans and cobots work on the same task but at different times. For example, a cobot might prepare a part that a human then inspects or finishes. The interaction is time-separated, meaning the human and the cobot are not working on the task simultaneously (Hjorth and Chrysostomou, 2022). Furthermore, in this mode, the cobot acts as an assistant to the human operator. It might provide necessary tools, hold objects in place, or perform other supportive tasks to ease the human's workload. The cobot 's actions are directly responsive to the human's activities (Gordon et al., 2023). Sequential collaboration and co-existence are the most diffused types of interactions adopted in HRI applications.

d) Cooperation with alternative exclusive use of the shared workspace. In cooperative collaboration, both the human and the cobot work on the same task at the same time, but they perform different actions. For instance, a cobot might hold a component steady while a human performs welding. This mode requires precise timing and coordination (Costa et al., 2022).

e) Hand Guiding or Lead-Through Programming: this involves the human operator physically guiding the cobot through desired motions or tasks. The cobot learns these movements and can then replicate them independently. This mode is often used for programming or teaching the cobot new tasks (Kan et al., 2021).

f) Collaboration with simultaneous use of the shared workspace and close interaction. In this advanced mode, both the human and the cobot have control over the same task simultaneously. This requires highly sophisticated control systems and safety mechanisms to ensure smooth and safe interaction (Herlant, 2018). Cobots in this mode can adapt their behaviour based on the human operator's actions. They use sensors and AI algorithms to understand and anticipate the needs of the human, adjusting their actions in real-time for optimized collaboration (Zhao et al., 2021).

Every method of collaboration is appropriate for a range of tasks and work situations. The choice of mode is determined by criteria such as task complexity, safety issues, necessary precision, and desired amount of human involvement. As cobot technology advances, these modes improve, allowing for even more smooth and efficient HRC.

In this context, criteria for designing and implementing cobots in collaborative workplaces for HRI applications must be followed (Gualtieri et al., 2022).

To supplement these standards, more substantial and identifiable technical deliverables (such as technical specifications and technical reports) are provided to better integrate the information included, as seen in Figure 2.14. These regulations are crucial in promoting the safety of machinery and equipment on the EU market, thereby protecting the health and safety of users and consumers. Compliance with the Directive helps to ensure that machinery is designed, built, and utilised safely, lowering risks, and preventing accidents and injuries.

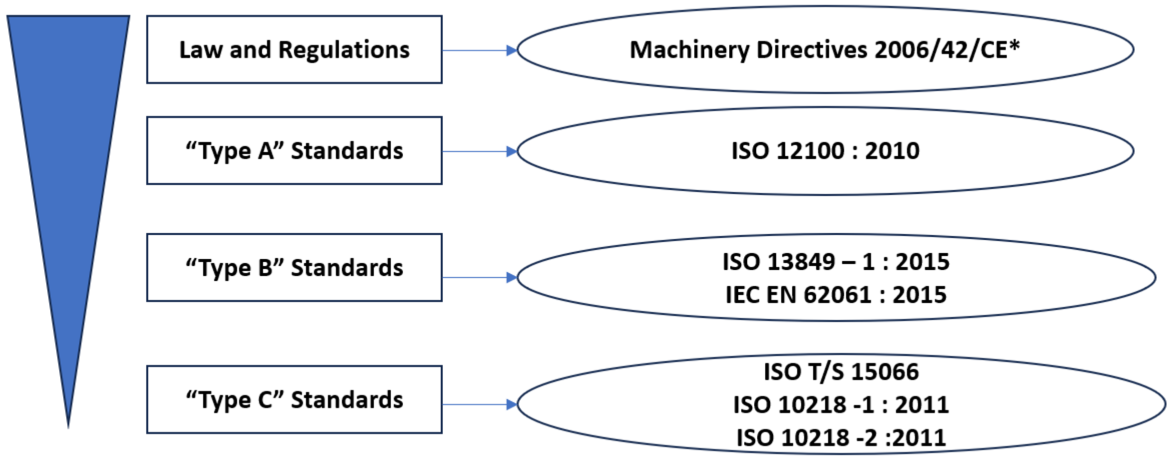


Figure 2.14 – *Guidelines for HRC*

The standards are grouped into the following primary groups, which target varying levels of specifics in the design framework for the realisation of machines:

- The Machinery Directives 2006/42/CE* are applied to ensure a high level of safety for machinery and equipment placed on the European market. It sets out essential health and safety requirements that machinery must meet before it can be placed on the market or put into service within the EU. Machinery that meets the requirements of the Machinery Directive must be affixed with the CE marking before it can be placed on the EU market. The CE marking indicates that the machinery complies with all relevant EU directives and regulations, including the Machinery Directive.
- Type-A standards cover methodology and fundamental concepts for designing and producing machines. They are fundamental safety criteria that apply to all machines (ISO 12100:2010 Safety of Machinery).
- Type-B standards address generic safety needs that are general in the design of most equipment.
- Type-C standards specify extensive safety requirements for a single machine or set of machines. They are machine safety standards that establish an expectation of conformity for the fundamental legal conditions addressed in the standard. Occupational dangers associated with industrial equipment vary depending on the nature of the hazards.

These standards, defined as harmonised standards, represent the only way for the design of the system, defining its state of the art and making compatible with other systems. Though these standards are not mandatory for designers, they must be applied to guarantee the quality of safety of cobot applications in industrial processes.

These standards provide guidelines for the design, implementation, and operation of cobots. The most relevant safety standards for cobots include:

- ISO 10218-1 and ISO 10218-2: These are the primary international standards for industrial robot safety. Part 1 (ISO 10218-1) covers the general requirements for industrial robots, while Part 2 (ISO 10218-2) addresses the requirements for the robot system and integration.
- ISO/TS 15066: This is a technical specification supplementing ISO 10218 standards. It provides detailed guidance on the safe design, implementation, and operation of collaborative industrial robot systems. ISO/TS 15066 specifically addresses safety-related issues when humans and robots share the same workspace and includes guidelines on maximum allowed power and force for various parts of the human body in the event of an accidental collision.
- EN ISO 13849-1 and EN 62061: These European standards cover the safety of machinery and control systems. While not specific to robotics, they are often applied in the context of cobot safety to assess and mitigate risks associated with the control systems and software used in robotic applications (Robinson, 2008).

These standards typically cover aspects such as:

- Risk Assessment: Procedures for conducting risk assessments and determining necessary safety measures.
- Safety-Related Parts of Control Systems: Requirements for the performance and reliability of safety-related parts of control systems.
- Collaborative Operation Modes: Specifications for different collaborative modes (SRMS, HG, SSM, PFL).
- Protective Measures: Guidelines on protective measures such as safety distances, guarding, and emergency stops.

Adherence to these standards is crucial for the safe integration of cobots in industrial environments. They help ensure that the design, installation, and operation of cobots minimize the risk of injury to human workers, while also maintaining efficient and effective operation. As cobot technology evolves, these standards are periodically reviewed and updated to reflect new safety concerns and technological advancements.

2.3.9. Choice of Cobot's End-Effector

An end-effector is a device or tool that attaches to the extremity of a robotic arm and is an important component of robotic systems. Essentially, it is the part of the robot that interacts directly with its surroundings to fulfil a specified task. The design and functionality of an end-effector are heavily influenced by the robot's intended use. An end effector's principal job is to do the task for which the robot is designed, such as grabbing, welding, cutting, painting, assembling, or any other specified action. (Li and Fritz, 2015).

There are various types of end-effectors, each designed for different tasks. Common types include:

- Grippers: Used for grasping, holding, and moving objects. They come in various designs, such as two-finger (parallel or angular), three-finger, or more complex forms for handling irregularly shaped objects.
- Welding Torches: For robotic welding applications.
- Spray Guns: Used in painting or coating applications.
- Drills and Screwdrivers: For assembly tasks that involve drilling or screwdriving.

- Cameras and Sensors: For inspection tasks where the robot needs to see or sense its environment.

Some robots are designed with interchangeable end-effectors, allowing them to perform a variety of tasks. Quick-change systems enable the robot to switch between different end-effectors automatically. Moreover, end-effectors are designed to provide precision and control in their operations. For example, grippers may have force control to handle delicate objects without damaging them.

The material and design of an end-effector depend on its intended use, the environment in which it will operate, and the properties of the objects it will handle (e.g., size, weight, surface texture). Many end-effectors are equipped with sensors that provide feedback to the robot's control system, such as force sensors in grippers or vision systems in cameras. This feedback is crucial for tasks that require precision or adaptability to varying conditions.

To conclude, End-effectors are essential for extending the capabilities of robotic systems, enabling them to interact with and manipulate their environment effectively. The selection or design of the appropriate end-effector is crucial for the success of any robotic application. The Figure 2.15 shows the typical types of grippers used in manufacturing for industrial HRC activities.

Figure 2.15 – *Types of grippers*

2.3.10. Key Performance Indicators in Human-Robot Collaboration

To conclude this chapter, this section describes the key performance indicators (KPIs) highlighted in literature review for industrial collaborative applications between operators and cobots.

The evaluation of appropriate KPIs is an ongoing challenge to improve efficiency, productivity in HRC.

Other writers use different KPIs to track and monitor the execution of HRC tasks. However, because HRC covers a wide range of topics, a systematic classification and gathering of these KPIs is introduced to address the many features of KPIs in HRC for industrial processes.

Table 2.1 presents the classification of KPIs in HRC.

Table 2.1: Overview of the distinctive KPI's adopted in some research studies in HRC dealing with Productive, Economic, Safety, and Ergonomics aspects.

Authors	Productive aspects	Economic aspects	Safety aspects	Ergonomics aspects
Zimmermann [8]	Job Execution Time; Actuation Latency; Pose Travel Time.	Cost of Robot Energy Consumption	Position Accuracy; Position Repeatability.	
Dannapfel et al. [10]				Ergonomic Assessment
Galin et al. [28]	Takt Time; Energy expended		Speech and physical contact; Robot's path trail	Visual perception
Papanastasiou et al. [30]	Workstation cycle time	Return Of Investment (ROI)	Left and right side–cycle deviation	Operators'stress
Chromjakova et al. [31]	Availability; Lead Time; Data complexity		System incident reaction time	Human-cobot ethical cooperation
Horst et al. [32]	Cobot's accuracy and repeatability	Time to full ROI		
Colim et al. [33]	Time data; Production Rate; Variability;	Material Consumption		Physical Ergonomic Assessment
Zanchettin[34]	Accuracy of the operator; Time required to perform the task		Rate of assistance given by the robot	Value of displacement from the ergonomic posture
Bouchard and Couture [35]	Cycle Time, Cycles Completed, Yield, Efficiency, Wait Time, Disconnected Time			
Landini et al. [36]			Reportable health and safety inicidents	Physical and mental workload

Furthermore, it should be noted that there is no predetermined collection of general performance indicators for every organisation, but the cautious selection is established by the company's own aims. Furthermore, gathering data for any KPI requires a significant amount of effort. The performance optimisation of the robotic cell must be an ongoing activity. Dynamic changes in those new smart technologies seeking to reinvent manufacturing plants, and managers should focus on the KPIs to see what consequences those changes have in the long run (Caiazzo et al., 2022).

2.4 ERGONOMICS IN HRC

Ergonomics is the scientific study of how individuals interact with other system components. It employs theories, concepts, data, and procedures to enhance human well-being and overall system performance. It is the process of designing workplaces, items, and systems to suit the people who use them rather than pushing them to adapt to technology. The history of ergonomics can be linked back to past civilizations, although its officially recognised growth began in the beginning of the twentieth century (Stanton et al., 2012).

In 1857, Polish academic Wojciech Jastrzębowski invented the term "ergonomics" in his work "The Outline of Ergonomics, or the Science of Work". However, it was not until World War II that ergonomics received widespread attention. Because of the war's complicated and sophisticated technology, it became clear that customising equipment and systems to meet the user's physical and cognitive skills may increase productivity and safety. This marked the birth of ergonomics as a distinct scientific discipline devoted to optimising human-machine interactions. Effective ergonomic design can bring to higher productivity, improved work quality, reduced discomfort and injuries, and higher worker satisfaction (Karwowski, 2006).

However, when new technology is introduced into an organisation, the ergonomic aspects are often overlooked (Gladysz et al., 2023). A research study confirms that optimising job allocation while considering ergonomic considerations increases efficiency and acceptance. Moreover, the concept design considers human mental and physical viewpoints at the same time by suggesting a hand-guiding on the robot to allow users to have control over the system, having the robot as a helper instead of a robot giving an object (Hemono et al., 2023).

Key aspects of ergonomics include (Stanton et al., 2012):

- Physical Ergonomics: it relates to the individual's responses to physical and physiological work demands. Repetitive tasks, muscle use, workplace layout, and safety are among the topics addressed.
- Cognitive Ergonomics: it comprises mental processes including perception, recall, reasoning, and motor reaction, all of which have an impact on human-system interactions. This may include cognitive workload, decision-making, performance, human-computer interaction, human dependability, work stress, and training.
- Organizational Ergonomics: it focuses on optimising socio-technical systems, including their organisational structures, policies, and processes. Topics such as teamwork, communication, work design, telework, and flexible working hours are included.

In HRC, the first two types of ergonomics are crucial to determine an effective collaboration between human and robot (Simone et al., 2021).

Several studies in the discipline of physical ergonomics research have investigated various assessment methodologies and their applicability in the workplace. One prominent study focused on ergonomic examinations in various occupations, emphasising two popular methods: Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA). These methods are used to evaluate the risk of work-related musculoskeletal disorders (WMSDs) in a variety of occupational settings, including diverse industries and professions (Hignett and Mcatamney, 2000; Mcatamney and Corlett, 2004).

Other observational methods were applied in the evaluation of physical strain in industrial settings. These are OCRA (Rana et al., 2020), the Key Indicator Method for Manual Handling Operations (KIM-MHO) (Klussman et al., 2010), and the Strain Index (SI) (Kapellusch et al., 2021).

Furthermore, some of the examined research used direct measuring ergonomic approaches. These technologies use sensors linked to workers' bodies to directly quantify the effect of risk variables on physical and biomechanical parameters (Merino et al., 2018; Lorenzini et al., 2023).

In cognitive ergonomics, on the other hand, work-related stress typically emerges when the demands surpass the worker's ability to perform. Stress has been related to detrimental effects on people's feelings, thoughts, and behaviours, and it has been found to have psychological ramifications for workers, such as a negative emotional state of worry and frustration. At the physiological level, it can disrupt unconscious vital functions such as heart and breathing activity, while at the physical level, it affects normal posture and body activity (Kim et al., 2021; Lagomarsino et al., 2022).

Physiological stress has further impacted on production activity since it is positively correlated with errors and attention spans at work, lowering worker quality and performance and resulting in new expenses and losses for businesses. Given the numerous effects of stress on human health and company efficiency, the literature emphasises the significance of studies focusing specifically on the stress phenomenon related to smart and intelligent manufacturing systems, suggesting appropriate assessments for stress evaluation to support the advancement of research in this field (Colim et al., 2021).

Among these measurements, the NASA Task Load Index (NASA-TLX) is a widely used, subjective, workload assessment tool developed by the Human Performance Group at NASA's Ames Research Center (Hart and Staveland, 1988). It is designed to provide an overall overview of the workload based on a weighted average of ratings defined in six subscales (Mental Demand, Physical Demand, Temporal Demand, Performance, Effort and Frustration Level).

These dimensions are evaluated by the person performing the task, reflecting their personal experience and perceived workload. After rating each of these areas, the scores are combined to create an overall overview of the workload. This tool is used in various fields, including aviation, healthcare, and automotive design, to define the workload associated with different tasks and environments. It helps understand how demanding a task is from the user's perspective, which is crucial in designing systems, interfaces, and workflows that are effective and user-friendly.

2.5 PHYSIOLOGICAL MEASUREMENTS

Physiological measurements are quantitative assessments of several functions and properties in the human body. These measurements are crucial to evaluate health, physical fitness, and physiological reactions of individuals to various stressors. They are commonly employed in healthcare, sports science, psychology, and research contexts. Here is a list of some common physiological metrics.

The deployment of these innovative measurements properly requires a rigorous design, the choice of appropriate technology, consideration of user experience and privacy, and good data analysis and interpretation methodologies. The specific approach will vary according on the deployment's circumstances and objectives.

Physiological measurements and subjective measurements both have their unique advantages in assessing distinct aspects of human health, performance, and psychological states. Moreover, physiological measurements are objective and quantifiable, which reduces the bias and unpredictability found in self-reported data. Many physiological indicators can be continually monitored over time to provide a dynamic picture of how they change in response to stimuli or activities. Furthermore, physiological assessments can detect changes that individuals may not consciously notice, making them a more sensitive tool for analysing responses to stimuli or interventions (Jakopin et al., 2017).

In terms of versatility, many physiological measurements (like heart rate, skin conductance, electroencephalogram) are non-invasive and cause no discomfort to the subject. They can provide immediate feedback, which is critical in different settings such as medical monitoring, athletic performance, and psychological research. Physiological measurements provide numerical data that can be deployed for statistical analysis and scientific inquiry. Heart rate variability, for example, can indicate cardiovascular health. Physiological measures have applications in a variety of sectors, including healthcare, psychology, ergonomics, and human-computer interface (Iredahl et al., 2015; Madan et al., 2017; Zhou et al., 2022).

Subjective measures, on the other hand, capture personal experiences and impressions that are important in understanding an individual's point of view, particularly in psychological and sociological studies. These measurements are frequently easier and less expensive to gather than physiological data, and they require only basic laboratory equipment. Subjective measurements can provide a more complete picture of a person's well-being, capturing aspects that physiological tests cannot. Nevertheless, they can be more sensitive to cultural and contextual factors affecting an individual’s experiences and responses (Puspasari et al., 2015; Panchetti et al., 2023).

Physiological and subjective measurements play significant roles in research and practice. The choice between them, or the decision to utilise a combination of both, is determined by the assessment's specific aims, the nature of the phenomena under investigation, and practical issues such as resources, expertise, and the population under study. In many circumstances, combining the two types of measures can provide a more complete picture than either strategy alone (Caiazzo et al., 2023).

Currently, no standards exist for both objective and subjective indicators. Objective indicators, particularly physiological ones, lack consistency not only in mathematical calculations but also in nomenclature. Each physiological signal feeds different series of algorithms for calculating stress levels, or the same signs with different labels and acronyms, complicating the comparison of results between investigations. Furthermore, the range of devices for biometric data gathering indicates a gap.

Although the type of sensors adopted depends above all on the context in which the experimental activities are carried out, small wearable devices are the most appropriate for measuring the physiological and physical activities of workers in in-field experimental activities but do not allow the integral signal to be captured or the original and continuous vital processes of the workers to be carried out since they provide a direct measure of the indicators, limiting the potential detailed analysis of data.

On the other hand, the most sensitive sensors and devices are difficult to integrate into practical industrial systems because they produce a significant percentage of artefacts and noise in the data obtained, and their installation may create discomfort for participants and workers. As a result, the literature lacks a compromise that justifies and standardises the widespread deployment of either type of device.

2.6 PERFORMANCE-BASED MEASUREMENTS

Performance-based metrics analyse an individual's ability to complete a task or activity, providing specific information about functional skills. Many performance-based assessments are standardised, which means they are administered consistently across individuals, increasing impartiality, and allowing for comparisons. These measures frequently produce measurable data, such as the time required to complete a job, the number of successfully completed items, or the distance covered in a physical exam.

Furthermore, performance-based assessments can be tailored to evaluate specific skills or competences, ranging from cognitive functions (such as memory or attention) to physical capacities (such as strength or endurance). When paired with other types of metrics (such as physiological or subjective), they enable a more thorough assessment of an individual's overall functioning, offering valuable feedback for individuals to understand their current level of performance and areas for improvement (Puente et al., 2014; Caterino et al., 2023).

To note, performance can be influenced by external factors like environmental conditions, emotional state, or fatigue, which should be considered during assessment. Some performance-based tests may require specific equipment or expertise to administer and interpret. These tests can be physically or mentally demanding for the participant, which might limit their suitability in certain populations.

2.7 NEUROERGONOMICS AND MENTAL WORKLOAD

The limitation in the Ergonomics domain is that all evaluations of the workers' cognitive state are qualitative and rely on overt performance measurements, which are often undertaken in post-hoc analysis. To address these disadvantages and give objective measures of workers' cognitive state, psychophysiological approaches, which were first utilised only in the medical profession, were recognised for use in HF/E investigations (Stanton, 2012). Andreassi (2000) suggested one of the definitions of psychophysiology: "Psychophysiology is defined as the study of the relationship between psychological manipulation and resulting psychophysiological responses, measured in living organisms, to promote understanding of the mental and bodily processes".

Traditionally, ergonomics research and practice has not considered neuroscience or findings concerning brain mechanisms that underlies human perceptual, cognitive, affective and motor processes (Parasuraman and Rizzo, 2006). This is not surprising, since Ergonomics has its roots in a psychology of 1940s that was firmly in the behaviorist camp (Parasuraman and Rizzo, 2006), where researchers were using solely the simplified stimulus response (S-R) approach, but also due to slow shifts from behavioral to cognitive approach in psychology itself. More recently, however the ergonomics was influenced by the cognitive psychology, but still the neuroscience continued to be ignored (Parasuraman and Rizzo, 2006). One of the main reasons for this is that primary interest of ergonomics is assessment of broad psychological constructs and high-level cognitive functions, which are still not likely to be effectively mapped in the neuronal network of brain functioning. For that reason, the focus on ‘large’ cognitive constructs still represents a major challenge for the neuroergonomics (Sarter and Sarter, 2003).

Neuroergonomics is a field that integrates neuroscience and ergonomics to research the brain and workplace behaviour. It focuses on comprehending how the human brain absorbs information and makes judgements in work settings. This discipline tries to create tools, devices, and systems that improve human performance and safety while reducing the possibility of error. Neuroergonomics uses neurological principles to increase workplace efficiency, productivity, and well-being. It covers a variety of topics, including cognitive burden, human-computer interface, and the physical and mental components of job design. Neuroergonomics and cognitive ergonomics are independent topics, albeit they share significant similarities. Cognitive ergonomics studies how mental functions such as perception, memory, reasoning, and response interact with other system components

Neuroergonomics, on the other hand, takes it a step further by incorporating ideas from neuroscience. It investigates how the brain functions in connection to job activities, utilising neuroscientific tools to better understand cognitive processes. Neuroergonomics seeks to optimise system design by studying how the brain processes information and responds to various inputs in work contexts (Mijovic et al., 2017). It is concerned with mental workload, decision-making, human-computer interaction, and similar topics (Dehais et al., 2020).

The term neuroergonomics is derived from the Greek terms neuro, meaning "relating to nerves or the nervous system," and ergonomics, which means "the study of work"—the study of the brain and its conduct at work. Neuroergonomics is a growing topic that investigates human brain function and behaviour in relation to behavioural performance in natural and everyday settings. Neuroergonomics has an impact on a wide range of disciplines; research have been conducted in the military, healthcare, employment, and educational settings, among others.

