# Master thesis

# Consideration of Ergonomic Aspects in Human-Robot Task Allocation Methods

carried out for the purpose of obtaining a Double Degree Master by EIT Manufacturing Master School in the specialization People and Robots for Sustainable Work (PR) with partner universities Mondragon Unibertsitatea (Entry University) and Technische Universität Wien (Exit University)

under the supervision of

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Faculty of Engineering

from


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Vienna, October 2023 Manisha Vijay Sampat

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Vienna, October 2023

Manisha Vijay Sampa

# Acknowledgement

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# Abstract

Human Robot Collaboration (HRC) has opened opportunities of task sharing between human and robots under an open workspace in manufacturing environment. Traditional task sharing philosophy in human robot teams have followed the leftover approach, where human is assigned task which are difficult for robot to perform. Contemporary research is now increasingly centered on developing flexible and adaptive task allocation strategies that ensure equitable sharing. However, majority of the algorithms present today still lack the focus on overall human well-being. The aim of this work is to consider human factors in task allocation. It addresses this in three folds: first addressing the task analysis and assignment that includes a thorough study of the factors to be considered for task allocation and the methodology used. The factors for analysis range in the focus from human, robot, process, and production perspective. Secondly, visualizing the task allocation strategy using digital tool Ema Work designer and finally the evaluation framework for ergonomics. This study therefore develops an algorithm and evaluation method designed to consider human factors in task allocation. The evaluation framework was tested on a ski assembly process, showcasing comparison of the ergonomic evaluation: physical and cognitive in two different case scenarios. Physical ergonomics details on the Ergonomic Assessment Worksheet (EAWS) score pertaining to load, posture, and repositioning score. The cognitive ergonomics framework defines a Mental Workload Index (MWLI) considering task demand, level of performance, level of resources, level of information processing, and level of decision making.

**Keywords:** Human Robot Collaboration, task allocation, ergonomics, Ergonomic assessment worksheet, Mental Workload Index

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# 1 Introduction

## 1.1 Motivation and Relevance

Collaborative robots, or cobots, are becoming increasingly popular in various industries, including manufacturing, logistics, and healthcare over the past decade. This rise is fuelled by the increasing demand for flexible, efficient, and safe manufacturing and assembly processes. With the wave of Industry 4.0, collaborative robots and adoption of collaborative processes has gained attention. It has played a significant role in promoting the use of collaborative robots, as it emphasizes the integration of digital technologies and automation in manufacturing. According to the International Federation of Robotics (IFR) report in 2022, the installations of collaborative robots have increased by nearly 50% between 2020 and 2021 and the same report predicts that by end of 2023 the sales of collaborative robots will reach 160,000 units per year, representing a Compound Annual Growth Rate (CAGR) of 30.4% [1].

The adoption of collaborative robots has revolutionized the way humans and robots interact and collaborate in manufacturing. Unlike traditional industrial robots that work behind safety barriers, collaborative robots work alongside humans, sharing the same workspace and tools. These features are making collaborative robots more appealing to industry and several businesses [2][3]. Collaborative robots are more affordable and easier to program than traditional industrial robots, making them accessible to small and medium-sized enterprises (SMEs)[1] that may not have the resources or expertise to implement industrial robotic solutions. However, the limited pay-load capacity and speed make them a choice limited to medium load type assembly and manufacturing. The lower price of collaborative robot arms in comparison to industrial robot is an alluring factor in manufacturing [5], however we still see the adoption of collaborative robots less in comparison to the traditional industrial robots, posing a gap and question of ways in which human and collaborative robots collaborate effectively [6]. An empirical study on adoption of collaborative robots in Portugal and France in six companies show that lack of enhanced operational efficiency and de-railing ergonomics are a blocker for industry to have an organizational shift to collaborative robots [7].
Human-robot collaboration has become an increasingly important aspect of modern manufacturing, with various processes used today to facilitate collaboration between humans and robots. Currently, the most prominent use of collaborative robot in the industry is for assembly applications [8] which desire the most extend of collaboration between the human and robot. With the technical improvements in sensing, actuation,