Thus, neuroergonomics has a significant impact; nevertheless, there are currently few books that provide students, practitioners, and researchers, even those outside of academia, with a single, go-to source covering state-of-the-science material regarding neuroergonomics (Ayaz and Dehais, 2021).

Neuroergonomics arose as a unique field of research in the late twentieth and early twenty-first centuries, relying on the foundations of traditional ergonomics as well as advances in neuroscience. It emerged from a need to comprehend the complicated relationships between brain functions and work contexts, especially as technology became more interwoven into daily duties. Raja Parasuraman and Matthew Rizzo popularised the term "neuroergonomics" in their important 2006 book, "Neuroergonomics: The Brain at Work". They attempted to bridge the gap between neuroscience and human factors/ergonomics by examining the brain's role in workplace activities and settings (Parasaruman and Rizzo, 2006).

2.7.1. Mental Workload

Workload is the quantity and intensity of work demands placed on an individual. This can include physical tasks, cognitive processes, and emotional stress. Workload is frequently evaluated in terms of how well these demands match an individual's strengths and resources. Understanding workload is critical in ergonomics and workplace design to prevent employees from being overburdened, which can lead to stress, lower productivity, and health issues. Effective workload management seeks to strike a balance in which people are challenged but not overwhelmed, maintaining efficiency and well-being (Kantowitz, 2020).

Mental workload (MWL) is the cognitive effort necessary to complete an activity. It refers to the mental capacities used during task performance, such as attention, memory, decision-making, and problem solving, as shown in Figure 2.16. Mental burden is an important issue in ergonomics and human factors since it influences a person's performance and well-being. A high MWL can lead to errors, lower productivity, and stress, whereas a low MWL can cause boredom or under-stimulation. Properly managing mental strain is critical for improving job performance and guaranteeing safety in a variety of contexts, particularly complicated or high-risk environments such as aviation, healthcare, and driving. It is a multidimensional concept that refers to the amount of mental effort and energy required to complete a task or a series of actions (Longo et al., 2022).

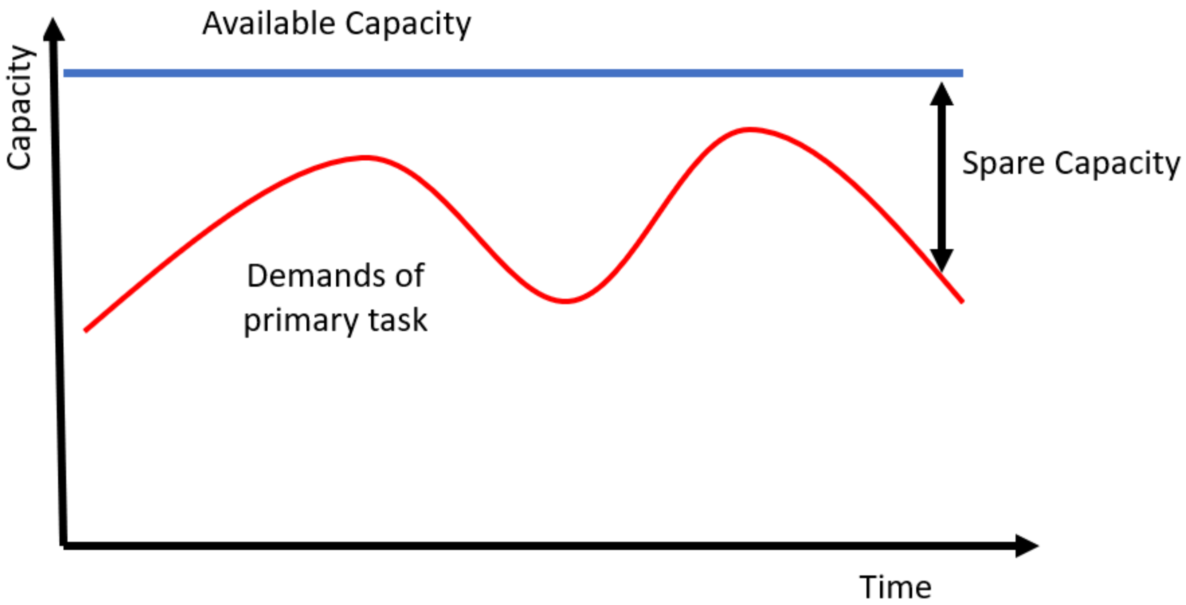


Figure 2.16 – *Mental Workload as the gap between the Available Capacity and the Demand of the primary task*

The definition of MWL can be understood from several perspectives:

- Capacity Demand Perspective: from this view, MWL is defined as the proportion of an individual's cognitive capacity that is being used to perform a task. Human cognitive capacity is limited, and different tasks demand varying amounts of this capacity. When a task requires a high proportion of this capacity, it is said to impose a high MWL.
- Subjective Experience: MWL is also defined by the subjective experience of the individual performing the task. This involves feelings of effort, stress, and strain

that a person might report while engaging in a task. Subjective measures, like self-report questionnaires, are often used to assess this aspect.

- Performance-Based Definition: MWL is inferred from the performance on a task. If a task leads to reduced performance, increased errors, or longer reaction times, it is often interpreted as a sign of high MWL.
- Physiological Response: MWL can also be defined in terms of physiological responses. Certain bodily functions, like heart rate variability, brain activity patterns, and pupil dilation, can change in response to increased cognitive demands, thus providing an indirect measure of MWL.
- Task Characteristics: sometimes, MWL is defined in terms of the characteristics of the task itself, such as complexity, duration, amount of information processing required, and the level of multitasking.

In summary, MWL is a concept that encapsulates how much cognitive effort is required to perform a task, influenced by the individual's cognitive capacity, the demands of the task, and the individual's subjective experience. It's a dynamic concept that varies not only between different tasks and environments but also between individuals.

Humans' ability to obtain information has an impact on their MWL. When there is an abundance of information, individuals may experience overload, making it harder to comprehend and make judgements. This overload can raise mental burden, causing tension, disorientation, and impaired decision-making ability. The ease with which information can be obtained influences mental effort. Easily available information can lessen the mental effort necessary to locate and use it, lowering the MWL. In contrast, if the access of knowledge is difficult or time-consuming, the mental effort may increase (Leva et al., 2022).

The trustworthiness and usefulness of the information are other important considerations. High-quality, relevant information can help to streamline decision-making processes and reduce MWL. Poor-quality or irrelevant information, on the other hand, might raise MWL because it requires more effort to check and sift through. Individual differences in cognitive capacities, such as memory capacity, attention, and processing speed, influence how information affects mental effort (Xiao-ming and Jie-fang, 2009). People with better cognitive capacities may be able to process information more efficiently, resulting in a lesser mental effort under the same settings as those with lower cognitive capacities. According to the Ebbinghus curve, Figure 2.17, about 50% of a person's memory capacity is lost after 1 day:

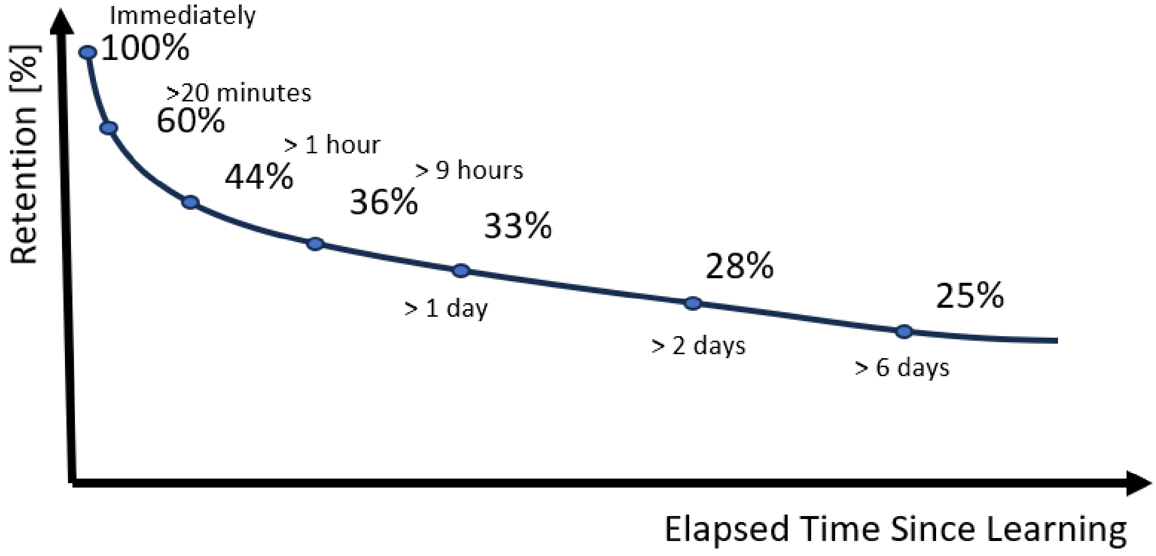


Figure 2.17 – *Ebbingaus Forgetting Curve*

Ebbinghaus' Forgetting Curve empirically shows the gradual reduction in memory recall over time. This curve depicts how information is lost over time when no attempt is made to keep it. It was developed by Hermann Ebbinghaus, a German psychologist, in the late nineteenth century, based on his experimental research of memory and forgetting (Ferreira et al., 2023).

Furthermore, Miller's Law, Figure 2.18, developed by cognitive psychologist George A. Miller, describes the limits of human memory ability, particularly short-term memory. Miller proposed that the average number of objects an individual can keep in working memory is roughly seven, plus or minus two. This suggests that most people can store five to nine items in their short-term memory. This theory has influenced a variety of sectors, including psychology, design, marketing, and communication. It determines how information is presented to make it more digestible and remembered, such as in website design or instructional materials (Cowan, 2015).

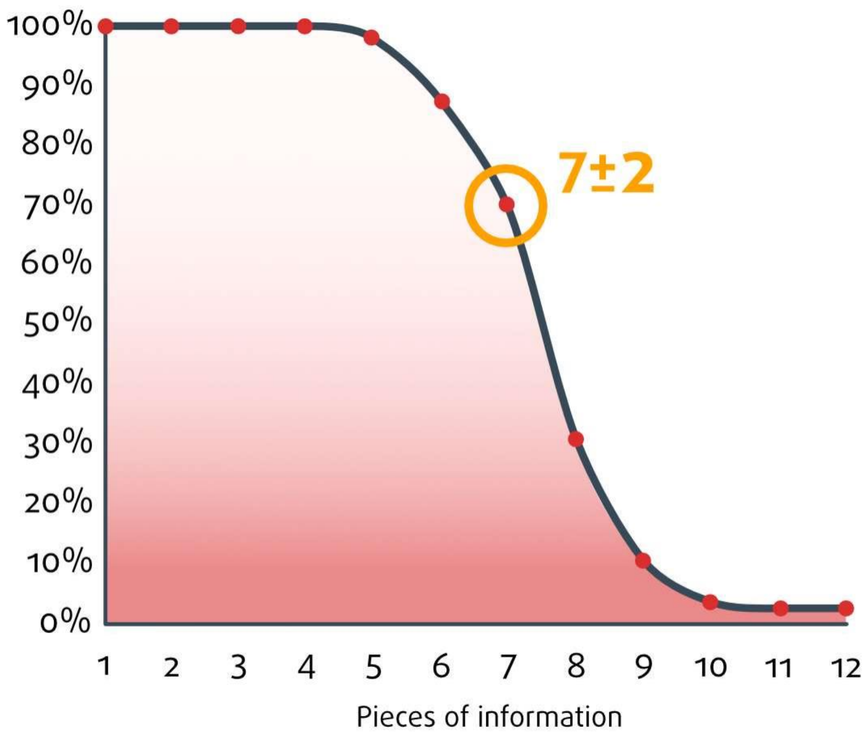


Figure 2.18 – *Miller's Law Curve (Cowan, 2015)*

The task's complexity also impacts this relationship. Access to required information, especially for complicated jobs, can lessen MWL by offering direction. However, for easier jobs, too much knowledge may complicate the process and raise the mental burden. Thus, using technology to manage and filter information has a substantial impact on MWL. The proper use of technology tools can lessen MWL by organising and prioritising information. However, learning to utilise these technologies or coping with poorly designed interfaces may temporarily raise MWL (Cowan, 2022).

Many businesses, particularly those in industrialised countries, have shifted away from physical labour and towards knowledge-based work. This shift emphasises cognitive tasks such as information processing, decision-making, and problem solving, making MWL more important for job performance. In many high-stakes contexts (e.g., aviation, healthcare, nuclear power operations), MWL is critical because cognitive overload can lead to errors with serious repercussions. In these situations, mental burden strongly influences the quality of decision-making and situational awareness, which is often more important than physical exertion (Nielsen and Brix, 2023).

Furthermore, with the growth of automation and advanced technology, many jobs have seen a major reduction in physical workload. However, this has frequently resulted in higher mental demands, as employees are asked to monitor systems, make judgements based on complex information, and manage numerous activities at once. The nature of work has changed as more people participate in prolonged computer use, multitasking, and dealing with information overload. These modifications increase the prominence of cognitive demands and their impact on total work performance (Ávila-Gutiérrez et al., 2022).

Thus, when designing workplaces, tools, and systems, MWL must be taken into account in order to create user-friendly and efficient environments. This includes designing software interfaces, arranging control rooms, and even organising labour assignments. Understanding mental effort is critical for building appropriate automation and technological aids. Properly designed technology can eliminate excessive mental effort, freeing individuals to focus on more important tasks.

By monitoring and managing MWL, it is possible to predict situations where errors are more likely and take proactive steps to prevent them. The key is to understand and balance the MWL to ensure safety, health, and productivity in today's fast-paced work environments (Fan and Smith, 2017).

Grech et al. (2009) argued that the relationship between effort and fatigue could be dynamic, with the optimal degree of exertion changing over time. Workplace performance suffers as a result of a heavy workload and weariness. A heavy workload is related to the fit or gap between task needs and people's capacities.

Prolonged work tiredness can be caused by a variety of factors. First, weariness is thought to be caused by high job demands and insufficient job control (Fan and Smith, 2017). Job demands refer to the workload, whereas job control refers to the individual's ability to control work activities. Second, fatigue is influenced by individual variations such as personality, coping styles, and health-related behaviours (Laaksonen et al., 2009).

Third, weariness is closely linked to shift work, which disturbs the sleep-wake cycle and deprives workers of sleep, lowering levels of performance (Ferguson et al., 2008). Furthermore, in the railway business, the working environment and tasks frequently necessitate constant vigilance, which might contribute to weariness (British Office of Rail Regulation, 2012). According to Lal and Craig (2001), known environmental factors impacting vigilance include noise, vibration, environmental contaminants, and a variety of stimuli.

2.7.2. How to Measure Mental Workload

Measuring workload can be approached through several methods, each focusing on different aspects of workload:

- Subjective Measures: these involve self-report questionnaires or scales where individuals rate their perceived level of workload. An example is the NASA Task Load Index (NASA-TLX) or the Subjective Workload Assessment (SWAT), which assesse workload based on factors like mental demand, physical demand, and perceived performance (Hart and Staveland, 1988; Zak et al., 2020).
- Behavioral Measures: these are based on task performance metrics. For example, if a task becomes more challenging and a person's performance deteriorates, it may indicate increased MWL. Reaction time, error rate, and task completion time are typical metrics used (Luzzani et al., 2023).
- Performance Measures: this approach evaluates workload by observing changes in performance on tasks. Decreases in accuracy or increases in task completion time can indicate high workload (Caterino et al., 2023).
- Neuroimaging Techniques: Advanced methods like functional Magnetic Resonance Imaging (fMRI) or Positron Emission Tomography (PET) can be used to observe brain activity in specific areas, offering insights into MWL. However, these methods are more invasive and less practical in everyday settings (Winstein et al., 1997; Causse et al., 2021).
- Physiological Measures: These include monitoring physiological responses such as heart rate variability, brain activity, or eye movements. Changes in these

responses can correlate with changes in MWL (Caiazzo et al., 2023; Upasani et al., 2023).

- Dual-Task Methods: this approach involves having the person perform a secondary task in addition to the primary task of interest. The theory is that the more MWL the primary task requires, the poorer the performance on the secondary task (Pusica et al., 2024).

Each method has its strengths and limitations, and often, a combination of these approaches is used to obtain a comprehensive assessment of workload. The choice of method depends on the context of the assessment, the type of task being performed, and the resources available.

The MWL, as a multidimensional entity, has been broadly described as the resources available to meet the demands of an activity. Not only can an extremely high workload diminish human performance, but a low workload reduces the operator's motivation and interest in the task (Leva et al., 2022). In high workload settings, perception resources are drained, leading in deafness to auditory alarms, disregard for all incoming information, a slowing of decision-making, and a worsening in attentiveness. As a result, a modest workload is required to ensure a safe and effective work environment. Taking human brain data into account should aid in the precise and continuous evaluation of the mental state and effort of the operator.

2.7.3. Cobot and MWL

Workload has a substantial impact on productivity when humans collaborate with robots. A well-balanced workload can boost productivity because robots can undertake repetitive or physically demanding jobs, freeing up people to focus on more complicated or decision-making duties. This collaboration may reduce human weariness and errors, resulting in more efficient work processes. However, if the burden is not effectively handled, it might result in operational inefficiencies. For example, over dependence on robots may erode human skills, whereas underutilization of robots may result in unneeded human workload. Thus, achieving peak production necessitates a deliberate distribution of duties and responsibilities between humans and robots (Hopko et al., 2022).

More gradual cobot speeds were found to increase perceived team-fluency. This effect can be linked in part to the lack of transparency surrounding the cobot's goals, or perceptions of poor safety created by the motions, with two studies revealing that operators have a tendency to respond more slowly when the system's transparency is low (Koppenborg et al., 2017). Operators were shown to be more comfortable when employing 'human aware' cobots, which actively strive to predict the operator's next action (Lasota and Shah, 2015).

Similarly, it is vital to examine how a cobot buddy will affect the operator's workload. As shown in Figure 2.19, the Yerkes-Dodson law shows that operator performance is strongly connected to the operator's cognitive arousal, with hyperarousal (overload) associated with stress and anxiety and underarousal associated with sleepiness and job disengagement (Corbett, 2015).

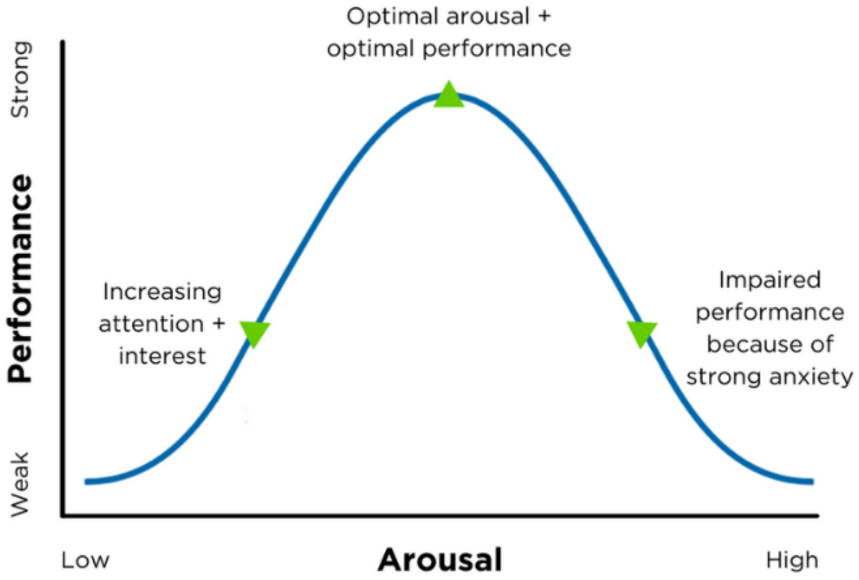


Figure 2.19 – *The Yerkes-Dodson Law (Corbett, 2015)*

The design of jobs resulting in operator overload can lower operator satisfaction while increasing tension and anxiety. Hyperarousal is not only dangerous to workers, but it can also lead to increased operator errors, resulting in workplace injuries. Underloading the operator, on the other hand, might result in boredom and task disengagement, lowering work performance and raising the likelihood of slips or lapses. To maximise operator performance and engagement, the operator should not be overloaded or underloaded (Weidemann and Russwinkel, 2021).

The deployment of cobots is frequently meant to offload labour from the operator to the robot; yet, the introduction of cobots might raise cognitive load on the user by providing more complicated tasks or needing greater situation awareness cognitive resources to complete the activity. Such burden must be considered to avoid operator fatigue, anxiety, and reduced performance (Hopko et al., 2021).

Authors claimed that age might influence trust in automatized systems: older people would be less prone to work with robots rather than younger ones (Scopelliti et al., 2005; Lee et al., 2009; Schaefer et al., 2014). Because cobot operators differs of various ages, age implications must be considered.

Moreover, male, and female views of cobot capabilities, behavioural influence, and proxemic spacing have been shown to differ and, in some situations, to be more relevant than age (Nomura, 2017). Perceptions, values, and acceptance of cobots are different depending on male and female social behaviours and social norms (Mutlu et al., 2006). Finally, workers' pre-experience is discovered to be a major component influencing workers' states (Wurhofer et al., 2015).

The combination of both subjective and objective measures is essential for accurately determining the impact of MWL on HRC. Subjective measurements, which were discovered to be more extensively employed, provide implicit information on the current state of the operator’s behaviour; yet, because most subjective data are discrete, dynamic state interpretation is more difficult to capture. In contrast, objective techniques are frequently able to provide explicit continuous assessment, thus providing further insight into the mechanical effects of workload instantly as they occur (Jahedi and Méndez, 2014).

Authors showed the application of both subjective and objective approaches to evaluate mental stress. They developed a cognitive workload classifier based on brain monitoring's determined spectral power density and coherence features. Furthermore, they discovered that the results of the subjective measurements are consistent with the results of workload observation (Amirhossein and Ehsan, 2019).

Physiological measurements might objectively quantify and assess the level of MWL. These included: EEG, where increased cerebral cortical activation in the brain correlated with higher levels of MWL (Amirhossein and Ehsan, 2019); eye tracking, where average fixation time and pupil dilation were evaluated (Tang et al., 2019), (Kuz et al., 2018); heart rate monitoring, where respiratory sinus arrhythmia (RSA) was calculated but heart rate features were not explicitly reported (Kato et al., 2010).

2.8 ELECTROENCEPHALOGRAM MEASUREMENT (EEG)

Electroencephalography, or EEG, is a non-invasive, real-time, portable, and compact electrophysiological method that records the electrical activity of the brain by inserting electrodes on the user's scalp. EEG is a measurement of the brain's voltage fluctuations as sensed by scalp electrodes. Voltage variations caused by ionic current inside and between brain neurons account for the majority of electrical activity. The collected signals will subsequently be amplified, digitised, and transmitted to a computer or mobile device for data processing, as illustrated in Figure 2.20. It approximates the total electrical activity of neurons. EEG electrodes must detect the activity of a large number of neurons. The timing of their activity is critical. Synchronised brain activity generates greater signals (Biondi et al., 2022).

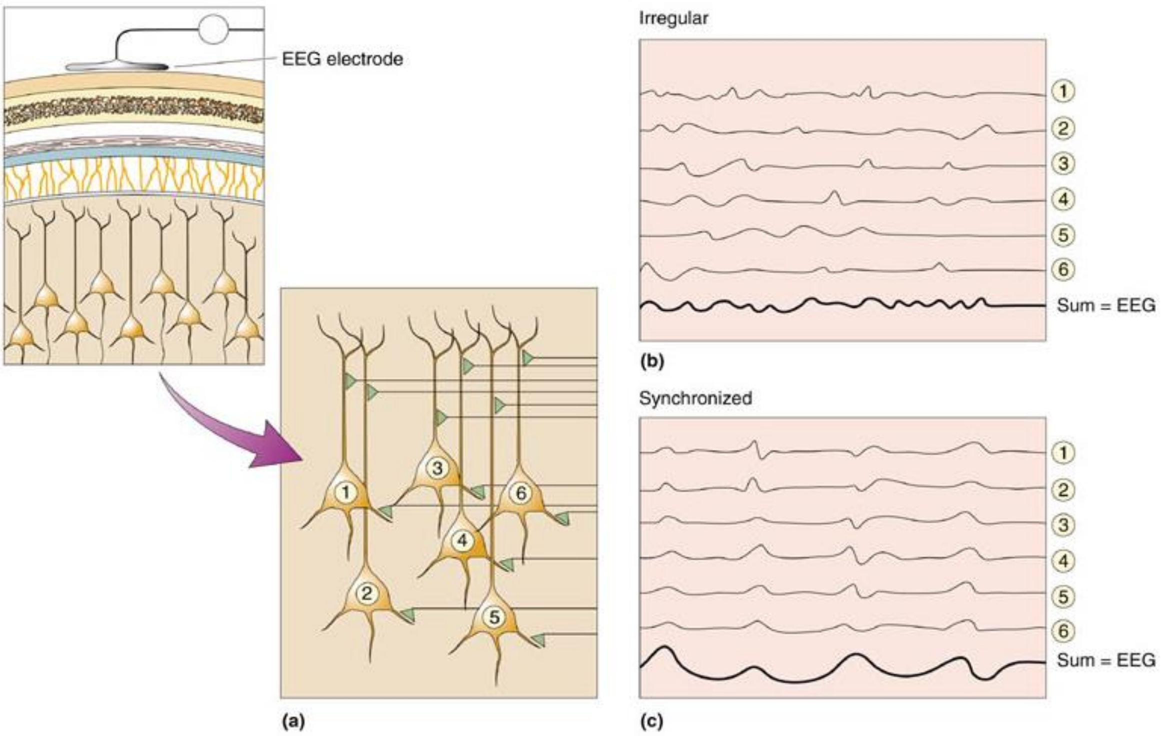


Figure 2.20 – *Neural Activity of the brain (Lago and Cester, 2017)*

The origins of EEG may be traced back to the late nineteenth century when scientists began to investigate the electrical activity of the brain. In 1875, British surgeon Richard Caton conducted animal tests that revealed the presence of electrical potentials in rabbit and monkey brains. In 1902, German psychiatrist Hans Berger began studying the electrical activity of the human brain. In 1924, he invented the first human EEG recording, which used electrodes put on the scalp and an ink writing technique to record brain waves. Berger's findings signalled the start of contemporary EEG.

Between the 1930s and 1940s, EEG technology advanced, with improvements in electrode design and recording procedures. During this time, researchers made key findings about many types of brain waves, including alpha, beta, delta, and theta waves, which are each connected with a particular level of consciousness and brain activity. EEG rose to popularity in clinical and research settings beginning in the 1950s. It became an indispensable tool for identifying neurological conditions like epilepsy and sleep disturbances. Researchers also started using EEG to research brain function and map cortical activity during different cognitive activities.

In the 1980s, the introduction of digital EEG equipment transformed the field, allowing for more precise and efficient data gathering and analysis. This period also saw breakthroughs in EEG electrode technology, with the introduction of smaller, more comfortable electrodes suitable for long-term monitoring. EEG continues to evolve in the late twentieth century and early twenty-first century, with the introduction of computerised EEG processing techniques and the integration of EEG with other neuroimaging modalities such as fMRI (functional Magnetic Resonance Imaging) and PET (Positron Emission Tomography). These advancements offered up new avenues for investigating brain function and connectivity.

In the present day, EEG is still an important tool in neuroscience, with applications spanning from clinical diagnosis and treatment to cognitive neuroscience and brain-computer interfaces. Ongoing research continues to improve EEG techniques and seek new pathways for understanding the complex workings of the human brain. (Sutter and Kaplan, 2017).

The International 10-20 System, sometimes known as the 10-20 system, is a standard way for describing and applying scalp electrode locations during an EEG (Electroencephalography) examination, as shown in Figure 2.21. This system is extensively utilised in both research and clinical settings for EEG recording and is based on the relationship between an electrode's placement and the underlying area of the brain. It ensures that EEG electrodes are put in the same areas across individuals, resulting in reliable and reproducible results.

The numbers '10' and '20' denote the actual distances between nearby electrodes, which are 10% or 20% of the skull's total front-back or right-left distance, respectively. It employs certain anatomical markers on the skull, such as the nasion (the bridge of the nose), inion (the bump at the rear of the skull), and preauricular points (in front of each ear) to precisely position the electrodes (Ives-Deliperi and Butler, 2018).

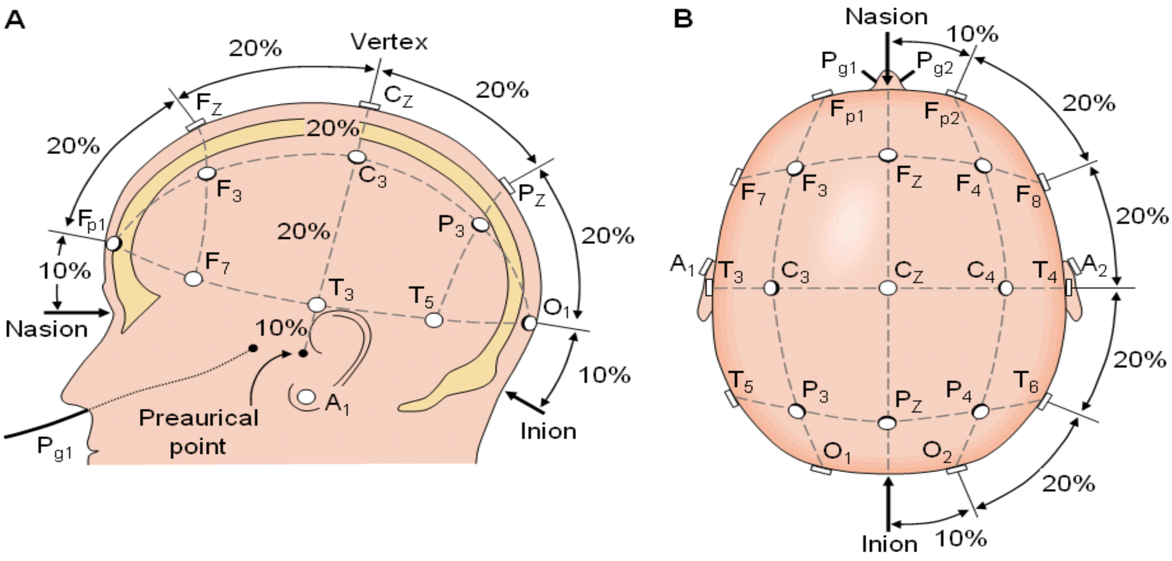


Figure 2.21 – *International 10'-20' System (Martins et al., 2015)*

Electrodes are named based on the area of the brain they are positioned over. Fp (Frontopolar), F (Frontal), T (Temporal), C (Central), P (Parietal), O (Occipital) are the key letters used. Even numbers (2, 4, 6, 8) are used for electrodes on the right side of the head, and odd numbers (1, 3, 5, 7) for those on the left side. The letter 'z' refers to an electrode placed on the midline (like Fz, Cz, Pz).

The recorded electrical activity is displayed as waveforms. Different patterns of brain activity produce different waveforms, which can be analyzed for various purposes. For instance, certain types of waveforms are associated with specific neurological conditions. Brain waves are typically split into four frequency bands: delta, alpha, beta, and gamma. The Delta band has the lowest frequency, and the Gamma band has the highest frequency (Zhu et al., 2022).

Each band has unique characteristics and contains information that represents individual nervous system activity. Power spectral analysis is used in frequency band analysis and categorization to visualise the EEG power of each frequency band. The brain waves are dominant in different state of behaviours:

- Delta waves are mainly observable in the deep sleep (Yahua and Murat, 2014).
- Theta waves are observable in the wakeful state, and they can represent the consciousness slips towards drowsiness, or when one fall into light sleep (Yahua and Murat, 2014).
- Beta waves indicate the awake state or when person is engaged in active thinking and solving complex problems when a person is focused on the task (Makada et al., 2016).

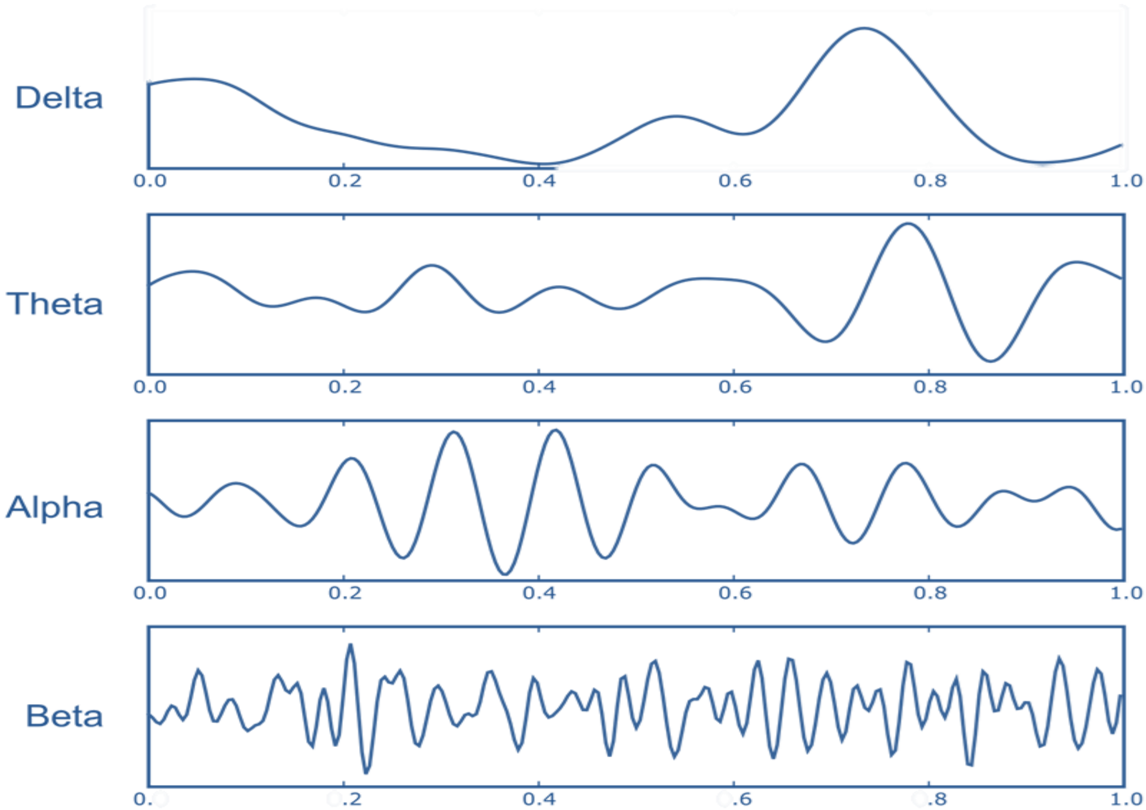


Figure 2.22 – *Classification of brain waves through EEG analysis (Alhudhaif, 2021)*

Figures 2.22 shows a classification of brain waves through EEG analysis. Differences in brain mapping of the relatively high-beta wave in the temporal lobe can help determine participants' stress. Furthermore, alpha band power fluctuations in the centre-parietal and parietal areas have been found to be responsive to MWL, mental effort in attentive stimulus processing, and expectancy. Several indices based on beta band power and/or the ratio of beta band power to alpha or theta band power have also been studied (de Vries et al., 2017; Ismail and Karwowski, 2020).

EEG offers advantages and limitations when compared to other neuroimaging metrics, making it both beneficial and hard in Neuroergonomics applications (Bagheri and Power, 2020). The primary benefits are:

- high temporal resolution (Duraisingam et al., 2017),
- portability for usage in real-world settings (Koyas et al., 2013), and
- affordability.

However, EEG approaches have three notable drawbacks:

- low spatial resolution (Yang et al., 2019),
- the presence of undesirable nonbrain signals or "artefacts" (Zhu et al., 2017), and
- the long setup time (Jao et al., 2018).

Despite these limitations, recent advances in EEG technology have resulted in the introduction of wireless EEG systems, which allow participants to work without interference and use dry electrodes rather than wet systems, reducing setup time (Wang et al., 2016; Arico et al., 2016). Furthermore, automatic artefact detection software [34] has been created to improve signal quality. EEG analysis approaches are divided into four categories: time domain, frequency domain, time-frequency domain, and nonlinear. EEG indices are trustworthy measures of the brain's spontaneous activity. In this regard, we believe it is crucial to investigate studies on EEG indicators in cognitive tasks (Durantin et al., 2014).

2.8.1. EEG's Metrics

EEG is applied to analyze MWL metrics. These metrics are obtained from EEG signals and can provide information on a person's mental effort, attention, and cognitive processing. Some studies compute a specific workload index using combinations of EEG features (e.g., ratios of power in different frequency bands) designed to quantify MWL directly) (Bjegojević et al., 2022).

Coelli et al. (2015) present several methods for calculating this index, including $\beta/(\alpha+\theta)$, β/α, and $1/\alpha$. Pope et al. (1995) tested several variants of this index and discovered that beta power / (alpha power + theta power) was the best predictor of task participation. Mijovic et al. (2017) found that a higher ratio of high to low frequency waves ($EI = \beta/(\alpha+\theta)$) implies increased mental engagement in an activity.

Research investigations examined real-time human brainwave responses using EEG signal analysis and pre-processing. In the literature review, various power ratios of brainwaves were investigated to determine the mental state of the human in a relaxation (Alpha waves) or stress/engagement (Beta waves) phase. This study report showed the β/α ratio to analyse the MWL. An increase in the theta/beta ratio is widely used as a measure of cognitive load or mental exertion since it reveals the balance of cognitive processing and awareness (Horrey, Wickens, 2005; Bagheri and Power, 2020).

Changes in the Alpha/Beta Ratio can also indicate alterations in attentional demand and mental stress. Higher alpha activity usually suggests a state of relaxation, less cognitive effort, or inactivity in terms of MWL. As mental effort increases, alpha activity decreases, indicating greater attention and engagement with the task.

On the other hand, Beta activity is linked to alertness, focused attention, and active cognitive processing. An increase in beta activity can signal higher levels of mental engagement and workload.

The alpha/beta ratio can indicate the balance between calm and active cognitive states. A smaller ratio may imply a state of alertness and engagement (greater MWL), whereas a higher ratio may indicate relaxation or disengagement. This ratio varies with the level of cognitive effort imposed by a task, making it an effective indicator for monitoring variations in MWL (Ryu and Myung, 2005).

In EEG investigations, analysing the alpha/beta ratio can provide insights into how people manage varying degrees of cognitive load, particularly in tasks that involve prolonged attention, problem solving, or decision-making. It is especially beneficial in areas where understanding cognitive engagement and workload is crucial, such as educational research, workplace efficiency studies, and human-computer interface design.

However, it is important to note that individual differences and task environment might alter the interpretation of the alpha/beta ratio, as well as other EEG metrics. Furthermore, mental effort is a multidimensional concept that may not be well reflected by a single metric. As a result, the alpha/beta ratio is frequently utilised in concert with other EEG features and cognitive evaluations to provide a more complete picture of MWL.

Because the application of EEG in HRI manufacturing activities is still in its early stages, the authors proposed that objective measurements should be performed alongside traditional subjective and observational ones to gain a better understanding of the operator's cognitive state. Although this research defined multiple criteria for the evaluation of HRI task performance, the analyses did not highlight the use of EEG in HRI to analyse the operator's neural activity during the tasks (Longo, 2016).

In HRC scenarios, some authors claimed that cobots reduce the operator's MWL. Some studies, however, indicated that cobots increased MWL (Mühlemeyer, 2019; Chowdhury et al., 2020; Borges et al., 2021). However, these studies relied just on subjective assessments obtained through surveys or questionnaires. Thus, there is still a need to explore MWL in HRC tasks using objective investigations (Storm et al., 2022; Faccio et al., 2022).

2.9 BRAIN COMPUTER INTERFACE (BCI)

A Brain-Computer Interface (BCI), also called a Brain-Machine Interface (BMI), is a technology that allows the brain to communicate directly with an external device. This interface is often implemented with sensors that monitor and interpret brain signals. These neural impulses, produced by brain activity, can be converted into commands for operating computers, prosthetic limbs, wheelchairs, and other equipment.

The earliest concepts and experiments related to BCIs emerged in the 1960s and 1970s. Researchers like Jacques Vidal explored the possibility of using brain signals to control external devices. Vidal coined the term "BCI" in 1973. The development of BCIs gained momentum in the 1980s and 1990s, driven by advancements in neurophysiology and computing technology. In 1988, researchers at the University of California, Los Angeles (UCLA), led by Dr. P. Michael Leahy, demonstrated a BCI system that enabled paralyzed individuals to control a computer cursor using brain signals. The 2000s marked significant progress in BCI research and development. Researchers began to explore various methods for acquiring brain signals, including EEG, fMRI, and invasive techniques like electrocorticography (ECoG) and intracortical electrodes. The mid-2000s saw a surge in interest and investment in BCIs, fueled by advancements in machine learning, signal processing, and neurotechnology. Researchers achieved notable milestones, such as enabling paralyzed individuals to control robotic limbs and prosthetic devices using their brain signals (Kubler, 2020).

In recent years, BCIs have become more accessible and versatile, with applications ranging from healthcare and assistive technology to gaming and entertainment. Non-invasive BCIs, particularly those based on EEG, have become more portable and affordable, opening up new possibilities for widespread adoption.

BCI technology is continually advancing and has problems, such as increasing accuracy and speed of interpretation, as well as making devices more user-friendly and less invasive. Despite these challenges, BCIs have great potential for improving human-machine interaction and assisting people with various disabilities (Aggarwal and Chungh, 2022).

Active and passive BCIs (aBCIs or pBCIs) are two different approaches to using brain signals to operate a computer or device. The differentiation between them is based on the type of brain activity being recorded and how it is used in the interface.

In an active BCI, the user intentionally modulates their brain activity to transmit orders or messages to the computer. This modulation is typically accomplished through specialised mental tasks or concentrated efforts. For example, a user may envision moving their left hand to move the cursor left or focusing on a specific visual pattern to select an option. The BCI system recognises deliberate changes in brain activity (such as certain EEG patterns) and converts them into commands. Active BCIs are commonly employed in applications that need direct control, such as moving a prosthetic limb, controlling a wheelchair, or typing on a virtual keyboard (Shishkin, 2022).

Passive BCIs, on the other hand, eliminate the need for the user to actively manage their brain activity. Instead, they monitor and adapt to the user's natural brain activity, eliminating the need for active manipulation. These technologies are intended to comprehend or interpret the user's current state, such as detecting levels of concentration, relaxation, or stress. A passive BCI, for example, may modify the lighting in a room based on the user's level of relaxation, or it could alert a motorist if they are drowsy. Passive BCIs are frequently employed to improve human-computer interface or for monitoring, rather than direct control (Hinss et al., 2023).

In essence, active BCIs require the user to consciously manipulate their brain activity in order to interact with a system, whereas passive BCIs merely monitor the user's normal brain states and do not require conscious effort to manage the interface. Both types have distinct applications and are useful in various circumstances within the field of neurotechnology.

In Figure 2.23, an example of real-time acquisition of Signals through Brain Computer Interface.

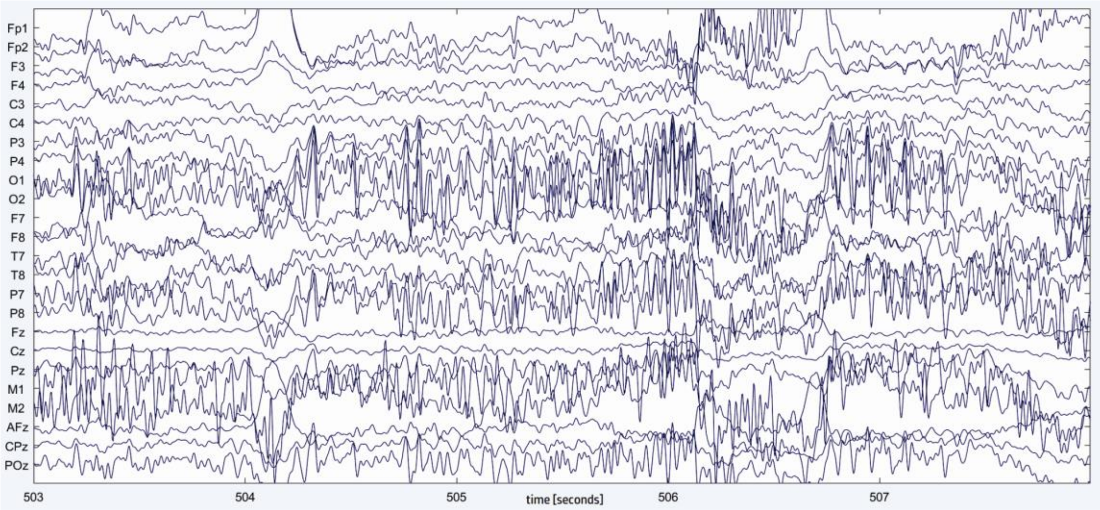


Figure 2.23 – *Real-Time Acquisition of Signals through Brain Computer Interface (Savkovic et al., 2022)*

2.9.1. Other BCI's Approaches

Other approaches and classifications within the field of BCI technology are presented. These can be categorized based on various aspects such as the method of signal acquisition, the nature of the interaction, or the purpose of the BCI. Here are some additional approaches:

- Reactive BCIs are a subtype of active BCIs. These systems measure the user's brain response to external stimuli. For example, a common reactive BCI technique is the Steady-State Visually Evoked Potential (SSVEP), which uses the brain's response to visual stimuli at specified frequencies to operate an interface (Bi et al., 2014).