[1] Small and Medium size enterprises are defined so basis the number of employees, turnover and financials in the balance sheet [4]

and artificial intelligence, more use cases of human robot collaboration have surfaced. However, major challenges in such interaction are the reconfigurability, safety, ergonomics, and task flexibility [9]. Task allocation methods have been a topic of research to gain interest of the industry and resolve the challenges faced in Human-Robot Collaboration (HRC), however, the prevalent method of task allocation between the human and robot is the traditional 'leftover approach'[10]. There have been several research interests in exploring more feasible, dynamic and capability based complementary task allocation methods [11]. These methods define task allocation based on the 'best fitting' approach but are rarely applied in the industry. The leftover approach poses threats in lack of worker satisfaction due to low task diversity and no specific focus on worker cognitive and physical load. Musculoskeletal disorder (MSD)[2] is a common collateral effect observed in three out of five workers in the industry as per European Agency for Safety and Health at Work (EU-OSHA) [12]. As methods of dynamic task allocation are popular research areas in the past of couple of years, ergonomics and worker safety is now gaining interest. Nevertheless, there exists a gap in devising task allocation methods that are optimized based on worker discretion and ergonomic safety level to reduce the MSDs. The goal of this research is to understand, identify and implement task allocation methods in human robot teams[3] that utilize the situation of environment and task at hand, human and robot capability and focus on balancing the physical and cognitive load on worker.

## 1.2 Problem definition and research questions

With the inception of Industry 4.0 and new technologies (including collaborative robots), the demand for highly trained individuals and workers has increased and so is the need for increased safety and employee well-being. According to the EU Strategic Framework on Health and Safety at Work 2021-2027 [14] "*Nobody should suffer from job-related diseases or accidents. It is also an important aspect of both the sustainability and competitiveness of the EU economy".* Irrespective, MSD remain the highest reason for work-place related injuries or disorder in the EU and contribute to about *60*% of the total injuries or disorders [16]. It also elaborates that about three in every five workers in the EU28[4] countries report backache or muscular pain in upper limbs. Due to the workdays and productivity lost due to MSDs, Germany lost about

[2] As per OSHA, Musculoskeletal Disorder (MSD) is a condition that affect the muscles, nerves, blood vessels, ligaments, and tendons [13]

[3] Human robot teams are defined as *"humans and robots, who perform joint tasks, share common goals, interact socially and exhibit task interdependencies." [14]*

[4] EU28 refers to countries in the European Union namely, Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden, (including the United Kingdom (UK), however from February 2020 onwards it is called as EU27 [18]

€17.2 Billion in production loss in 2016. It has therefore become a focus in the EU to work towards and adapt towards improving the working conditions of the industries. This has forced the businesses to adopt a human-centric design approach for their new processes and workplaces [17]. According to ISO 9241-210 [19], a human centric design is defined as *“an approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and applying human factors/ergonomics and usability knowledge and techniques”.* It aims at providing more comfortable and accessible workspace for the worker to be able to focus on their desired effectiveness for prolonged time. Industrial and collaborative robots served as a mean to aid human in substituting for tasks that were repetitive, unsafe, or compromised human ergonomics in the long term. However, this does not hold true for the current scenario in the industries, the task sharing between human and robot is carried out mainly on the approaches of leftover tasks where the human is allocated tasks that are either difficult to be automated or require higher investment in automating and therefore serve as an economical substitute[10]. Human and robot collaboration was introduced also as a mean for enhancing human talents [2] with the aim of enhancing on the pros of individual member of the team. This is completely defied currently by the compensatory approach followed for task allocation. These allocation methods restrict the use and enhancement of human skills and does not offer any worker flexibility and work satisfaction [10][11]. In addition, these methods compromise on the human factors of ergonomics for human collaboration. Task allocation in the most adaptive way is a topic of research from as far as in the 90’s. In [20] the authors propose a method of evaluating the task and resources and therefore decide a robot trajectory, however this method also raised safety concerns. Similarly, in [21], the author describes a quantitative algorithm that takes into consideration task balancing with the final aim of reducing assembly time with no focus on safety or ergonomics. More lately, there are also methods studied to achieve a collaboration by understanding the human monitoring using machine learning (ML) models [22]. Increased concerned over safety in both the hardware and software approach of these technologies has also awaken many research interests. In [23][24][25] the authors present a laser sensor-based solution to monitor the proximity between the robot and worker to condition the speed of the robot and in severe cases even stop it. While all these research deal with either productivity, flexibility or safety, ergonomics is a factor not considered very extensively in many research. Authors in [26][27] briefly study the ergonomic impact due to human robot collaboration, nevertheless the focus on specific ergonomic factor has been minimal and the work in this research aims to fill that gap and identify ergonomic factors that can optimize the task allocation methods in human robot teams. Therefore, the main research question of this thesis is:

***How can task allocation algorithms in human-robot collaboration be optimized for ergonomics?***

The term collaborative robot will be extensively used as a substitute to robot as the research aims at devising optimal methods of task allocation between a human and collaborative robot (cobot) to improve ergonomic conditions in an assembly process. Developing a new task allocation method is not the scope of this study, rather integrating and evaluating ergonomic factors in existing methods is studied. The study focuses intensively only on the physical and cognitive ergonomics of the worker. The sub-objectives of the study will be to examine the existing task allocation algorithms and optimize them considering physical and cognitive ergonomics which can then be modelled and visualized on a process simulation tool with appropriate evaluation methods to define the optimization in the presented algorithm. Hence the sub-objectives of this study are formulated as follows.

- ***I. What are the various methods for task allocation that can be analysed?***
- ***II. How will the task allocation method be modelled and visualized for ergonomics?***
- ***III. How can task allocation methods be evaluated for ergonomics?***

## 1.3 Research Methodology and approach

The study in this thesis is conducted with the amalgamation of the system development approach described by Nunamaker et al. in [28] , design science research methodology proposed by Johannesson and Perjons [29] and the simulation-based research methodology studied by Yin et al. in [30]. The approach of the thesis deals with the iterative approach of constructing a conceptual framework, developing a structural architecture, analyzing the design of the system, building the model, evaluation of the system. In this structure the simulation-based methods are integrated in the analysis and evaluation methods as described in Figure 1.

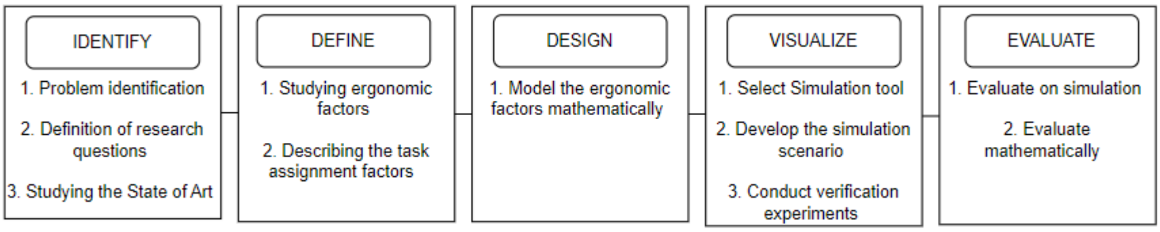



Figure 1: Research methodology and approach (Own figure adapted from [28], [29] and [30])

The development of methodology of integrating ergonomics to task allocation in human-robot teams is broadly classified into five steps also described in Chapter 4.

i) Describing the ergonomic factors

The initial objective to work upon the developed research framework is to study the literature and identify the major ergonomic factors that would contribute to the overall design, development, and evaluation of ergonomics in task allocation. Major factors along the physical, cognitive, and organizational ergonomics are listed to develop the task assignment methodology.

ii) Designing a task assignment framework

The task analysis is carried out to understand the task along various domains of human and robot considering their benefits and limitations. In addition, economic factors are considered to compare the cost as well as the efficiency and productivity to meet the forecasted demands. The work defined in this thesis also considers the nature of the part and process to analyze and assign tasks to the most appropriate agent.

iii) Modelling the ergonomic factors

With the focus on ergonomics, the factors narrowed during the analysis phase are mathematically described and modeled to be integrated into the evaluation of task allocation for ergonomics. The physical ergonomic factors are further integrated into the visualization for ergonomics and the cognitive and organizational factors are mathematically modelled for evaluation.

iv) Visualization of assembly

Once the factors are selected and mathematically modelled, the digital simulation platforms for ergonomics are described and finally selected based on factors of availability, functionality, and experience in the use of the platform. The use case is visualized directly as used in the Digital Simulation of Ergonomics and Robotics (DSER) course for Ski assembly using the Ema Work designer platform. The direct ergonomic and time cycle evaluation functions are used elaborated in Section 4.2.

v) Evaluation of ergonomics

The evaluation of the task allocation is considered in two stages, using the digital tools, and second empirically using the formulas devised for each of the ergonomic factors. Based on the evaluation and input, the task assignment is altered suitably and iteratively worked upon. Two scenarios of task allocation are compared and evaluated.