- Hybrid BCIs integrate two or more distinct BCI techniques, or BCI technology with non-BCI communication technologies. For example, a hybrid BCI may employ both EEG and EMG (electromyography) inputs, or it could integrate brain-computer interface with eye-tracking technologies. Often the purpose is to improve the system's efficiency, accuracy, or robustness (Fu et al., 2023).
- Invasive BCIs include implanting electrodes directly into or on the brain's surface. These devices can deliver high-resolution information, but they come with surgical risks. Non-invasive BCIs, on the other hand, rely on scalp sensors (like EEG). They are safer and easier to operate, but they often have lesser signal resolution and are more susceptible to noise (Guo et al., 2022).
- Closed loop BCIs give the user real-time input that can be utilised to make system adjustments or for neurofeedback training. The user's brain activity influences the system, which in turn influences the user's brain activity, resulting in a feedback loop (Xu et al., 2014).

Some BCIs are intended for extremely particular purposes, such as neurorehabilitation, communication for locked-in syndrome, gaming, or even creative expression. These BCIs are designed to meet the requirements and limits of their respective use case. Each of these approaches addresses unique requirements and obstacles in the field of BCI. The appropriate technique is determined by considerations such as the intended use, the user's condition, the desired accuracy, and the practicality of applying a specific technology. The field is constantly changing, with new techniques and technologies developing as research advances.

3. DESIGN OF EXPERIMENTS

An experiment is a methodical approach designed to verify, refute, or confirm the validity of a hypothesis. Experiments provide insight into cause-and-effect relationships by revealing what happens when a certain factor is modified. Experiments are important to the scientific process and are utilised in a variety of fields, including the natural sciences, social sciences, psychology, and medicine (Favero and Belfiore, 2006).

Experiments are classified into three types: laboratory experiments (conducted in controlled lab settings), field experiments (conducted in natural settings), and natural experiments (in which the experimenter does not manipulate the variable but instead observes natural occurrences).

Key components and characteristics of an experiment include:

- Hypothesis: a hypothesis is a testable prediction about the relationship between two or more variables. It's the starting point of any experiment.
- Variables: in an experiment, there are typically at least two variables: the independent variable (the one that is manipulated or changed) and the dependent variable (the one that is measured or observed). There may also be controlled variables, which are kept constant to ensure the experiment's validity.
- Controlled Environment: experiments are often conducted in controlled environments where extraneous variables can be minimized. This control allows for more accurate determination of cause and effect.
- Manipulation: the experimenter manipulates the independent variable and observes the effect of this manipulation on the dependent variable. This manipulation is the core of experimental design.
- Randomization: random assignment of subjects or units to different conditions or treatments is a common technique in experiments. This helps ensure that the results are due to the manipulation of the independent variable and not some other factor.
- Replication: experiments should be replicable, meaning that when someone else conducts the same experiment under the same conditions, the results should be consistent with the original experiment's findings.
- Observation and Data Collection: careful observation and data collection are crucial. This data is analyzed to determine whether the results support or contradict the hypothesis.
- Analysis and Interpretation: after the data is collected, it is analyzed, often using statistical methods, to determine the significance of the findings.
- Conclusions: based on the analysis, conclusions are drawn about the hypothesis. These conclusions can lead to a better understanding of the studied phenomenon or to further research.

- Ethical Considerations: in experiments involving human or animal subjects, ethical considerations are critical. This includes obtaining consent, ensuring safety, and treating subjects humanely.

The Design of Experiments (DOE) is a statistical methodology for designing, carrying out, analysing, and interpreting controlled tests to determine the factors that may impact a specific response or outcome. DOE, invented by Sir Ronald A. Fisher in the early twentieth century, is frequently utilised in sectors like as engineering, manufacturing, medicine, and agriculture to optimise processes, increase product quality, and shorten development timelines (Favero and Belfiore, 2006).

Key aspects of the DOE include:

- Objective Definition: the first step in DOE is to clearly define the objectives of the experiment. This involves stating the problem, the response variables to be studied, and the goals of the experiment (e.g., optimizing a process, comparing different treatments).
- Factor Identification: identify the factors (independent variables) that are thought to influence the response variable. These factors might include process parameters, environmental conditions, materials used, etc.
- Level Setting: for each factor, decide on the levels (values) at which it will be tested. Levels could be quantitative (e.g., temperature settings) or qualitative (e.g., types of material).
- Selection of Experimental Design: choose an appropriate experimental design based on the objectives, number of factors, levels, constraints, and resources. Common designs include factorial designs, fractional factorial designs, response surface methodology, and Taguchi methods.
- Randomization: it is the process of randomly assigning the treatments to experimental units. This is crucial for reducing bias and the effects of extraneous variables.
- Replication: it involves repeating the experiment multiple times to ensure that the results are not due to random chance. Replication improves the reliability and accuracy of the results.
- Blocking: it is a technique used to control for variables that are not of primary interest but may affect the response variable. By 'blocking' these variables, their impact can be minimized.
- Conducting the Experiment: run the experiment as per the design, carefully controlling and recording the factors and their levels.
- Data Analysis: to analyze the collected data using statistical methods. This often involves the use of the analysis of variance (ANOVA), regression analysis, or other statistical tools to determine the effect of the factors on the response variable.
- Interpretation of Results: interpret the results to draw conclusions about the relationships between factors and the response. Determine if the findings are statistically significant and relevant to the practical context.

- Optimization and Recommendations: based on the analysis, make recommendations for process optimization, improvement, or further experimentation.

DOE provides a structured approach to experimentation that is more efficient and informative than traditional one-factor-at-a-time experiments. An example of a general model of a process system considering the controllable and uncontrollable factors influencing the system is shown in Figure 3.1

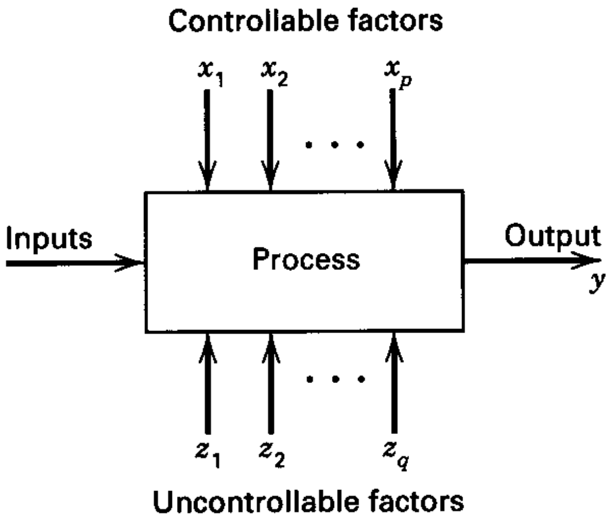


Figure 3.1 – *General model of a process or system*

3.1 COMPARATIVE ANALYSIS

A comparative analysis is a methodological approach that compares several products, concepts, entities, or phenomena. This form of analysis is commonly employed in subjects such as literature, history, sociology, psychology, economics, and business. The primary purpose of a comparative analysis is to find parallels and contrasts between the subjects under study, allowing for a more in-depth understanding of each and deriving insights that would not be obvious when considering them separately (Janneke et al., 2008).

Key elements and steps in a comparative analysis include:

- Selection of Comparison Subjects: the first step is to choose the items or concepts to be compared. These could be texts in literature, historical periods, policies, economic theories, companies, products, etc. It's crucial that the chosen subjects share enough common ground to make the comparison meaningful.
- Criteria for Comparison: define the specific aspects or criteria on which the comparison will be based. These criteria should be relevant and significant to the subjects being compared.
- Data Collection and Research: gather information and data on each subject. This step involves thorough research to obtain a comprehensive understanding of each item.

- Identification of Similarities and Differences: analyze the collected information to identify both similarities and differences based on the predefined criteria. This is the core of the comparative analysis.
- Contextual Analysis: understand and analyze the context in which each subject operates. This can involve historical, cultural, social, economic, or political contexts, depending on comparison.
- Synthesis and Interpretation: combine the findings to draw conclusions or insights. This involves interpreting the significance of the similarities and differences and what they reveal about the subjects.
- Presentation of Findings: organize and present the findings in a structured format. This could be in the form of a comparative essay, report, or presentation. The presentation typically includes an introduction, a body where comparisons are detailed, and a conclusion summarizing the findings and their implications.
- Critical Analysis: engage in critical thinking to challenge assumptions, explore alternative perspectives, and evaluate the implications of the findings.

A comparative analysis can serve various purposes, such as:

- To understand each subject more deeply by viewing it in relation to another.
- To develop arguments or hypotheses by using the comparison as evidence.
- To make informed decisions or recommendations, especially in business and policy contexts.

Overall, a comparative analysis is a powerful tool for gaining insights, understanding relationships, and making informed evaluations and decisions.

In the following section, the PhD work presents the comparative analysis assessed for three laboratory experimental ssettings: the first, in which participants performed an assembly task without any intervention in the workstation; the second, in which the participant performed the task in collaboration with the cobot, aiding the candidate through the assembly activity; the third, in which the participants performed the task in collaboration with the cobot and guided by means of P-Y aspects.

The goal of this investigation is to show how participants' mental effort, efficiency, and production change across these three scenarios. Furthermore, the study employed observational measurements to compute the productivity index in terms of accurately completed components across the three scenarios. EEG sensors are mounted on the candidate to collect quantitative data for comparison analysis and to assess the operator's MWL during two different tasks. The quantitative and objective EEG analysis results for the MWL provided in Chapter 4 are supported by observational measurements of the corrected components used to correlate the MWL with production rate. Furthermore, a qualitative analysis employing questionnaires is useful for assessing the user experience when working with the robot in a collaborative setting.

3.2 PARTICIPANT SELECTION

The number of participants was defined through the sample size criteria adopted through the software tool G*Power (Aarts et al., 2014; Kang, 2021).

G*Power is a statistical power analysis tool that is widely used in a variety of domains, including psychology, medical research, and the social and natural sciences. It assists researchers in determining the appropriate sample size for a certain study. This is critical to ensuring that the study has enough participants to identify a true effect, assuming one exists. It provides many statistical tests, making it useful for a variety of data analyses. It also provides graphical alternatives such as power curves, which can be quite useful for visualising the relationship between various statistical factors. Finally, G*Power is free to the public and offers an easy-to-use interface, making it accessible to those without substantial statistical knowledge. In summary, it helps determinate the appropriate sample size and power, thereby increasing the efficiency and validity of the research.

The parameters used for the analysis are:

- Test Family: this specifies the broad category of the statistical test (e.g., t-tests, F-tests, χ^2-tests).
- Statistical Test: within each test family, you select the specific statistical test you plan to use (e.g., ANOVA, regression, correlation).
- Type of Power Analysis:
  - A priori: determines the sample size required to achieve a desired power level.
  - Post hoc: calculates the power of an existing study based on the sample size and effect size.
- Effect Size (f) = an estimate of the magnitude of the phenomenon being studied. G*Power provides means to calculate effect size based on input data or prior research. Generally, acceptable magnitudes of effect size for research studies are between 0.2 and 0.6.
- Error Probability (α): the probability of making a Type I error, which is rejecting the null hypothesis when it is actually true ($H \neq H0$). Commonly set at 0.05.
- Power ($1 - \beta$): the probability of correctly rejecting the null hypothesis when it is false (i.e., the study's ability to detect an effect if there is one). Typically, researchers aim for 80% power (0.80).
- Number of Groups or Measurements: relevant in designs involving multiple groups or repeated measurements.
- Correlations and Non-sphericity Correction (ε): used in more complex designs like Analysis of Variance with repeated measures (ANOVA RM), where correlations among repeated measures and the violation of sphericity assumption are considered.

The test family selected is F-test which is a type of statistical test that is used to compare the variances of two or more groups to see if they are significantly different from each other. In ANOVA, the F-test is used to determine whether there are any statistically significant differences between the means of three or more independent groups.

Regarding the type of statistical test, ANOVA repeated measures (ANOVA RM) within factors was deployed. ANOVA RM with repeated measures within factors is a statistical method used to analyze data where the same subjects are subjected to multiple conditions or measured at multiple time points. This type of ANOVA is particularly common in experimental designs where the same group of participants is exposed to all levels of the independent variable (Miller et al., 2022).

The type of power analysis is a priori.

In this PhD work project, the number of measures analysed is equivalent to the number of observation periods for each scenario constructed. The trials include three situations (standard, collaborative, and collaborative guided), each with three observations.

Thus, the suitable number of participants for the comparative analysis was assessed through ANOVA RM analysis within factors in the G*Power tool, with these inputs:

- Effect size f = 0.4 – moderate magnitude.
- Error Probability α = 0.05.
- Power β = 0.8.
- number of groups = 1.
- number of measurements = 9 (Number of periods observed during the task x Number of conditions).

The Figure 3.2 shows the suitable total sample size for the analysis is 7.

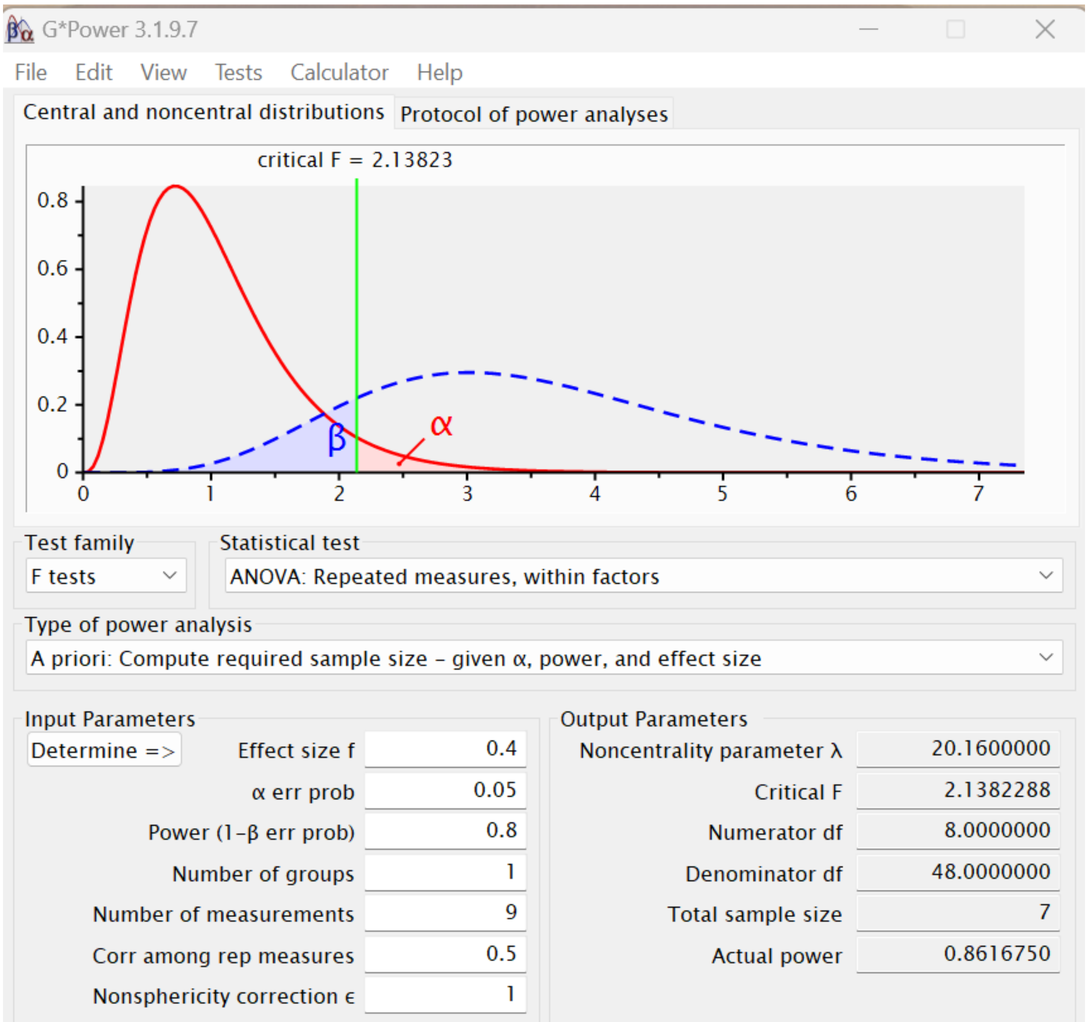


Figure 3.2 – *G*Power analysis results*

The study involved 10 male right-handed university students, with a mean age of 23.3 ± 3.3 years (Table 3.1). Before completing an authorization document established by the administration of the Faculty of Engineering at the University of Kragujevac in Serbia, all participants were informed of the task procedure and objectives. The average body weight was 88.5 ± 16.4 kg, and the average height was 184.2 ± 5.8 cm. None of the subjects had previous experience in the assembly area or with the robot. The participants were not under the influence of any drugs that could interfere with EEG. Moreover, they were told not to drink any alcoholic drink the day before the tests, like not to drink coffee for at least three hours before the study. They assured that they had slept well the night before the test. All subjects had normal or corrected-to-normal vision.

Table 3.1 – Characteristics of the participants

Candidate Number	Age	Body Weight (Kg)	Height (cm)
1	26	94	188
2	24	105	190
3	26	80	188
4	23	78	177
5	23	95	185
6	20	100	180
7	22	84	190
8	22	83	178
9	24	78	182
10	23	75	180

3.3 EXPERIMENTAL DESIGN

The laboratory setting represents a realistic replication of industrial assembly workplace ranging from simple to complicated interactions between people and cobots. The Figure 3.3 shows the workplace where participants carried out the experiments.

Figure 3.3 – *Set up of the Workplace Environment*

In the design of the laboratory industrial assembly workstation, particular consideration was paid to the “golden zone area” where operators perform the tasks handling materials and components. This area allows workers to attain the best efficiency and output, reducing movements of the upper-limb part of the body during the activity of reaching components by arms. The golden zone guidelines promote workplace organization while lowering muscle effort and the incidence of work-related musculoskeletal disorders (WMSD). Because the golden zone is unique to each worker, the workstation ensures that the workspace and arrangement of supplies, components, and tool placements may be changed to the individual demands (Sanders and McCormick, 1993).

In addition, the developed workstation is adjustable in height and tailored to the anthropological traits of the participants. After reviewing scientific research papers, it is possible to conclude that the best alternative for workers is to execute tasks on flexible workstations with adjustable heights. Also, the industrial work chair is height-adjustable, composed of durable materials, and characterized by stability when altering the participants' weight (Wilks et al., 2006).

The working area is customized with innovative technologies to properly imitate the complicated conditions seen in a natural work environment and to allow for improved testing of participants' behavior during manual assembly jobs. This workstation includes an industrial computer that monitors and controls the performance of different job tasks, processes monitorization, and communicates with the operator via HMI devices. A touchscreen PC is linked to the system for task definition and stimulus delivery.

Beyond that, careful consideration is taken with lighting. Lighting is an essential component in the ergonomic design of an assembly workstation. It is critical to give a good light source to avoid straining their eyes when completing work tasks. Individual reflectors that create overlaid solid shadows can induce eye strain, resulting in weariness and a loss of concentration. Homogeneous LED lighting was set up on the new industrial lean workstation since it produces only gentle shadows, which are easier on the eyes. There is also an audio 5.0 system to replicate the sounds of the industrial area (Stanton et al., 2012). The designed workstation represents the laboratory infrastructure for conducting neuroergonomic experiments and studying the behavior of operators at the workplace, as shown in Figure 3.4.

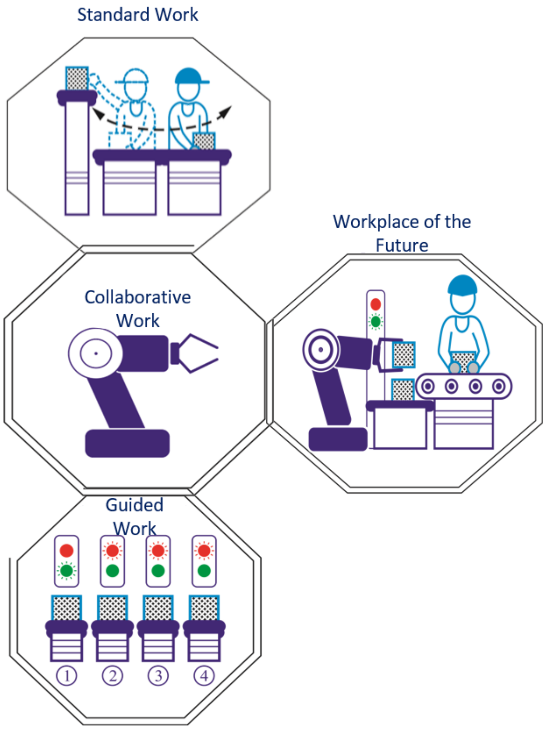


Figure 3.4 – *Conceptualization of the three different scenarios*

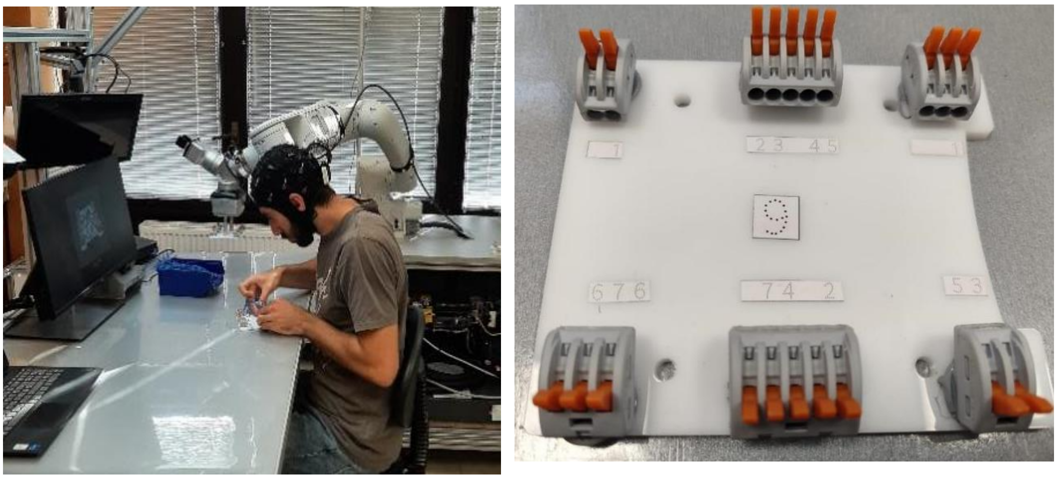
The idea is to lower the level of mental and physical workload during the activity performed by the participants. Based on workstation construction and integrated elements, three basic scenarios could be performed for purposes of workers behavior comparative analyses:

- Standard work - manual assembly ativities are completed without any specific intervention or enhancement at the workplace. Work is done on the workstation "as is" with no intervention from other systems.
- Collaborative work - participants complete work activities collaborating with a cobot, which performs repetitive, uncomplicated tasks that do not involve thinking or decision-making.
- Collaborative Guided work - participants complete the identical labour activities as in the second scenario, but with the addition of the poka-yoke system. The poka-yoke system plays a function in directing operators through the repeated process of assembling parts and components from operation to operation, generating the start of each future phase in a predetermined sequence of steps and thereby preventing human errors.