## 1.4 Composition and structure of the work

**Chapter 2 Theoretical fundamentals** of this thesis delves into the theoretical basics of human-robot collaboration. This includes understanding collaborative robots in assembly processes, safety in human-robot collaboration, human-robot relationship, and human-robot interaction methods. Additionally, it addresses the significance of ergonomics in human-robot collaboration and how it can be optimized to ensure safety and well-being of associates. Through this exploration, the aim is to provide a comprehensive understanding of the theoretical foundations that underlie the effective design and implementation of collaborative manufacturing systems.

**Chapter 3 State of Art/Literature** survey a systematic literature survey is conducted to determine the state of art in task allocation methods in human robot teams. The initial methodology of the literature review is described. The results are summarized with respect to the research questions, presenting a structured meta-analysis followed by a summary of the total reviewed literature both qualitatively and quantitatively. A detailed study on existing literature for human robot task allocation methods and methods used for visualizing these task allocation methods. To incorporate ergonomics in task allocation, ergonomic factors are studied.

**Chapter 4 Methodology** is devoted to quantitative implementation of task allocation algorithms. It defines the overall structure of task analysis, factors influencing the task assignment based on factors including human, robot, part, and process analysis. The second part of the chapter addresses the overall visualization of the task assignment using the digital simulation tool for ergonomics and finally addresses the evaluation of task allocation for ergonomics. It focuses on the physical, cognitive, and organizational ergonomics aspects described and narrowed in Chapter 3.

**Chapter 5 Implementation and evaluation** builds and implements on the existing framework described in Chapter 4. It implements the framework on the ski assembly use case using the Ema Work designer platform. The use case is studied for initial task assignment for the process steps based on factors analyzed in Chapter 4 addressing human, robot, part, and process factors. The assembly sequence is then visualized for the use case and developing some improvements based on the evaluated ergonomic scores for postures, load handling, forces, and duration. It also describes the enhanced detailed method of analyzing the cognitive and organizational factors related to an overall Mental workload index (MWLI).

**Chapter 6 Discussion and Outlook** encompasses the discussion of the overall work. It apprehends the results obtained, overall benefits and limitations of the approach and summarizes the work, also highlighting and discussing the possible enhancements to the work described in this thesis.

# 2 Theoretical basics

In this Chapter, the essential basics that are needed as a background for this study are explained. The topic of this work deals with considering ergonomic factors for human-robot task allocation method and hence this chapter will deal with topics of **Collaborative Robots, Human Robot Collaboration and Ergonomics**.

## 2.1 Collaborative robots in assembly systems

Collaborative robots have gained significant attention in academia and research and have gradually made their way into industrial manufacturing and assembly applications, working alongside human operators. Unlike traditional industrial robots, which are typically confined to separate workspaces with protective barriers, these collaborative robots, or collaborative robots, have enabled enhanced productivity and reduced costs by safely operating alongside human workers. This chapter aims to provide a comprehensive overview of collaborative robots, including their concept, practical applications, and associated advantages and disadvantages.

### 2.1.1 History of Robots

Looking back at history, it is evident that the fascination with robots existed long before the first robot was invented. Karel Capek, a Czech author, contributed significantly to the naming of robots by introducing the term "robot" in his play "Rossum's Universal Robots" in 1921 [31]. From the Czech word "robota" a robot means "to work unfree". The play depicts the concept of cheap labor through artificial humans and how the robots eventually outlive their human creators. In industry, two types of robots are prominent, namely classical industrial robots and collaborative robots.

#### I. Industrial robots

The year 1960 marked the introduction of the very first industrial robot, dubbed "Unimate". The following year, General Motors (GM) had already implemented it in their production line. After the successful implementation of industrial robots in the automotive industry during the 1970s, other industries followed suit.