The three experimental settings are shown in the figures below: I) standard scenario (SS) - Figure 3.5a - in which the participant performed the task without any assistance (the robot) in the workplace; II) collaborative scenario (CS) - Figure 3.5b - in which the participant performed the task engaging with the robot in the workplace; III) collaborative guided scenario (CGS) - Figure 3.6a - in which the participant performed the task collaborating with the robot and was guided all over the task through labels attached to the component defined with with P-Y principles – Figure 3.6b

(**a**) (**b**)

Figure 3.5 – *(a) Standard Scenario (SS). (b) Collaborative Scenario (CS)*



(**a**) (**b**)

Figure 3.6 – *(a) Collaborative Guided Scenario (GCS). (b) Particularity of the third scenario: the presence of P-Y principles through number labels*

In total, the number of tests for each participant is 9 (N_tests = N_participants x N_scenarios = 9).

Each test lasted 90 minutes. The total number of components required to accomplish for each scenario was 75 (N_components). The distribution of the components was random.

The scenarios took place throughout the year, with a minimum timeframe of four months. The reason was to avoid recall bias when comparing the cognitive burden in the three scenarios (Xiao-ming & Jie-fang, 2009). as illustrated in Figure 2.17 through the Ebbingaus curve.

The participants accomplished a replication of an industrial product that is an abstraction of the connection plate which is composed of a metal base made of sheet steel with built-in threaded elements and a transparent acrylic cover connected by an aluminium hinge (three materials combined). For educative reasons, the prototype is lightweight, has no sharp edges, and is made of plastic (see Figure 3.7a). The designed job reminded wire-harnessing operations performed in manufacturing workplaces (Figure 3.7b).

(a) (b)

Figure 3.7 – *(a) Assembly components used for the laboratory experiments. (b) Components in real case scenarios*

This task, which is similar to wire-harness assembly activities, was chosen due to a limited amount of research studies on the neuroergonomic analysis of these activities when supportive technology, such as robots, are used. These harnesses are widely utilised in several kinds of industries, including car, aircraft, electronics, and industrial machinery. The assembling procedure is thorough, necessitating accuracy and attention to detail. These activities necessitate a combination of manual dexterity, attention to detail, and the ability to understand complex wiring diagrams. Some components of wire harness installation might become repetitious, resulting in mental fatigue and decreased attention over time. This monotony can actually increase the cognitive work needed to maintain constant performance. Automation has been used in some elements of wire harness assembly, although much of the labour is still done manually due to the complicated and customised nature of many wire harnesses (Navas Reascos et al., 2022).

Following their arrival, participants got familiar with the materials and surroundings. Each candidate received clear instructions on how to complete the assessments, and as well as an explanation of the activity's aim. Then they were fitted with the EEG cap and allowed to sit in the adjustable ergonomic work chair. The steps were same in all situations. Initially, each applicant was trained for 15 minutes prior to the start of the activity in all the scenarios, in accordance with the experiment procedure. To avoid memory bias, the participant did not engage with the robot during the collaborative scenario training session. Following the training phase, in all circumstances, the individual began the tests after resting for 5 minutes as a baseline.

The temperature was kept constant at 23 ± 1.5 °C throughout the studies. The tests were conducted in the morning, beginning at 9 a.m.

To reduce the possibility of electrical interference, the computer linked to the EEG device via Bluetooth was set to the maximum distance. Smartphones and other electronic devices were kept outside of the workstation. Moreover, no one was permitted to enter the laboratory during the experiments. To ensure that the results were unaffected, these criteria were same for the three scenarios. The assembly tasks accomplished by the participants consisted of different steps performed in the three scenarios:

1. Take the plate placed on the right side of the participant and correctly place it in front of the participant on the work desk of the workstation. In the first scenario, the plates are grouped in groups and put on the operator's right side of the manual

assembly desk. In the other circumstances, the cobot delivered the plate to the operator on the right side, then entered the manual assembly area and waited for the participant to finish the work. The cobot arranged the plate for the participant to take. Throughout this phase, ergonomic concepts were employed to allow participants to grip the component without overextending their arms (Stanton et al., 2012).

2. Take seven wires from the container, one by one, set in the assembly area, and connect them to the plates. The connections were illustrated by a graphic from the mounted PC touchscreen. The participant did not know which order scheme would display on the monitor. To eliminate bias in the results, the connection between the schemes was randomised. In the first scenario, the participant accomplished the task without any external assistance in the assembly area. As opposed to in the collaborative scenario, as the operator built the scheme, the robot returned to pick up and transport the other scheme to the location where the participant would retrieve it. Moreover, in the collaborative guided scenario, the participant was instructed to complete the task using the labels associated with the schemes in order to avoid errors.
3. Set the plate on the slide located to the left side after having performed the task and touch the PC touchscreen to progress to the next scheme.

3.4 COLLABORATIVE SCENARIO

In the collaborative scenario, the industrial cobot used for the tests was the MELFA ASSISTANT from Mitsubishi Electric, shown in Figure 3.8 (Mitsubischi Electric).

Figure 3.8 – *Mitsubishi MELFA ASSISTA cobot*

The Mitsubishi MELFA ASSISTA is a cobot built to work alongside humans in various industrial and manufacturing settings. The MELFA ASSISTA is built to ensure safe operation around humans. It typically includes safety features such as collision detection and compliant movement, which allow it to stop or adjust its path when it encounters an obstacle, including a human co-worker. This makes it suitable for shared workspaces without the need for traditional safety barriers. These cobots have user-friendly programming interfaces, and they may occasionally be controlled and programmed using touch panels or handheld training devices. This makes them accessible to operators who need substantial robotic programming skills. Furthermore, MELFA ASSISTA cobots are often developed for a variety of tasks, including assembly, inspection, material handling, and packaging. Their versatility makes them appropriate for a wide range of operations in a number of industrial settings. Despite being collaborative and user-friendly, these cobots maintain the precision and efficiency that Mitsubishi Electric's industrial robots are known for. They can complete assignments with high accuracy and consistency in quality.

The MELFA ASSISTA's design often focuses on space-saving and ergonomic characteristics, making it easy to integrate into existing workflows and places. These cobots can frequently be combined with various automation systems and technologies, increasing their functionality and versatility in a networked industrial setting.

The MELFA ASSISTA's payload (the weight the robot can carry) and reach (the distance the robot can stretch) are intended to match the requirements of typical collaborative applications. Specific models will have varying specs in this regard.

In connection with safety, integrated safety elements include a robot controller with safety-rated motion supervision, a sensor system to monitor the collaborative workspace, and grippers with pressure control (Figure 3.9). The position controller ensures that the current position always matches the set point of the commanded motion with the smallest feasible difference. Actuators control the robot's position in order to restore its motion following a collision or departure. The impedance control measures the force between the manipulator and the human. The control system supervises the robot's actions and establishes limits to prevent collisions in the environment. This component can manage position, motion, force, and dynamic effects. (Caiazzo et al., 2022).

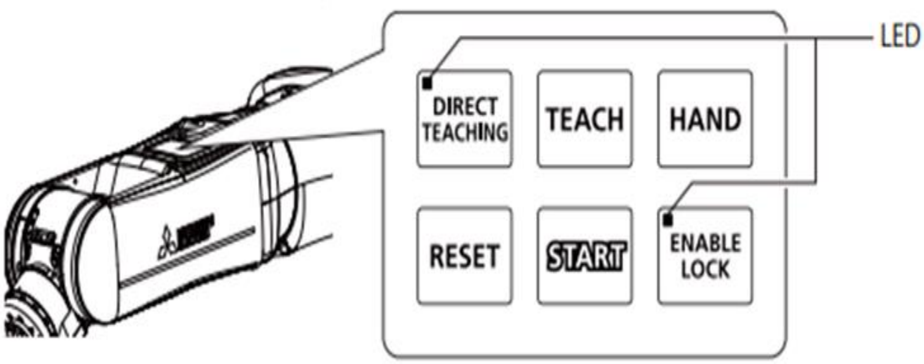


Figure 3.9 – *Mitsubishi MELFA ASSISTA Cobot Architecture*

Authors used RT Toolbox3 for management of a cobot. RT Toolbox3 is a robot programming and simulation software developed by Mitsubishi Electric. It's designed for use with Mitsubishi's range of industrial robots. This software provides a comprehensive suite of tools to aid in the programming, control, and simulation of robotic systems for various applications in manufacturing and other industrial processes. This PC software supports everything from system startup to debugging, simulation, maintenance, and operation (Wang and Chang, 2020). RT Toolbox3 allows users to create, edit, and manage robot programs. It supports a range of programming languages and offers a user-friendly interface for coding and command input. One of the standout features of RT Toolbox3 is its simulation capability. Users can simulate robot movements and operations in a virtual 3D environment. This helps in planning, visualizing, and optimizing robot tasks before actual deployment. The software includes tools for motion planning and trajectory optimization, ensuring that robot movements are efficient, smooth, and safe. It provides diagnostic tools for troubleshooting and debugging robot programs, helping users to identify and resolve issues more efficiently. RT Toolbox3 can integrate with CAD (Computer-Aided Design) software, allowing users to import 3D models of parts and environments. This integration aids in more accurate and realistic simulation and programming. The software usually features a graphical user interface that is intuitive and easy to navigate, making it accessible for users with varying levels of programming experience. RT Toolbox3 supports teaching methods where users can guide the robot to desired positions and record these positions to create a program. It also allows playback of these movements for verification and refinement. It includes safety and compliance tools to ensure that robot operations adhere to industry standards and safety regulations. The software often allows customization to meet specific application needs and is flexible enough to handle a wide range of robotic applications, from simple pick-and-place tasks to complex assembly operations. Finally, RT Toolbox3 can communicate with other industrial systems and devices, facilitating integration into broader automation systems.

The design and implementation of cobots in workplaces are becoming increasingly important due to the myriad benefits they offer in terms of efficiency, safety, and flexibility. Cobots can foster a more collaborative work environment where humans and machines leverage each other's strengths. This synergy can lead to innovative processes and products. The thoughtful design and implementation of cobots are critical in modern workplaces to ensure safety, improve efficiency, and maintain flexibility, all of which are key drivers in the current rapidly evolving business landscape.

The strategic location of the robotic workstation was a crucial factor in the collaborative scenario's design. It was critical to set up the collaborative setting, considering the presence of the participant and other systems in the workstation, respecting the concepts of the comparative analysis. (Arai et al., 2010).

The robot's speed was critical for determining HRC activity because the participant worked concurrently and near the cobot. In this manner, the robot station was positioned 1000 millimetres from the operator. The cobot speed chosen for an HRC work was 250 (mm/s), based on the literature review and the cobot's technological attributes for an interactive activity.

A further significant aspect of the design was selecting the appropriate end-effector to grip the components and allow the robot to interact with its surroundings and the operator in the workplace. The design and functionality of an end-effector are largely determined by the robot's intended application.

Figure 3.10 – *VGC10 Electrical Vacuum Gripper*

The robot end-effector deployed to carry the pieces was the VGC10 Electrical Vacuum Gripper, suitable for HRI activities (VGC10 Electric Vacuum Gripper), as shown in Figure 3.10.

Unlike traditional vacuum grippers that rely on compressed air, an electrical vacuum gripper like the VGC10 is powered electrically. This often makes it more energy-efficient and easier to integrate into various systems, as it does not require pneumatic infrastructure. These grippers are usually designed to be compact and lightweight, making them ideal for use with smaller industrial robots or cobots. Their size and weight allow them to be easily mounted on different types of robotic arms.

An important feature of electrical vacuum grippers is the ability to adjust the suction force. This makes them versatile for handling a wide range of objects, from very delicate to relatively heavy items. Many of these grippers are designed for easy integration with various robot brands and models, offering plug-and-play compatibility.

The gripper applied a pneumatic inner force to identify whether it was holding the item or not. It was selected to pick and position light components with a thin coating. The gripper was also customisable, making it easier for the robot and the human to work together during the gripping phase. In this case study, to pick and carry the light component accomplished by the participant, the limit force set to allow the robot to move again to the initial position was defined as 20 kPa.

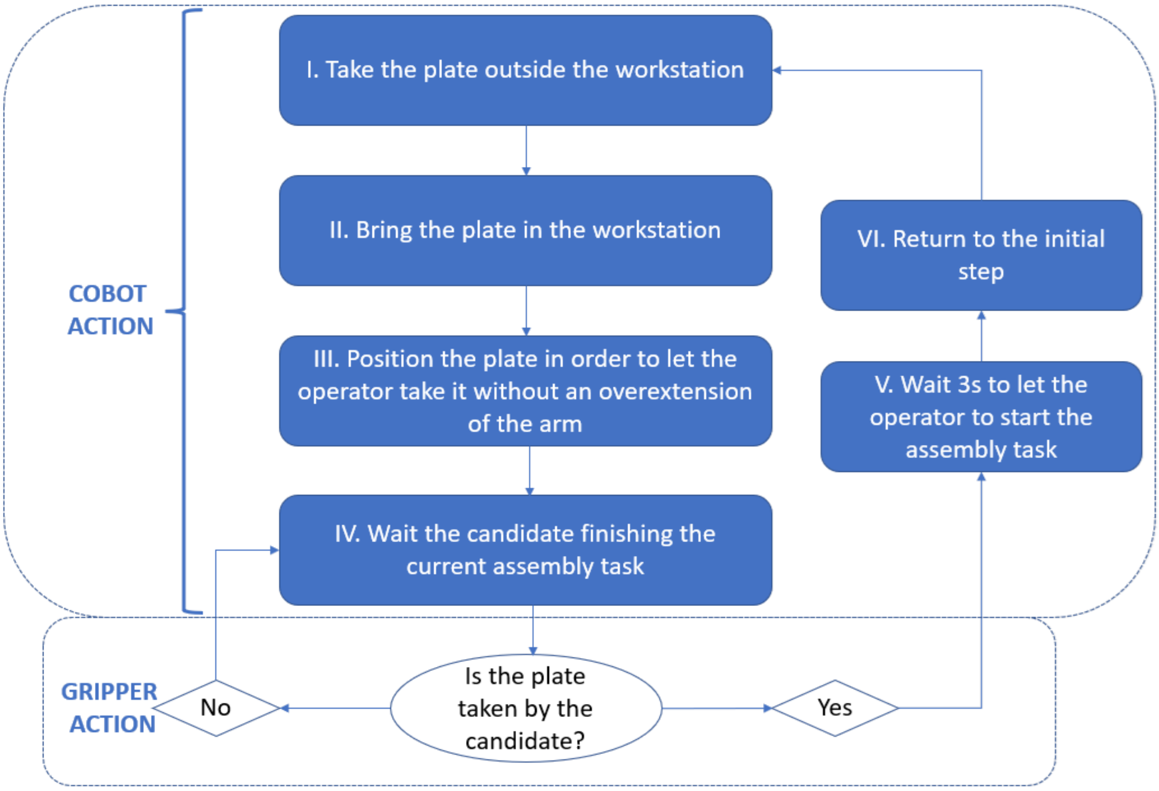


Figure 3.11 – *Sequential collaboration: cobot and gripper action logic (Caiazzo et al., 2023)*

Furthermore, it was designed a logic to define a suitable for human-robot collaborative activity, as shown in Figure 3.11: only once the operator gripped the piece did the robot "understand" to return and pick the other piece. Based on the literature review, the interaction is a sequential partnership (Hjorth and Chrysostomou, 2022).

3.4.1. Risk Assessment for the Implementation of the Cobot

Mechanical risk evaluation for machinery is a systematic procedure aiming at identifying, analysing, and managing the potential sources of damage, or hazards, associated with machine operation, maintenance, and workplace interactions. This procedure is critical for guaranteeing worker safety and health and is an essential component of occupational safety and health management programmes. The purpose is to identify potential hazards that machines may cause and then develop methods to minimise or eliminate these risks (Kozłowski et al., 2023).

A thorough mechanical risk assessment is critical for preventing accidents and injuries, ensuring compliance with legal requirements, and fostering a safety culture in workplaces where machinery is employed. The Machinery Directive (2006/42/EC) specifies the legal criteria for the design and construction of machinery to ensure safety.

The first step involves identifying all the potential hazards associated with the machinery. This includes moving parts that can cause injuries, points of operation, hot surfaces, electrical hazards, and any other aspect of the machinery that could pose a risk to operators or others in the vicinity.

Once hazards are identified, the following stage is to assess the risk associated with each one. This includes the possibility of the hazard causing an injury or accident, as well as the severity of the outcome. Factors such as the frequency of hazard exposure, the number of persons affected, and existing management methods are considered.

The Risk Evaluation process entails comparing the projected levels of risk to preset risk criteria to determine whether the risk is acceptable. Prioritising risks by severity and likelihood ensures that the most significant issues are addressed first.

Based on the risk evaluation, appropriate control measures are identified and implemented to eliminate the hazard, or if that's not possible, to reduce the risk to an acceptable level. The hierarchy of control measures typically starts with eliminating the hazard, followed by substitution with a less hazardous process or material, engineering controls to prevent access to hazards, administrative controls to limit exposure, and personal protective equipment (PPE) as a last resort (Kozłowski et al., 2023).

All findings, decisions, and actions taken during the risk assessment process should be thoroughly documented. This documentation serves as a record of the risk management efforts and can be used for future reference, training, and compliance purposes.

Risk assessments should be reviewed and updated regularly or when there are changes in machinery, processes, or working conditions that could affect the risk profile. Continuous monitoring is essential to ensure that control measures remain effective and to identify any new hazards.

In HRC applications, the risk matrix for risk for mechanical risk assessment is deployed to evaluate the level of safety of the collaborative scenario (Gualtieri et al., 2021).

Severity (Se) is the potential impact of a risk event that should occur. Severity is usually categorized into levels, such as:

1. Minor (e.g., minor injuries requiring first aid like scratches or bruises)
2. Moderate (e.g., injuries requiring medical treatment but not resulting in long-term disability)
3. Major (e.g., serious injuries leading to long-term disability)
4. Catastrophic (e.g., death or multiple serious injuries)

The Risk Class Index (CI) is estimated through the formula:

$$CI = Fr + Fr + Av \tag{3}$$

Where:

- Fr (Frequency): it evaluates the average interval between frequency of risk exposure and its duration and can assume an integer value between two and six. Indeed:
  - 2 - interval between exposure is more than a year.
  - 3 - interval between exposure is less or equal than a year but more than two weeks.
  - 4 - interval between exposure is less or equal than two weeks but more than a day.
  - 5 - interval between exposure less or equal than a day but more than an hour. Where the duration is shorter than 10 minutes, the above values may be decreased to the next level.
  - 6 - interval between exposure is less or equal than an hour. This value must not be decreased at any time.
- Pr (Probabilty): it is the probability of occurrence of a hazardous event and can assume an integer value between one and five. Here:
  - 1 – Negligible: when the possibility of human herror never occurs.
  - 2 – Rarely: Human error is unlikely.
  - 3 – Possible: Human error is possible.
  - 4 – Likely: Human error is likely.
  - 5 – Very high: human error behavior is such that the likelihood of error is very high.
- Av (Avoidance): it is the possibility of avoiding or limiting harm and can assume an integer value equal to one, three or five. Here:
  - 1 – Likely: it is likely that the contact with moving parts behind an interlocked guard will be avoided in most cases.
  - 3 – Possible: it is possible to avoid an entanglement hazard where the speed is slow.
  - 5 – Impossible: it is possible to avoid an entanglement hazard because a part of machine becomes live because of an electrical insulation.

The matrix is divided into three areas:

- The red area: protective measures must be implemented immediately to reduce risk;
- The yellow area: protective measures are recommended to be implemented to further reduce the risk.
- The green area: the risk is considered adequately reduced.

In this regard, considering the collaborative scenario implemented, the suitable values to mark in the risk matrix are:

Se = 1: as the robot speed is set at collaborative mode (250 mm/s) and the component is lightweight and has no sharp edges, the participant might only have scratches during the interaction with the machine.

Fr = 6: the interaction with the robot happens less or equal to 90 seconds.

Pr = 2: the human error would be unlikely. The participant is sat during the whole activity, at a suitable distance from the cobot to avoid the contact during its movement. It could happen that the piece could drop from the cobot’s gripper. However, since the distance between the cobot and the participant is set at a safe value, the probability would be very low. Also, the participant could grasp the component before the end-effector enters the manual assembly task (or golden zone). In this case, through the embedded safety sensors of the robot, there would be a warn signal noise that the piece was removed before the movement of the robot ends. However, the logic of the robot understands this situation and refer that the robot could undergo the next task, returing to its initial position to grasp the next piece. This situation never happened during the experiments. However, we assign a value of 2 as an unlikely possibility of human error.

Av = 1: there are no barriers between the human and the operator, though the avoidance of collision is ensured due to the fact the the participant is in the same position for the whole task and the cobot movement, at low speed and at a reasonable distance determined through safety guidelines, does not interact with the body of the participant.

Thus CI = 6 + 2 + 1 = 9. The risk is adequately reduced, as shown in Figure 3.12.

Figure 3.12 – *Risk assessment matrix for the implementation of the cobot in the workplace (Barbiero, 2019)*

3.5 COLLABORATIVE GUIDED SCENARIO

The purpose of the third scenario is to analyze the MWL of participants through the EEG cap while assembling the components in collaboration with the cobot and through the hints defined with Lean Principles aspects (P-Y) to reduce the human-error.

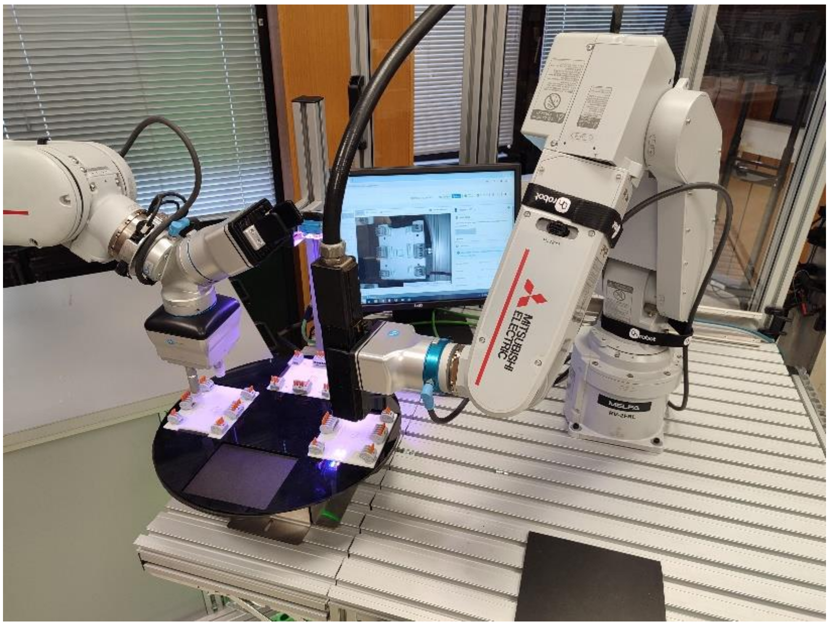


Figure 3.13 – *Collaborative Guided Scenario Set up*

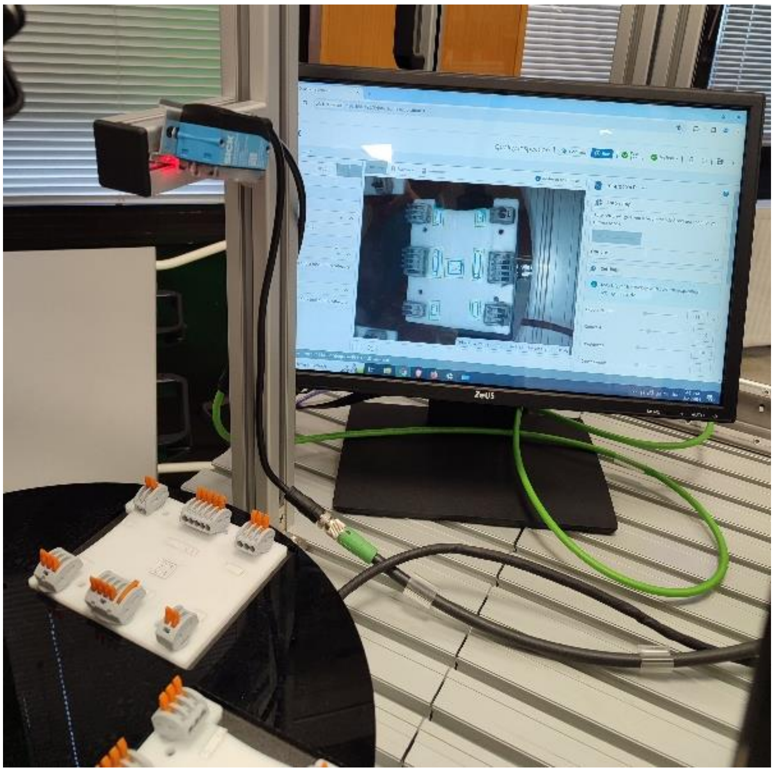


Figure 3.14 – *Quality Inspection Phase*

In this scenario, the assembly task is supported by an automized quality inspection phase in which a second robot carries the component in the Quality Control area to inspect weather the labels printed on the component are correctly placed or not, as shown in Figure 3.13 and Figure 3.14.

Thus, the setup of the Collaborative Guided Scenario (CGS) involved the implementation of other modules in the modular assembly workplace set up for the laboratory experiments. Further modules involved are:

- the Mitsubishi Electric industrial robot RV-2FRL-D-S25: this module is added next to the Melfa Assista cobot to carry the component in the Quality Check Phase before the assembly start is carried out by the participant. The RV-2FRL-D-S25 is a type of industrial robot known as a "6-axis articulated robot." This means it has six degrees of freedom, allowing it to move in multiple directions and angles, like the flexibility of a human arm. The payload capacity of this robot is typically specified as 2 kg.

- the Inkjet printer domino A100: this module is added as end-effector of the Mitsubishi Electric industrial robot RV-2FRL-D-S25 to print the Poka-Yoke labels on the piece to guide the operator during the activity. It uses inkjet technology to spray droplets of ink onto the component.
- SICK Inspector 611: this module is added to the workplace with the function to support the Quality Check Phase of the labels printed by the Inkjet printer domino A100 through the Mitsubishi Electric industrial robot RV-2FRL-D-S25. The inspection is visible on the touch-screen device mounted on the robotic work desk.

4. NEUROERGONOMIC ASSESSMENT AND EEG PRE-PROCESSING

To assess the MWL, both objective and subjective measurements were deployed. Mobile devices are selected based on the tasks to be accomplished, as well as the features and specifications of the workplace. In general, physiological sensors should be deployed to accurately monitor the workers' circumstances. Given their sensitivity to physical activity, not all of them may be selected optimally.

Figure 4.1 shows the EEG cap mounted on the head of participants deployed in the collection and analysis of EEG data for our laboratory experiments. The sensors consisted of sintered Ag/AgCl.

Figure 4.1 – *Electroencephalogram (EEG) gel-based cap (mbrainTrain)*

The data was acquired using electrodes put on the individuals' scalps. Each electrode measured the voltage generated by neural activity in the brain where it was inserted. The EEG data were recorded using the SMARTING wireless EEG equipment. (Fraboni et al., 2021).

The SMARTING wireless EEG system is a technology designed for capturing brainwave data without the restrictions of traditional, wired EEG systems. This system offers a more comfortable and flexible way to record EEG data, making it suitable for various research and clinical applications. One of the primary features of SMARTING is its wireless capability, which allows for greater mobility for the user. The absence of wires connecting the EEG cap to a recording device makes it easier to use in a range of settings, including while the subject is moving. SMARTING is designed to transmit EEG data in real-time, allowing researchers to monitor brain activity as it happens without significant delays. The system's portability makes it suitable for field studies, ambulatory assessments, or studies involving movement, such as walking or performing physical tasks. Despite being wireless, these systems typically maintain a high standard of data quality, with minimal artifacts from movement or interference, which is crucial for reliable EEG analysis (mBrainTrain).

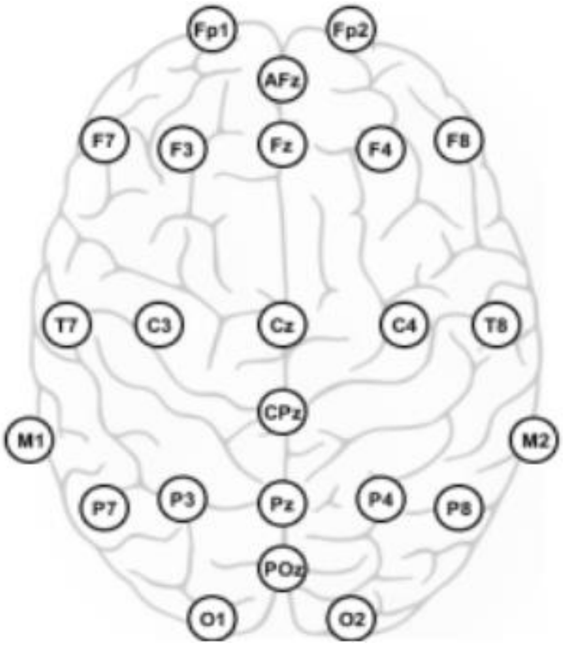


Figure 4.2 – *International 10-20 System – view from the software*

The lightweight EEG amplifier (85 × 51 × 12 mm, 60 g) was securely attached to a 24-channel electrode cap. The SMARTING interacted with the recording computer using Bluetooth. Figure 4.2 illustrates the location of 24 electordes on the software, positioned according to the 10-20 System (Ives-Deliperi and Butler, 2018):

- frontal (Fp1, Fp2, AFz, F3, F7, Fz, F4, F8).
- central (Cz, CPz, C3, and C4).
- temporal (T7, T8).
- parietal (CPz, Pz, P3, P4, P7, P8).
- occipital (O1 and O2).
- midbrain (M1 and M2).

According to the experimental procedure, the required electrode impedance should be below 5 kΩ, which was also specified by the SMARTING software. A reference approach was established for the montage electrode system cap.

Data was obtained using the software SMARTING STREAMER 3.4.3, which enabled a computer to connect with the devices. EEG metrics were evaluated by analysing the neural brainwave pawer ratio (β/α) as markers of stress/engagement or relaxation during the assessments.

The task and participant's activity and EEG data stream were synchronized with Streamer software (version 3.4.3, mBrainTrain) via the Lab Streaming Layer (Kothe et al., 2024).

The Lab Streaming Layer (LSL) is a system developed to capture and distribute time series data in real time during research experiments. It is especially important in neuroscience and psychophysiology research, but it can be used in any domain that demands exact synchronisation of high-bandwidth data streams, such as EEG, motion capture, and other sensor data. LSL is designed for synchronising streaming data from many sources, which is essential for investigations that require the integration of various forms of physiological and behavioural data. It can handle high data rates efficiently, which is critical for neuroimaging approaches that produce vast amounts of data efficiently. LSL supports various data types and is compatible with many different hardware and software systems used in research, making it a versatile tool for experimental setups. Nevertheless, data can be processed in real-time, enabling applications such as biofeedback, neurofeedback, and real-time data visualization or analysis. Finally, LSL is open source, allowing researchers to customize and extend it according to their specific project needs. LSL is widely used in research that requires precise timing and integration of multiple data streams, and it plays a crucial role in advancing the methodologies in fields that rely heavily on complex data collection and analysis.

In Figure 4.3, an illustration of the design of the modules interconnected in the modular assembly workstation designed at the laboratory is shown: the LSL software interconnected the other modules to exchange data (EEG data).

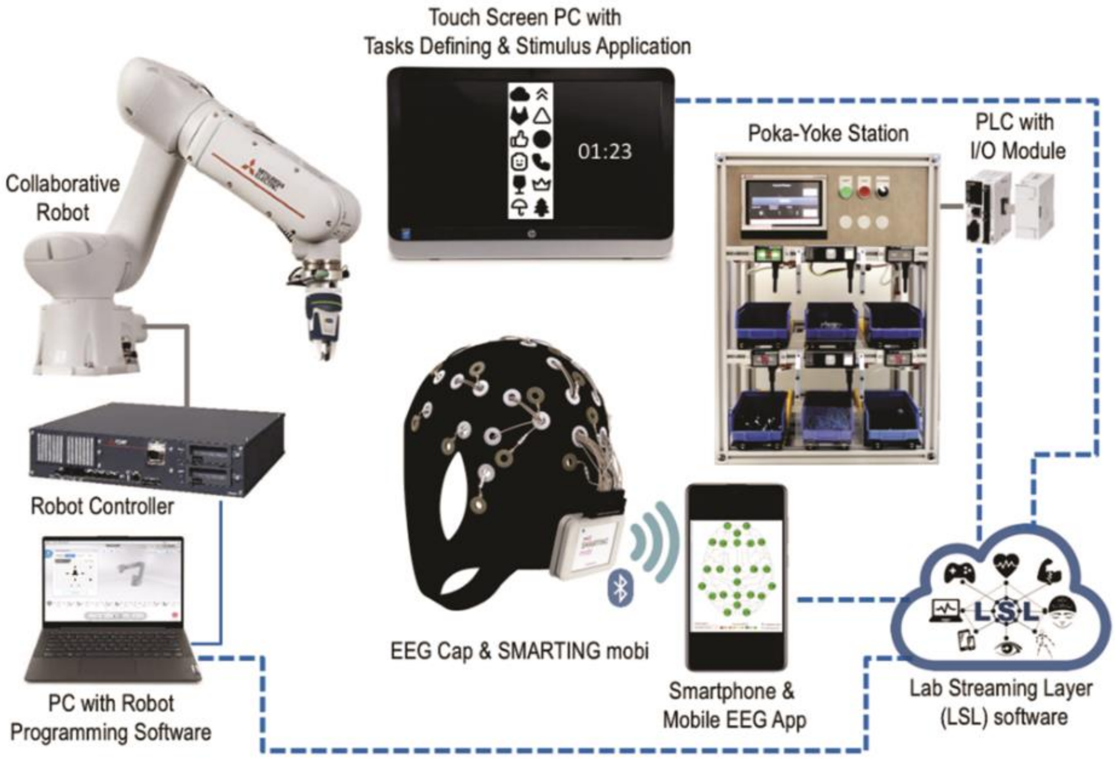


Figure 4.3 – *Set up of the LSL software with other modules (Savkovic et al., 2022)*

In terms of subjective measurement to analyse the MWL, participants completed the NASA TLX at the end of each scenario. The Human Performance Group at NASA's Ames Research Centre created the NASA Task Load Index (NASA-TLX), a widely used subjective workload assessment instrument. It is intended to generate an overall workload score using a weighted average of ratings from six subscales. These subscales represent multiple aspects of perceived burden in tasks, making them useful to a wide range of work environments and scenarios, including aviation, healthcare, and others. The multidimensional subjective assessment assesses the mental, physical, and temporal demands, effort, performance, and amount of dissatisfaction that participants faced during the task in both circumstances. Participants rate each of these dimensions using a scale. The evaluations are then aggregated, typically with varying weights, to generate an overall workload score. This aids in determining how difficult a task was from the user's perspective. The lowest point is 1, and the highest is 10 (Fiorineschi et al., 2020).

In addition, at the end of the tests in the collaborative scenario, participants answered open questions about their collaborative activity with the cobot, its fluency and motion (whether aggressive or not), how safe and comfortable they felt interacting with it, and whether the workplace setting was better in the standard or collaborative scenario.

In terms of performance assessment, a unique checklist was developed to differentiate between correct and incorrect components completed by participants to measure the overall session's efficiency.

4.1 EEG PRE-PROCESSING SET-UP

The EEGLAB 2021.1 toolbox (MATLAB 2021.a) was used for preprocessing and data analysis. EEGLAB is a widely used open-source MATLAB toolbox for processing and analyzing EEG (electroencephalography) data. It is designed for use by neuroscientists, psychologists, and others in the field of brain dynamics research. It EEGLAB offers a graphical user interface (GUI) that allows users to easily navigate through various EEG data processing steps. EEGLAB supports importing data from various EEG data file formats and allows exporting processed data for further analysis or visualization. The toolbox includes functions for filtering, artifact removal, re-referencing, and other preprocessing steps necessary for cleaning and preparing EEG data for analysis (Delorme and Makeig, 2004).

The data were grouped into different frequency bands (Chacon et al., 2021):

- Delta (between 0.5 and 4 Hz): highlighted in a state of sleeping.
- Theta (between 4 and 8 Hz); highlighted in REM phase.
- Alpha (between 8 and 12 Hz): highlighted in an awake state while being concentrated and relaxed.
- Beta (between 13 and 29 Hz): highlighted while being in a state of stress and engagement.
- Gamma (between 25 and 45 Hz): highlighted in a state of processing information and making voluntary movements.

The pre-processing phase of EEG data is a crucial step in EEG analysis, where raw data are cleaned and prepared for further analysis. EEG recordings are sensitive to various types of noise and artifacts, so pre-processing is essential to ensure the data accurately reflects neural activity. The typical steps involved in EEG data pre-processing include (Suarez-Revelo et al., 2018):

- Filtering:
    - High-Pass Filtering: Removes slow drifts in the data, often caused by physiological processes like breathing.
    - Low-Pass Filtering: Eliminates high-frequency noise, which can be caused by electronic equipment or environmental factors.
    - Band-Pass Filtering: Keeps frequencies within a specific range, often used to isolate certain types of brain waves (e.g., alpha, beta, delta, theta waves).
- Artifact Removal:
    - Eye Blink Artifacts: Eye blinks and movements create large artifacts in EEG data. Techniques like Independent Component Analysis (ICA) are often used to identify and remove these artifacts.

  - Muscle Artifacts: Muscle movements, especially facial muscles, can also produce artifacts. These are typically higher frequency signals and can be reduced using filtering and ICA.
  - Electrode Popping: Sudden, large spikes in the EEG signal due to electrode movement or bad electrode contact are identified and removed.
- Re-Referencing: EEG data are usually recorded with respect to a reference electrode. Changing this reference (re-referencing) can be useful for highlighting certain aspects of the EEG signal.

Common average referencing or using a linked mastoid reference are popular methods.

- Downsampling: Reducing the sampling rate of the data (if it’s higher than necessary for the analysis) to decrease the data size and computational load.
- Segmentation: Dividing continuous EEG recordings into shorter epochs or segments, often time-locked to specific events (event-related potentials or ERPs).
- Baseline Correction: Adjusting the EEG signal by a baseline value, usually taken from a period where no experimental stimulus is presented, to account for background brain activity.
- Normalization: Scaling the EEG data to a certain range or distribution, which can be useful for comparing subjects or conditions.
- Bad Channel Detection and Repair: Identifying and interpolating data from EEG electrodes that were not functioning correctly during the recording.
- Time-Frequency Analysis (if applicable): Transforming the EEG data to analyze both time and frequency domains, useful for studying brain oscillations and event-related spectral perturbations.

In this methodology, a sample rate of 250 Hz was utilised. Pre-processing EEG signals often entails filtering the signal to remove artefacts such as eye movements, muscle tension, and noise. This study evaluated the MWL using the power ratio (β/α). (Ismail and Karkowski, 2020; Pusica et al., 2024).

Noise was reduced using a band-pass filter with a frequency range of 1-40 Hz. The discovery of poor channels enabled intervention in channels that were not collecting high-quality signals.

In this case, because the EEG cap included more channels in different parts of the scalp, it was possible to interpolate these channels with those near the scalp's area of interest. Matlab's artefact subspace reconstruction (ASR) technique allowed to detect and eliminate artefacts like eye movements and muscle strain. Finally, the independent component analysis (ICA) was performed to separate the signals into additive and independent components (Kaliraman et al., 2022).

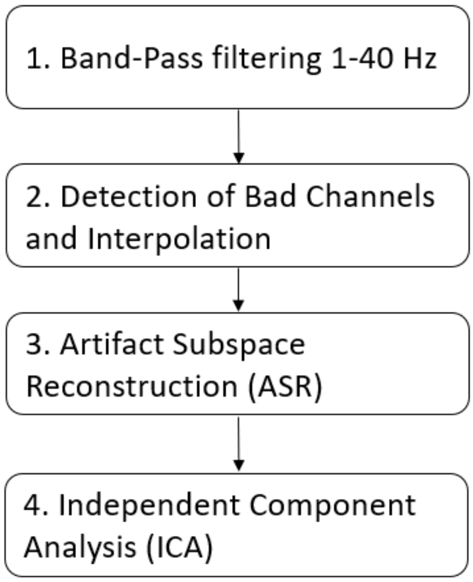


Figure 4.4 – *Flowchart of the EEG pre-processing phase (Caiazzo et al., 2023)*

A representation of the steps of the EEG pre-processing phase designed for the tests is shown in the flowchart, in Figure 4.4.

4.1.1. Significance of the Results through Statistical Analysis

Finally, to define the significance of the results, the data collected were evaluated through the statistical analysis.

In statistical analysis, the p-value, also known as the probability value, measures the degree of evidence against a null hypothesis. It is utilised in hypothesis testing to establish the statistical significance of an experiment's outcomes (Di Leo and Sardanelli, 2020).

If the p-value is less than a preset threshold (alpha level, which is often set at 0.05), the result is considered statistically significant. This suggests that the observed data would be extremely implausible under the null hypothesis, indicating support for the alternative hypothesis.

A small p-value (usually ≤ 0.05) suggests significant evidence against the null hypothesis. Therefore, you reject it. A large p-value (> 0.05) suggests weak evidence against the null hypothesis. Thus, you are unable to reject it.

In statistical hypothesis testing, the null hypothesis (H0) is a broad statement or default position that there is no relationship between two observable events or no association between groups. On the other hand, the alternative hypothesis (H1 or Ha) may be something you desire to test or validate. It implies that there is a connection or effect.

The p-value is determined using statistical methods and represents the likelihood of receiving an observed outcome, or one more extreme, assuming that the null hypothesis is true. This calculation frequently requires the use of a statistical test, such as a t-test, chi-square test, ANOVA, etc.

The p-value should be considered in the context of the study. Other factors, such as the study design, sample size, and real-world significance, should also be considered.

4.2 MENTAL WORKLOAD RESULTS THROUGH THE EEG ANALYSIS

The MWL index of the participants in the three setting conditions was evaluated in three consecutive parts of the tests, each one of 30 minutes, and is presented in the Figure 4.5 below, from the Table 4.1, Table 4.2, and Table 4.3:

Table 4.1: Mental Workload Index (MWL) - Standard Scenario (SS).

Candidate Number	1st parts SS	2nd part SS	3rd part SS
1	0.772474606	0.692860351	0.704460397
2	1.041756482	0.99235386	0.975106769
3	1.009762146	1.021124855	1.028503097
4	1.281920772	1.364712446	1.369240439
5	0.735837045	0.680604662	0.656824445
6	1.164515278	1.128745483	1.13843409
7	1.060649624	1.002879283	0.926139392
8	1.009762146	1.021124855	1.028503097
9	1.033699144	1.052905738	1.026548916
10	1.164515278	1.128745483	1.13843409

Table 4.2.: Mental Workload Index (MWL) - Collaborative Scenario (with robot - CS).

Candidate Number	1st part CS	2nd part CS	3rd part CS
1	0.769286117	0.683612302	0.613492
2	0.693132066	0.677324776	0.5973241
3	1.061111957	1.045100041	1.036104363
4	1.289545341	1.259335851	1.131426059
5	0.47350241	0.408151724	0.399456098
6	1.213856242	1.163920243	1.15775252
7	0.851468278	0.83068285	0.794087422
8	0.961111957	0.845100041	0.836104363
9	0.930194153	0.922699171	0.918183756
10	1.013856242	1.003920243	0.95775252

Table 4.3.: Mental Workload Index (MWL) - Collaborative Guided Scenario (with robot and P-Y design – CGS.