According to ISO 10218-1:2011 (en) [32], an industrial robot is defined as an *"automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications."* An industrial robot should comprise of, but not limited to, a manipulator and end effector to perform the desired task at hand, sensors to act as the perceiving system of the robot, a controller that acts as the brain of the system, a programming device such as teach pendant to control the robot programs and a safety system such as emergency stops to ensure safe operations around the robot [33].

As shown in the World Robotics Report 2022 [1] of the International Federation of Robotics (IFR), 517,000 industrial robots were installed worldwide in 2021 and the adoption has increased by 31% in 2023. Furthermore, the development since 2012 shows annual growth (between 2012 and 2018), which is on average about 12% per year. Asia/Australia is by far the largest customer, followed by Europe and America.

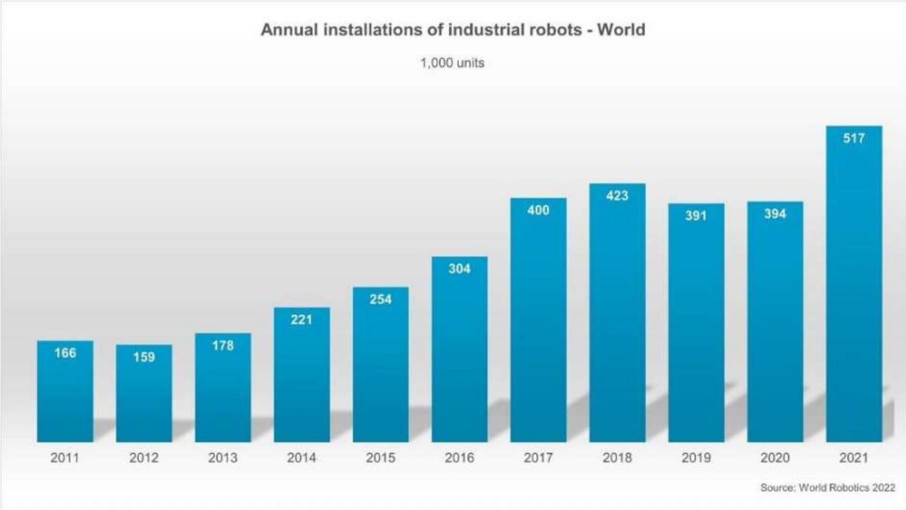



Figure 2: Annual Installations of industrial robots 2011-2021 [1]

The industry is moving towards high-mix, low-volume type of manufacturing, industrial robots in many cases fail to justify the cost of installation due to lack of flexibility and adaptability to deliver towards lot size one. In addition, the high cost of industrial robots is not economical for SMEs and hence the need for a more flexible robot with economical cost and capability to work alongside human was born in the form of collaborative robots.

## II. Collaborative Robots (Cobots)

In 1996, the concept of "Cobot" the acronym to Collaborative Robot was introduced by Colgate [35]. This term was derived from the aim of the original research project, which was to develop a safe robotic system that can work together with humans without the need for a safety fence, unlike conventional industrial robots. According to Colgate, *"A "collaborative robot" is a robotic device which manipulates objects in collaboration with a human operator."*

Collaborative robots are equipped with sensors and safety features such as force/torque sensors, capacitive skin, proximity sensors, etc, that allow them to interact with humans safely and efficiently. Unlike traditional industrial robots, collaborative robots are user friendly and easy to program, making them ideal for small-scale manufacturing and assembly operations. Additionally, collaborative robots are relatively inexpensive compared to traditional industrial robots, making them an attractive option.

### 2.1.2 Applications of Collaborative robots

In an industry survey in Austria (n=85) [38], in general, the use of cobots in production has decreased by 2.5% between 2021 (29.5%) and 2022 (27.1%), while the use of collaborative robots in pilot environments has increased by 2.8% during the same period. This suggests that companies are continuing to experiment with collaborative robots in non-production settings. Additionally, there has been a decline by 6.5% in companies planning to use collaborative robots in the future. At the same time, there has been an increase in the number of companies that have no plans to use collaborative robots at all (+6.3%).

In a survey in Sweden named *"Strategies for implementing Collaborative Robots for Operator 4.0"* in 2019 by Fast-Berglund and Romero [43] , the major application of collaborative robots was found in pre-assembly, inspection, kitting, joining, final assembly, packing, pick and place. The study found that Original Equipment Manufacturer (OEM) companies tended to prioritize assembly tasks, while SMEs ranked pick and place and material handling tasks higher. Cobot applications, specifically inspection and pick and place tasks, were ranked highest overall.