Candidate Number	1st part CGS	2nd part CGS	3rd part CGS
1	0.46818577	0.449082462	0.414646928
2	0.495741994	0.483022635	0.451628618
3	0.86263258	0.806475383	0.78148261
4	0.875375896	0.765949765	0.759658133
5	0.29292757	0.279212989	0.257896826
6	0.96223297	0.862404235	0.821719726
7	0.718651768	0.654736041	0.631027896
8	0.807322625	0.781813941	0.734006918
9	0.685569252	0.680237227	0.630932719
10	0.706210034	0.675140146	0.647749013

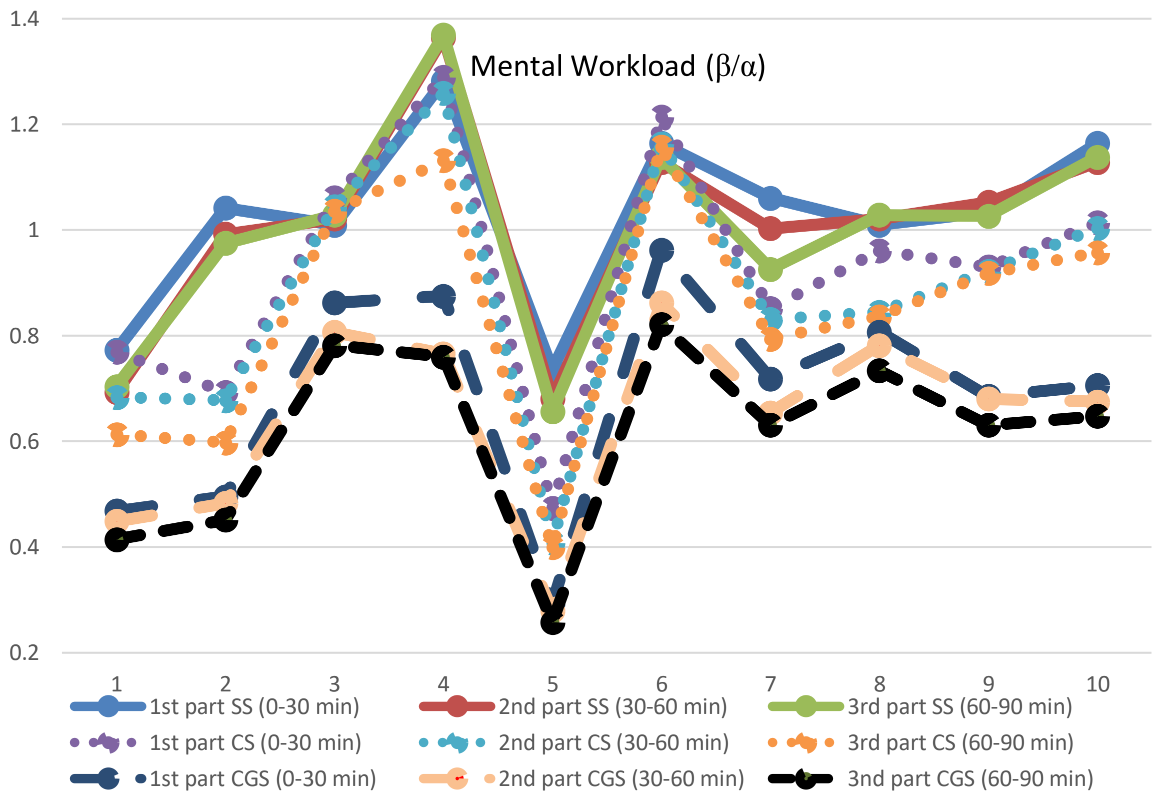


Figure 4.5 – *Mental Workload (Y-axis) over the participants (X-axis), in three consecutive parts (30 minutes each) analysed in the standard (SS – highlighted in dashes), collaborative scenario (CS – highlighted in scatters), and collaborative guided scenario (CGS – highlighted in dashes)*

Figure 4.5 shows that in the SS, the MWL fell somewhat during the exercise. Subjects 4 and 6 showed an increase in power ratio (β/α) during the second and third part of the test. ANOVA RM - $\alpha = 0.05$ - yielded P-value = 0.194, F = 2.459, and F_crit = 3.633. In the normal case, the MWL between the three test portions is not substantially different (P-Value > α), hence the null hypothesis cannot be rejected (H = H0).

In contrast, in the CS, all participants' MWL dropped along the activity. The ANOVA RM analysis ($\alpha = 0.05$) yielded a P-value of 0.00005, F value of 19.32, and F_crit of 3.633. The collaborative scenario resulted in a substantial drop (P-Value < α) in MWL across all three tests, rejecting the null hypothesis (H≠H0).

Finally, in the collaborative guided scenario (CGS), the MWL of the participants is the lowest compared with the other scenarios. From the ANOVA RM analysis ($\alpha = 0.05$), P-Value = 0.00003, F = 15.42, F_crit = 2.633. In the collaborative guided scenario, the MWL significantly decreased (P-Value < α) along the three parts of the tests observed and the null hypothesis is rejected (H≠H0).

Considering the variation between the overall parts of the two sessions, the MWL difference (Diff) is defined in Figure 4.6, from Tables 4.4, Table 4.5, and Table 4.6.

Table 4.4.: Mental Workload Index (MWL) difference - Standard Scenario (SS).

Candidate Number	Diff 2nd-1st parts SS	Diff 3rd-2nd parts SS	Diff 3rd-1st parts SS
1	-0.079614255	0.011600045	-0.06801421
2	-0.049402622	-0.017247092	-0.066649714
3	0.011362709	0.007378243	0.018740952
4	0.082791674	0.004527993	0.087319667
5	-0.055232382	-0.023780217	-0.079012599
6	-0.035769794	0.009688607	-0.026081188
7	-0.057770342	-0.07673989	-0.134510232
8	0.011362709	0.007378243	0.018740952
9	0.019206594	-0.026356822	-0.007150228
10	-0.035769794	0.009688607	-0.026081188

Table 4.5.: Mental Workload Index (MWL) difference - Collaborative Scenario (with robot - CS).

Candidate Number	Diff 2nd-1st parts CS	Diff 3rd-2nd parts CS	Diff 3rd-1st parts CS
1	-0.085673815	-0.070120302	-0.155794117
2	-0.01580729	-0.080000676	-0.095807966
3	-0.016011916	-0.008995678	-0.025007594
4	-0.030209489	-0.127909792	-0.158119281
5	-0.065350686	-0.008695625	-0.074046312
6	-0.049935999	-0.006167722	-0.056103722
7	-0.020785428	-0.036595428	-0.057380856
8	-0.116011916	-0.008995678	-0.125007594
9	-0.007494982	-0.004515415	-0.012010397
10	-0.009935999	-0.046167722	-0.056103722

Table 4.6.: Mental Workload Index (MWL) - Collaborative Guided Scenario (with robot and P-Y design - CGS).

Candidate Number	Diff 2nd-1st parts CGS	Diff 3rd-2nd parts CGS	Diff 3rd-1st parts CGS
1	-0.019103308	-0.034435534	-0.053538843
2	-0.012719359	-0.031394017	-0.044113376
3	-0.056157198	-0.024992773	-0.08114997
4	-0.109426131	-0.006291632	-0.115717764
5	-0.013714581	-0.021316164	-0.035030744
6	-0.099828734	-0.040684509	-0.140513243
7	-0.063915727	-0.023708145	-0.087623873
8	-0.025508684	-0.047807023	-0.073315706
9	-0.005332025	-0.049304508	-0.054636533
10	-0.031069888	-0.027391133	-0.058461021

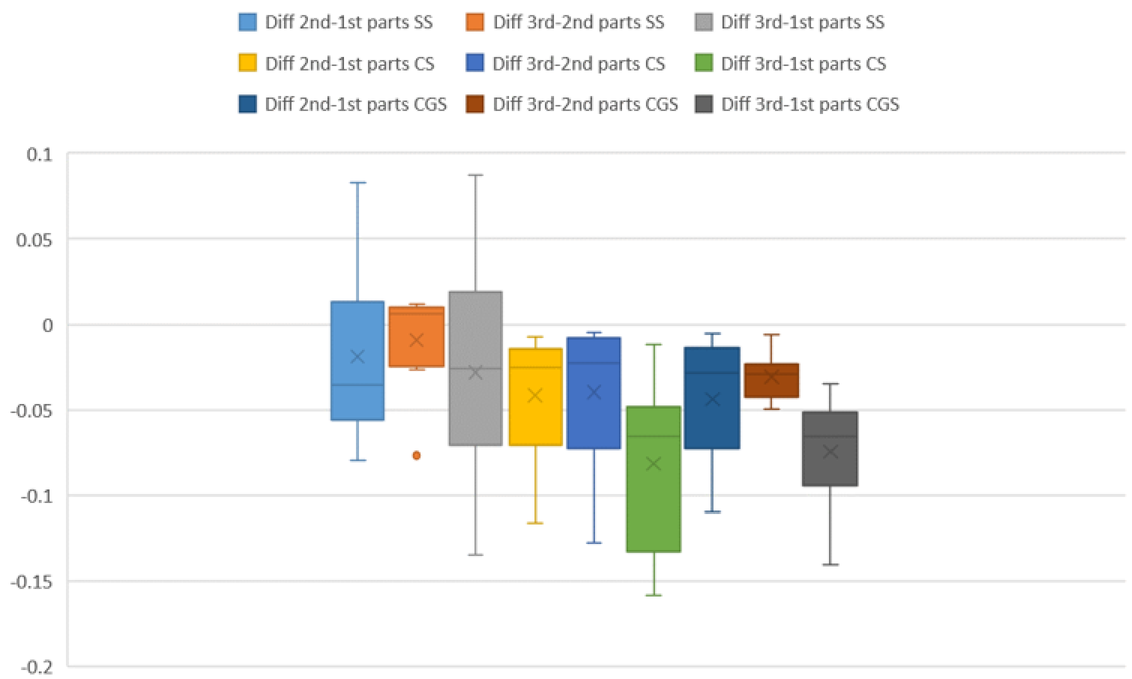


Figure 4.6 – *MWL variation (Y axis) between the three consecutive parts of the task session (30 minutes each) analyzed in the three scenarios*

ANOVA RM (α = 0.05) yields P-value = 0.0001, F = 6.367, and F_crit = 2.449. MWL differs significantly among parts (P-Value < α), rejecting the null hypothesis (H≠H0). To summarise, based on the statistical analysis of the various phases during the activity, the general tests in CS and CGS showed a more substantial drop in the participants' MWL than the SS. To clarify, an outlier is defined as the difference in MWL between the third and second halves of the standard scenario experiments. It signifies that the statistical analysis in the SS is inconsistent with the results of MWL in this scenario, emphasising a not sifnificant variance between the two portions.

5. SUBJECTIVE AND OBSERVATIONAL MEASUREMENTS

In this Chapter, it is shown the results through the NASA TLX given at the end of the tests to the participants. The evaluation is defined through the Tables 5.1-5.6.

Table 5.1.: NASA TLX – Mental Workload level results of the participants in the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	How mentally demanding was the task? SS	How mentally demanding was the task? CS	How mentally demanding was the task? CGS
1	7	4	3
2	5	4	2
3	6	4	3
4	9	7	5
5	7	6	4
6	8	6	3
7	6	5	4
8	9	7	3
9	7	5	2
10	8	6	4

Table 5.2.: NASA TLX – Physical Workload level results of the participants in the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka -Yoke design - CGS).

Candidate Number	How physically demanding was the task? SS	How physically demanding was the task? CS	How physically demanding was the task? CGS
1	8	6	3
2	6	5	4
3	1	1	2
4	6	5	3
5	5	5	3
6	6	4	3
7	6	6	3
8	3	1	2
9	6	5	2
10	7	6	4

Table 5.3.: NASA TLX – Temporal Demand level results of the participants in the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	How hurried was the task? SS	How hurried was the task? CS	How hurried was the task? CGS
1	10	10	5
2	7	4	4
3	6	5	3
4	7	6	4
5	7	7	5
6	7	5	4
7	8	8	3
8	8	9	5
9	7	6	3
10	8	5	3

Table 5.4.: NASA TLX – Performance level results of the participants in the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	How successful was the task? SS	How successful was the task? CS	How successful was the task? CGS
1	4	5	9
2	9	8	9
3	9	9	10
4	5	6	9
5	8	5	9
6	6	8	8
7	8	9	9
8	8	9	10
9	7	7	10
10	7	8	8

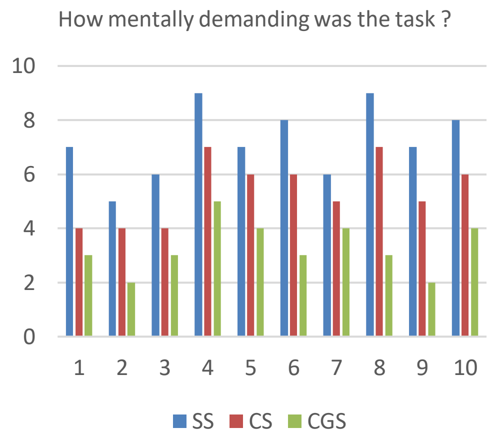
Table 5.5.: NASA TLX – Effort level results of the participants in the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	**How hard did you have to work? SS**	**How hard did you have to work? CS**	**How hard did you have to work? CGS**
1	10	8	5
2	2	2	2
3	4	3	2
4	8	7	4
5	6	6	3
6	9	7	4
7	10	10	5
8	3	1	1
9	6	5	3
10	8	6	4

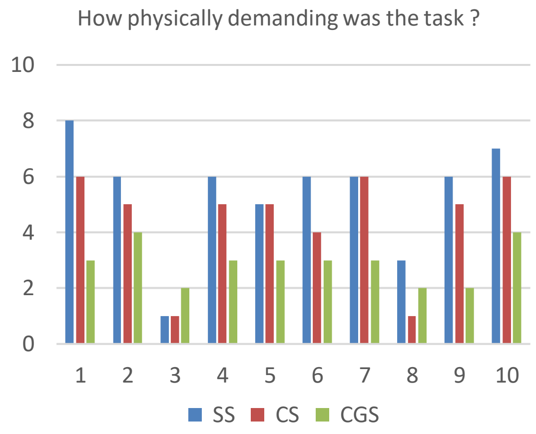
Table 5.6.: NASA TLX – Frustration level results of the participants in the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	**How stressful was the task? SS**	**How stressful was the task? CS**	**How stressful was the task? CGS**
1	7	5	3
2	3	2	2
3	1	1	1
4	7	5	3
5	6	6	2
6	6	3	2
7	7	7	2
8	7	5	3
9	3	2	2
10	6	5	4

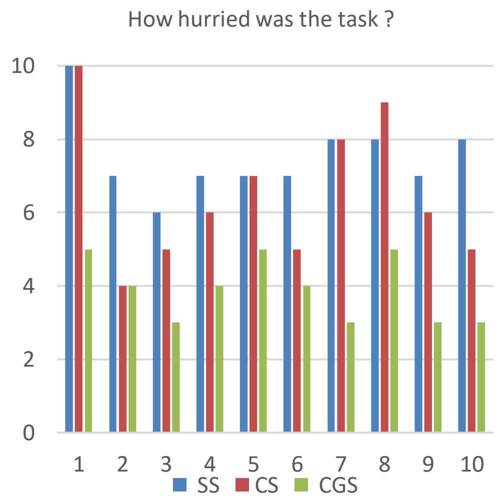
The graphic representation of the NASA TLX results from the tables is shown in Figure 5.1 below.



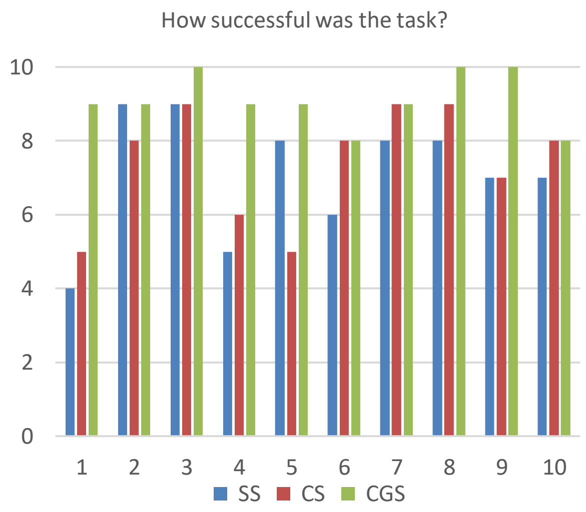
(a)



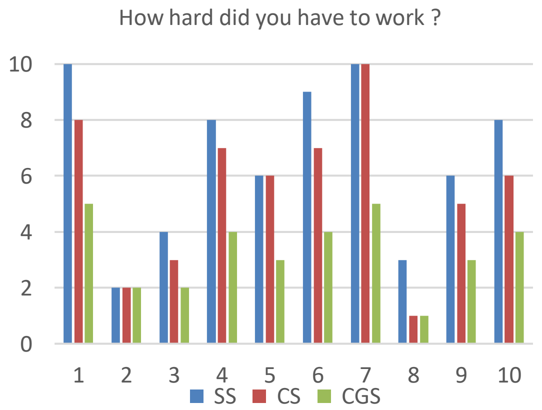
(b)



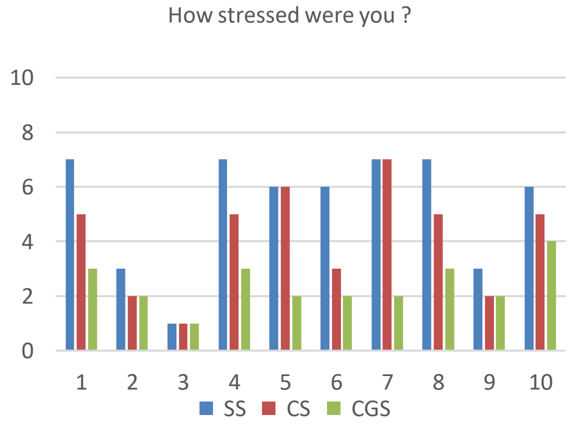
(c)



(d)



(e)



(f)

Figure 5.1 – *NASA TLX results in the three scenarios over the participants (X axis): (a) Mental workload; (b) Physical workload; (c) Temporal Demand; (d) Performance; (e) Effort; (f) Frustration*

The NASA TLX T-test comparing three scenarios ($\alpha = 0.05$) revealed: (a) Mental Demand, P-Value = 0.0004; (b) Physical Demand, P-Value = 0.08; (c) Temporal Demand, P-Value = 0.088; (d) Performance, P-Value = 0.046; (e) Effort, P-Value = 0.0085; and (f) Frustration, P-Value = 0.01.

The NASA TLX data show no significant difference in Physical Demand (P-value> α) between standard and collaborative situations, supporting the null hypothesis (H=H0). The T-test analyses of Mental and Temporal Demand, Effort, Performance, and Frustration revealed significant differences (P-value < α) across the three situations, leading to the rejection of the null hypothesis. In keeping with the EEG study, the NASA TLX demonstrated a lower level of MWL of the participants in the collaborative scenario versus the conventional scenario without the cobot.

In addition to the NASA TLX, at the conclusion of the experiments, participants were asked additional direct open questions about their experience with and without the robot, its fluency motion and trajectory (whether predictable or not), how safe and comfortable the interaction with it was, and whether the workplace setting was better in the standard or collaborative scenario. According to the answers of the participants, the assembly task with the robot resulted in a safer and more comfortable way to pick the plate from the gripper.

Also, the interaction was deemed more educational and pleasant. In terms of motion, the participants did not feel terrified when the robot moved, and its response when they seized the pieces from the gripper was not aggressive. Furthermore, the absence of plates on the work station, where the participant installed the component, was regarded more positively in the collaborative situation. The applicants had more room to assemble the component and were more confidence in their ability to complete the assignment, as they felt less distracted. Nevertheless, the candidates felt more at ease executing the work in the collaborative guided scenario. The connection with the robot and the support of the labels, which guided the participants along the tasks, allowed the participants to perform the assembly tasks more successfully, as show also in the NASA-TLX. Finally, in the CGS, the level of mental stress of the candidates dropped, according to the objective measurement through the EEG analysis in which the values of MWL are the lowest among the three scenarios.

Table 5.7.: Number of components accomplished by the participants in the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	N. components accomplished in SS	N. components accomplished in CS	N. components accomplished in CGS
1	48	62	75
2	39	64	75
3	60	72	70
4	49	54	73
5	52	61	73
6	40	46	75
7	34	65	69
8	45	55	75
9	65	74	75
10	43	60	69

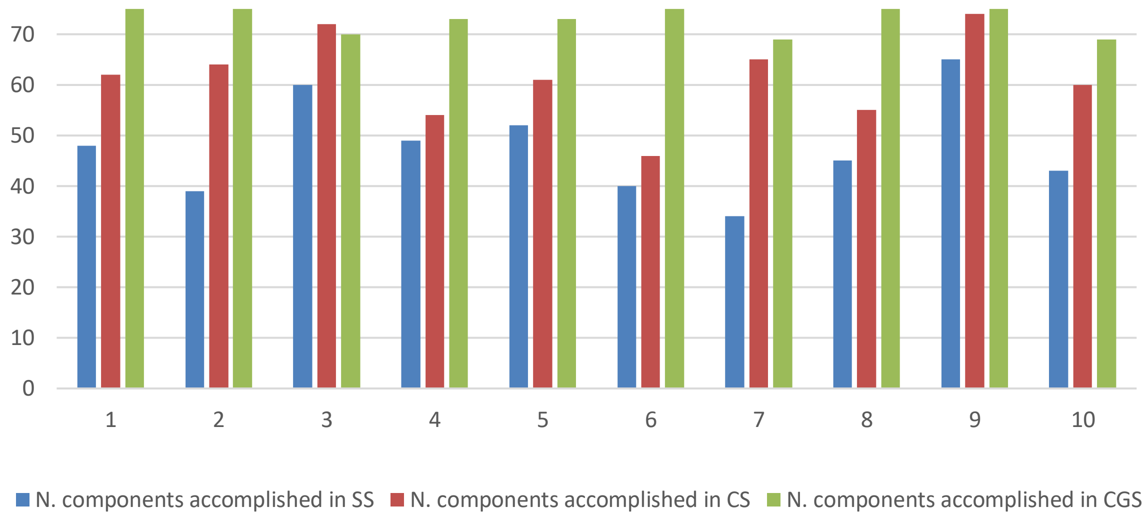


Figure 5.2 – *Number of assembly components accomplished correctly in the three scenarios – Y axis – over the participants – X axis*

According to the observational study conducted using the checklist on the participants' performance in the three scenarios, the candidates completed the task more successfully in the CS and GCS than in the SS, as indicated in Table 5.7. The T-test examination of performance comparing three scenarios yielded a P-value of 0.00018 ($< \alpha = 0.05$). Figure 5.2 shows that the CS and CGS completed significantly more pieces during the challenge.

The time required to complete the work did not differ between the SS and CS (Time Tests: 90 minutes); see Table 5.8 and Figure 5.3. This is also consistent with the Temporal Demand subjective measurement examined in the NASA TLX.

Table 5.8.: Time of the task accomplished by the participants to complete the tests the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	Time Task SS	Time Task CS	Time Task CGS
1	90	87	80
2	87	85	80
3	88	83	79
4	85	84	82
5	90	83	75
6	90	82	77
7	86	80	78
8	90	85	80
9	87	83	74
10	89	82	73

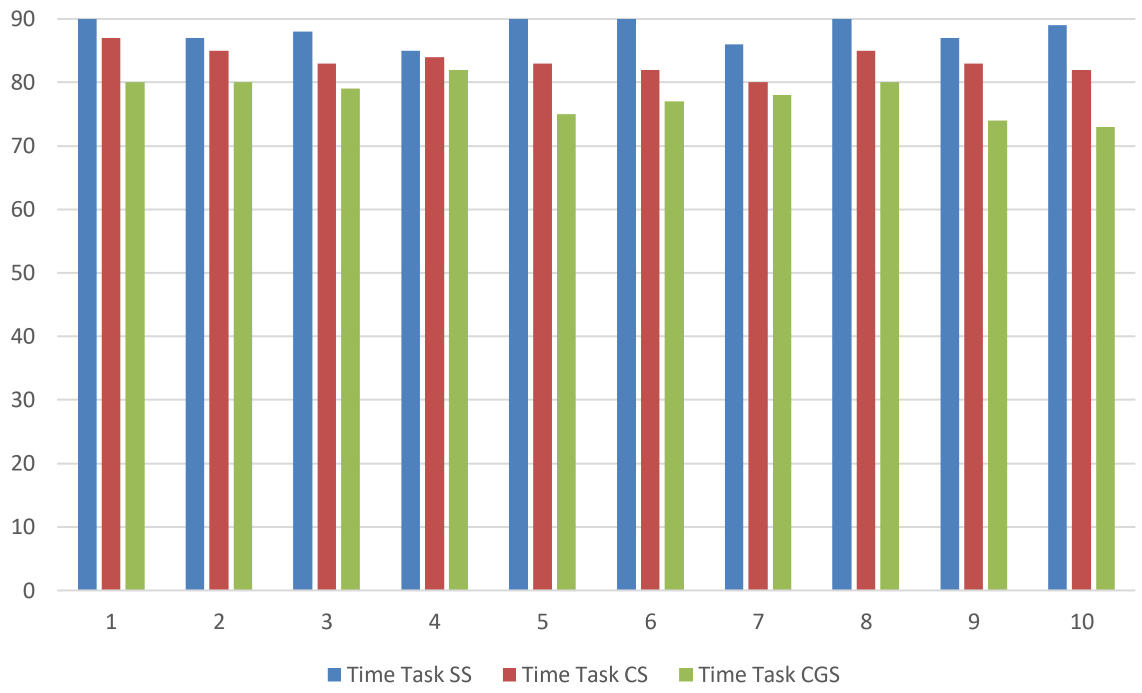


Figure 5.3 – *Time Task in the three scenarios – Y axis – over the participants – X axis*

To conclude this section, it was evaluated the efficiency index, expressed as the number of pieces correctly assembled over time in percentage defined through the Table 5.9.

Table 5.9.: Productivity index achieved by the participants to complete the tests the three scenarios (Standard Scenario – SS, Collaborative Scenario with robot – CS, Collaborative Guided Scenario with robot and Poka-Yoke design - CGS).

Candidate Number	Productivity SS (%)	Productivity CS (%)	Productivity CGS (%)
1	53.33	71.26	93.75
2	44.82	75.29	93.75
3	68.24	86.74	88.6
4	57.64	64.28	89.02
5	57.77	73.49	97.33
6	44.44	56.09	97.4
7	39.53	81.25	88.46
8	50.0	64.7	93.75
9	74.71	89.15	98.67
10	48.31	73.17	94.52

From the table, the Figure 5.4 shows the graphic representation of the efficiency index in SS, CS and CGS. The figure indicates that the efficiency in the scenarios with the robot, CS and CGS, is improved compared to the SS. Furthermore, in the CGS, participants accomplished the task better than in the CS, improving the quality of the assembly task.

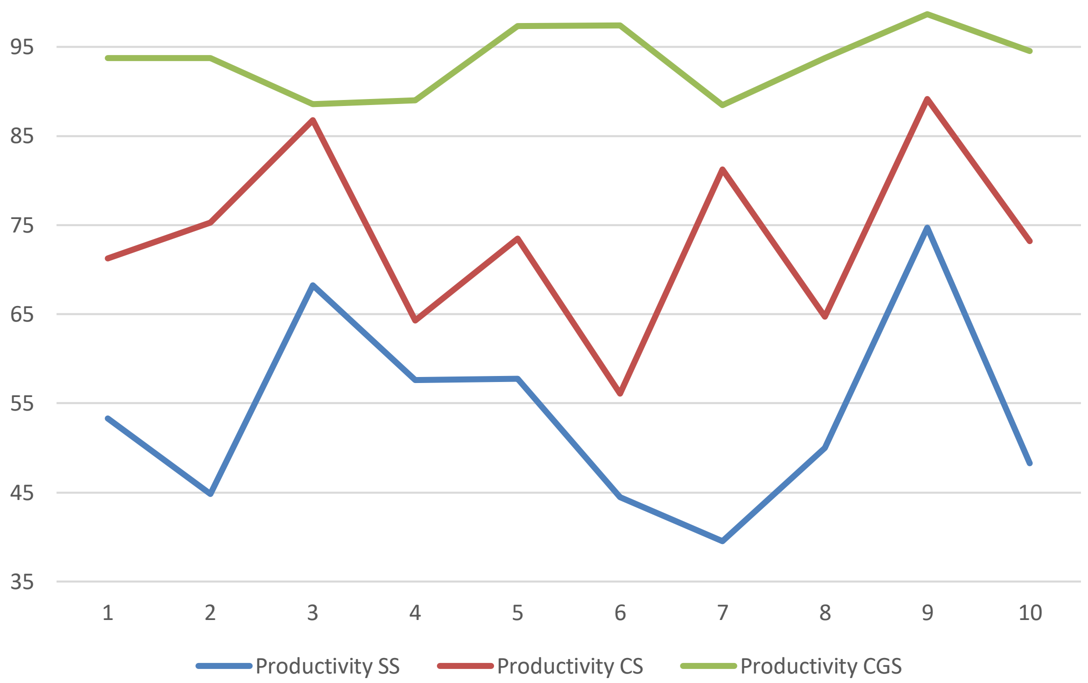


Figure 5.4 – *Productivity Index (in %) in the three scenarios – Y axis – over the participants – X axis*

6. DISCUSSION AND IMPLICATION OF THE WORK

MWL, assessed by EEG as the power ratio β/α (Beta - stress indicator, Alpha - relaxation indicator), was considerably lower in the CS and CGS compared to the SS. In the ordinary case, the MWL did not change considerably after three consecutive periods. However, some participants showed an increase in the power ratio β/α, comparable with Fraboni et al. (2021). In the other two cases, MWL declines more during the workday. In the second and third phases of the CS, the reduction of the MWL is larger, which is consistent with earlier research (Zakeri et al., 2021).

These findings showed up to be consistent with the subjective analysis, which was carried out using the NASA TLX, in which measurements of Mental Demand, Effort, and Frustration indicated a significant decrease in these parameters pointed out by the participant during tasks with the robot, in line with previous research (Ochoa, 2002; So et al., 2017; Katmah et al.). Nonetheless, there was no significant variation in Physical and Time Demands between the three scenarios. One probable reason is that the participant accomplished the activity while seated in the chair throughout the test, and the physical stress was equal in all three scenarios. In terms of time demand, interacting with the cobot did not minimise the time required to complete the entire task. This is also consistent with the average time completion of the components to assemble, which was the same in both cases. In CGS, the time demand was even lower than in the SS and CS to complete the tasks, and participants felt relaxed when working with the robot, which is also consistent with the significant reduction of the MWL. (Fraboni et al., 2021).

Finally, the checklist revealed a greater level of performance in terms of successfully completed components in the CS and CGS, in contrast to prior findings (Simone et al., 2025). To corroborate this, in the NASA TLX, participants reported more success in the collaborative activity with the cobot. Overall, the combination of these metrics revealed that the participants performed better in completing the work in the collaborative setting in terms of ergonomics and task performance.

Our results are consistent with prior study, which found that an HRI task performed better ergonomically than a standard manual assembly task (Fraboni et al., 2021; Gualtieri et al., 2022). Furthermore, this research is congruent with additional studies to improve the performance of HRI applications in industrial manufacturing environments (Colim et al., 2021).

In the framework of comparative analysis, the authors carefully developed the CS, and thus the CGS, regarding the design of the cobot module implementation, such that it did not alter the other systems involved, which were previously present in the SS. The purpose was to investigate the variance in MWL in each setting condition, using the single cobot as a distinguishing factor between the scenarios. The implementation of the cobot in the workplace followed a strict design of the workstation to install the cobot station while keeping safety considerations (Valori et al., 2021).

Furthermore, for the comparative study, it was appropriate to involve the same participants for assessments in all three scenarios to enable an accurate comparison of the results and to determine how the cobot intervention affected collaborative work. To the best of our knowledge, this is the first study to compare human performance with MWL in a comparative assessment with the same number of participants and the only discriminant being the cobot engaging with people in the workplace for an industrial HRC task.

Regarding the number of participants, the sample size was evaluated through ANOVA RM within factors in the G*Power tool, as shown in the previous sections of the design of experiments. Furthermore, the number of candidates engaging in a long laboratory session (90 minutes) and reported for this comparison research, conducting the tests in three scenarios (N_tests = 30), is comparable to HRI tasks for ergonomic assessment research (Gualtieri et al., 2021).

The methodology implemented in this study indicates the feasibility and validity of blending EEG data with subjective measurements (NASA TLX) and observational measures (checklist) in HRC tasks. The use of EEG is growing rapidly due to its suitability, effectiveness, and practicability in many circumstances (Katmah et al., 2021).

Manual assembly operations, such as wire harnessing, remain an obstacle in industrial processes. This has prompted the investigation and study of HRC systems that enable operators to work alongside robots. Thus, understanding the MWL in HRC is crucial (Chowdhury et al., 2020). However, the method of using wireless, real-time, objective metrics like EEG in industrial HRC tasks to define the MWL in terms of brainwave activity is still in its early phases (Zhou et al., 2022).

Certain authors have provided a strategy for measuring MWL in smart factories. However, the efficacy of these tests revealed no significant difference between a scenario without and with the robot (Villani et al., 2022; Caterino et al., 2023). Other research analysed MWL exclusively using subjective assessments (Fraboni et al., 2021; Gualtieri et al., 2022).

Compared to prior studies, this study presents an effective technique, with results demonstrating a reduced level of MWL and stress (EEG and NASA TLX) and a higher level of performance in terms of correctly created components (checklist). Furthermore, the purpose of our research activity is to determine an effective evaluation of MWL by a neuroergonomic assessment through analysing MWL utilising different measures.

The study was carried out in three distinct scenarios, each with the exact same number of participants, to evaluate the MWL of people working with and without the robot. Other studies looked at the cobot's contribution to HRI tasks with different groups of participants or a single group but with a range of tasks (Simone et al., 2021; Gualtieri et al., 2022). For the sake of the comparison and retain the cobot as the only distinguishing factor between the three situations, it was reasonable to choose the identical number of participants.

This study had limitations and issues. The study began with volunteers from the Faculty of Engineering at the University of Kragujevac in Serbia. Candidates with technical and analytical skills may be more eager to work with cutting-edge technology like the cobot while wearing the neuroergonomic EEG caps (Lin et al., 2007). This may explain why the participant felt more competent in dealing with the cobot.

Furthermore, participants who took the examinations in a collaborative setting may have had a better understanding of the task that had previously been completed in the standard scenario. We cannot completely exclude the chance that this will affect the research study's performance and be a constraint.

To eliminate memory bias, participants took the test four months after the tests in the typical situation, which is comparable with other research findings showing that a shift of brain memory is lost after one month (Xiao-ming and Jie-fang, 2009). Recruitment was also a difficult task. In the SS, twice as many people were recruited for the tests as were described in this article. Many students were reluctant to engage in the following CS and CGS for personal or academic pursuits because the three scenarios were held at different times.

In the literature evaluation, the MWL parameter (β/α) was found to be the most important in predicting participants' cognitive burden in three scenarios. Other studies employed different brainwaves, such as Theta waves, to evaluate the MWL (Hopko et al., 2022). However, the selection of a stress indicator remains contested (Ismail and Karkowski, 2020; Eyam et al., 2021; Panchetti et al., 2023). This is why, in this study, the scientists combined the quantitative analysis via the EEG with subjective assessments to define the fluctuation of the operator's cognitive traits in the three scenarios.

Finally, during the test preparation phase, it took a while to set up and mount the EEG neuroergonomic hat. Due to the layer of gel on the electrodes, participants had to wait 20 to 30 minutes before mounting the EEG hat. Bringing up EEG devices remains a time-consuming process. The primary problem was to administer gel in the electrodes to ensure adequate contact with the scalp.

However, the most innovative EEG devices can avoid this issue by using unique electrodes that do not require the gel, saving time during the setup process. Regarding the job duration (1.5 hours), we chose this period for MWL categorization because time is one of the limitations in MWL analysis. A shorter time frame may not have been enough to guarantee the quality of EEG data for MWL analysis. Longer time, on the other hand, may have altered memory bias and thus task performance. Furthermore, the more prolonged duration may have decreased the number of participants who were unable to administer the exams due to personal or academic obligations.

Although the outcomes are significant, it should be noted that the research was conducted in a controlled environment, such as a laboratory. Participants completed the activities in all three conditions while sitting in an enclosed workplace. However, motion artefacts and noise are usually dominating in industrial activities, and their presence may influence EEG collection.

In terms of experimental contexts, laboratory experiments fail to account for certain possible variables found in real manufacturing systems, such as temperature, noise, and the worker's sense of responsibility for the production process's success or unexpected breakdowns, all of which can have an impact on stress. As an added benefit, laboratory simulations allow for the use of the most sensitive measurements that would not be appropriate for use in a working environment, because their high sensitivity would result in the recording and collection of data that is heavily influenced by artefacts and is insufficient for reliable analysis.

However, measurements in manufacturing environments are constrained by the company's production process. Some production-process variables that may influence workers' stress levels, such as line speed or time constraints, cannot be examined since variations can have a significant impact on actual production flow, reducing corporate efficiency and productivity. As a result, measurements in real situations may be less precise and detailed than those in laboratories (Blandino, 2023).

Furthermore, environmental factors play a crucial part in stress assessment. Thermal discomfort, a new type of stress for workers, can result from both high and low temperatures (Mansi et al., 2022). Thermal discomfort, when combined with normal noise levels in real-world industrial settings, affects not only workers' physiological processes but also their subjective perceptions of stress (Abbasi et al., 2020; Gnecco et al., 2023). Furthermore, noise and bad lighting conditions cause errors in information perception during task execution (Ahmad et al., 2015).

The evaluation of these aspects may aid in the prevention of health problems and physical damage to workers, but it may also have a positive impact on the company's productivity (Mura and Dini, 2023).

Finally, worker-specific criteria such as gender, age, competence, experience, or background may be addressed in a more comprehensive study. There have been a few studies linking demographic variables to specific stress markers. This demonstrates that there is a gap in the literature that must be filled.

7. CONCLUSION

The deployment of cobots in manufacturing processes and work systems has increased in recent years. The rising deployment of these technologies in fenceless industrial areas has motivated researchers to investigate the operator's cognitive workload when interacting with the robot. Wearable sensors are being utilised to investigate the human reaction in terms of cognitive effort.

The goal of this PhD dissertation is to demonstrate the viability of assessing participants' workloads through a thorough analysis of subjective (NASA TLX), objective (EEG), and observational (checklist) measurements, comparing participants' mental workloads in three distinct situations performed in a laboratory setting. We designed three different scenarios: a standard scenario in which participants had to carry out random manual assembly tasks without any external intervention; collaborative scenario in which the participant had to carry out the assembly task along with the robot; and collaborative guided scenario in which the participants worked alongside the cobot and received instruction through P-Y labels.

The scenarios with the involvement of the cobot are developed with ergonomics and safety in mind, with the cobot embedded into the modular workstation so that participants can engage without affecting the location or involvement of other equipment. The goal of this study was to examine if the mental workload index parameter could be significantly employed to distinguish the participant's mental workload across the three scenarios. Lower mental workload levels were identified in activities involving the cobot utilising a variety of measurements. Furthermore, the observational study shows an improvement in productivity in both the collaborative and guided collaborative settings.

Regarding the proof of hypotheses defines at the beginning of this PhD dissertation:

H1 - The implementation of collaborative robot solutions can reduce the level of mental workload (MWL) during work activities.

H2 - Reducing the level of mental workload improves the efficiency, effectiveness, and quality of work activities.

H3 - It is possible to define mental workload through objective sensorial devices and measurement.

H4 - The use and implementation of collaborative robots has subjective positive impact on workers during work activities.

For the H1, it has been empirically showed that the implementation of cobots in the workplace, considering ergonomic and technical aspects to ensure a proper collaboration alongside the operator, has brought a significant reduction of MWL, proven with ANOVA statistical analysis, through the combination of objective (EEG) and subjective measurements (NASA-TLX). The proof of this hypothesis still presents some limitations. Firstly, the analysis was carried out for a sample of participants ($N = 10$). The chosen sample, though it was proper for the analysis under certain conditions, is still poor to define a thorough understanding of MWL trend in a HRC task. Further analysis should be addressed for a larger sample of participants.

Secondly, to adhere to the stipulated comparative evaluation, the same participants completed the task in all three scenarios over a minimum of four months. Whereas research investigations in the field of Neuroergonomics demonstrated that this timeframe was suitable for not having a memory bias of an activity performed by humans, the studies were only empirically shown. To the greatest extent of our knowledge, this is the first study to compare human performance and MWL in a comparative analysis with the same number of participants and the sole discriminant being the robot engaging with them in the workplace for an industrial HRC task.

For the H2, it has been shown that the reduction of MWL improves the level of efficiency, effectivity, and overall, quality of the task. The number of components accomplished by the participants over the time task, thus the productivity of the task, was shown to be higher when participants worked alongside the cobot. Specifically, in the third scenario, the level of productivity highly soared than in the standard scenario without the cobot.

Regarding the H3, it has been showed that through objective sensorial devices it was possible to evaluate MWL. The deployment of EEG paved the way to a real-time, efficient, non-invasive neuroergonomic analysis of MWL. Different parameters could be extracted to evaluate MWL.

Among the the power ratios presented in the literature review, the MWL parameter (β/α) was the most significant in determining the cognitive burden of participants in three situations. In other research, other brainwaves, such as theta waves, were used to analyse the MWL. However, today, the selection of a stress indicator is disputed. Furthermore, setting up and installing the EEG neuroergonomic hat took time during the test preparation period. Due to the gel on the electrodes, participants had to wait 20 to 30 minutes to mount the EEG cap. Indeed, setting up EEG devices remains a time-consuming operation.

For the H4, subjective evaluations such as the NASA-TLX and surveys revealed that the deployment of cobots had a favourable impact on participants during the assembly activity. According to the participants' responses, the assembly activity with the robot made it safer and more pleasant to take up the plate from the gripper. Furthermore, the encounter was deemed more educational and pleasurable. In terms of motion, the participants did not feel terrified when the robot moved, and its response when they seized the pieces from the gripper was not aggressive.

FUTURE RESEARCH

This research study opened the door for the neuroergonomic analysis of MWL in HRC. Further studies should be addressed in the evaluation of MWL through other efficient measurements to have a comprehensive analysis of its trend. The combination of these measurements would be suitable for a thorough understanding of the cognitive demands of operators in a HRC task. Furthermore, the ongoing research would consider the relationship of mental workload with physical workload. Further comparative analyses would allow to define hoe the physical workload trend evolves compared to the MWL in the HRC tasks. For this analysis, the deployment of electromyogram (EMG) sensors would be suitable for the analysis. Like the EEG, this measurement offers a real-time, efficient, compact, and non-invasive analysis of the physical demand of the operator in different parties of the bodies of participants while performing the task. The design of the system necessary to use, record, and interpret EMG data would be crucial to define the level of physical fatigue and to assess the relationship with the MWL.

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ANNEX 1: EXPERIMENT SET-UP PROTOCOL

- ASSEMBLY OF THE CAP:

1. Check whether the cap is well washed (there is no gel residue on the electrodes).

2. Put the cap on the head and confirm that it is centred.

3. Connect the amplifier to the cap connector.

4. Connect the amplifier in the SmartingStreamer3.4.3 software.

5. Select a sampling frequency of 250 Hz.

6. Select Measure impedance on ref to measure the impedance on the reference.

7. Start data streaming.

8. Fill the 3 electrodes with gel: the DRL white electrode, the left or right electrode of the DRL electrode, and the last REF blue electrode. Aim for the reference impedance in the software to show ideally less than 5 kOhms, and maybe up to 10 kOhms (must be light green and stable).

9. Stop streaming.

10. Select Measure impedance to measure impedances on all electrodes and start streaming.

11. Fill one electrode at a time with gel so that they are light green and stable.

12. After mounting, turn off streaming and select No impedance measurement.

13. Select the gyro data option.

14. Start streaming and view the EEG signals in the Show signals window.

- RECORD FILE (there is a video with the same instructions):

15. Run the experimental script depending on the task in the queue (.exp).

16. In the SmartingStreamer3.4.3 software, press the Record button

17. In the recording window, click on the refresh streams button

18. select the EEG stream

19. Select the Presentation stream.

20. Choose the location and name of the file. Start recording.

21. Run the experimental file by clicking the Run button.

NOTE: If no sound is heard, immediately stop the experiment, and record the file. Go to the Sound Settings of the computer and change the Output Device.

22. After the experiment, stop recording the file in SmartingStreamer3.4.3 software. If there were lost data, write down how much and for which file!

ANNEX 2: QUESTIONNAIRE FOR PARTICIPANTS

1. How was the experience with and without the robot?

2. How was the robot motion fluency in the interaction? (Predictable or not)

3. How safe and comfortable was the participant during the interaction?

4. Were you satisfied with the experience?

5. Did you feel an aggressive motion from the robot?

6. Was better the desk without the schemes next to you?

AUTHOR’S BIOGRAPHY

Carlo Caiazzo was born on April 11, 1995, in Naples, Italy. Carlo received his Bachelor of Science degree in Mechanical Engineering (ECTs 180) in November 2017 at the University of Naples Federico II, Italy. At the same University, he achieved the master’s degree in mechanical engineering for the Design and Production (ECTs180), successfully defending the experimental thesis about the analysis of the materials’ viscoelastic behaviour through Machine Learning Regression analyses. Nonetheless, during his academic studies, he was actively involved in Erasmus projects in Naples, taking part in an Erasmus national association. From March to September 2021, he pursued an internship toward a start-up, spin-off from the University of Naples Federico II, Italy.

Since November 2021, he is enrolled in the European Marie Sklodowska-Curie project, CISC (Collaborative Intelligence for Safety Critical Systems - Grant Number 955901). In the project, he focuses on the architecture to acquire real-time physical ergonomic assessment in the workplaces of the future. His subject is connected to the question of the overall architecture of the system that will be necessary to record and interpret physiological data for physical ergonomic assessment in Industry 4.0/ 5.0 settings for everyday tasks.

• **Spoken languages**

Italian - native

Neapolitan - native

English - advanced

Serbian - intermediate

Spanish - intermediate

• **Other skills**

General: Strategic planning; Strong cultural behaviours; Operations coordination; Analytical thinking; Team leadership; Makes others better; Goal-oriented

• **Stays and training abroad**

1. Secondment at IMR (Irish Manufacturing Research) in Mullingar, Ireland
2. Secondment at PILZ in Cork, Ireland

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