A study by Bauer [44] conducted a study on companies initial experiences with lightweight robots, analyzing 25 use cases in Germany, with most cases in the automotive (40%) and electrical engineering sectors (36%), in-line with the report seen for installation of industrial robots in [39]. The most common tasks included gripping parts (52%), mounting/joining (44%), quality control (40%), pick & place (36%), gripping multiple parts (32%), and loading machines (32%). A survey on the market share growth of cobots in 2022 [41] revealed that more that automotive applications still hold the most share in the application of collaborative robot (>24%). Similarly, for cobot applications in 2022, assembly tasks (40%), pick and place (20%), load handling (13%) and packaging (11%) shared most of the share [42], in line with the studies conducted earlier.

### 2.1.3 Features of Collaborative robots

Cobots fill the space between fully automated and entirely manual production lines. These robots can function alongside human operators without any physical barrier as they come equipped with advanced safety features such as collision detection and force feedback making them more flexible and adaptive to production needs.

Cobots are most distinguished with the traditional industrial robots in the following features as summarized in [2]:

i) Batch size and variability: Suitable for low volume and high product mix applications

ii) Deployment and programming: Quick on-site deployment and flexibility with easy programming. However, there have been many studies in making the Human-Machine interaction with collaborative robots more intuitive.

iii) Investment and Return on Investment (ROI): As already discussed, a collaborative robot is an economical option in comparison to its counterpart and generates an ROI in lesser duration.

In addition, Carlsberg reported a significant decrease in accidents at their plant in Frederica, Denmark after incorporating collaborative robots into their production line [39]. This not only improved safety for employees but also brought the plant closer to zero accidents. The case studies presented by Wevolver [40] suggests the use case of cobots for adhesive bonding processes, headlight adjustment and installation of pump wells in industries that have ergonomically aided human counterparts. A more intensive study and findings were summarized in [37], which elaborated on the technical aspects of a cobot that differentiates it from the traditional industrial robot and is summarized below in Table 1.

| Characteristic | Industrial Robot | Collaborative Robot |
| --- | --- | --- |
| Role | Replace a worker | Assist a worker |
| Human Interaction | Commands via programming languages | Intutitive and intelligent interactions: Gesture , speech recognition and anticipation of operators moves with sensors |
| Camera and computer vision | External camera and setup | Can be built-in and coupled with intelligent algorithms to support the application |
| Workspace | Separate workspace for robots and operators. Fenced workspace | Sharing the workspace , no fenced workspace |
| Work enevelop | Essential and rigid | Not relevant |
| Rapid handling of disruptions and obstruction | Usually requires a full re-setup after any distruction/obstruction incidence | Built-in standard or feature to handle obstructions |
| Re-programming | Rare | Frequent |
| Physical disruptions | Mostly Hazardous.Setup required for re-initiation | Safe with easy re-initiation |
| System self-awareness | Basic failure detection | Real-time monitoring of load , tactile pressure and axis locations |
| Agility | Rapid motions | Slow motions |
| Payload | High payload | Low payload |
| Acquisition cost | High | Low payload |
| Ability to work in dynamic environment, possibly with moving entities | No | Yes |

Table 1: Characteristics of Industrial Robot vs Collaborative Robot [37]

As seen in Section 2.1.1, the growth in adoption of industrial robots has been increasing year-over-year. However, the proportion of cobot adoption in comparison is less. There has been a 50% increase in 2021 adoption of cobots worldwide as shown in Figure 3, however it accounts for only 7.54% of the total sales and most of the applications are not used in direct interaction with humans to perform the task, for e.g., machine tending. Additionally, as highlighted in [38], the use of cobots is slowly stagnating due to reasons of economic turmoil and slowdown as far as Europe is concerned. The real costs of implementing a cobot in an industrial setting are typically about four times higher [46]. Safety aspects also present challenges that need to be met. When integrating a cobot into a factory, certification for each application may be necessary, depending on the country. ISO standard 10218 and technical specification TS 15066 are commonly used for this purpose. During the certification process, a risk assessment is required to evaluate dangerous situations [47]. However, every collaborative application must go through this process again, even if the same application has already been integrated in another company, resulting in high effort and costs.

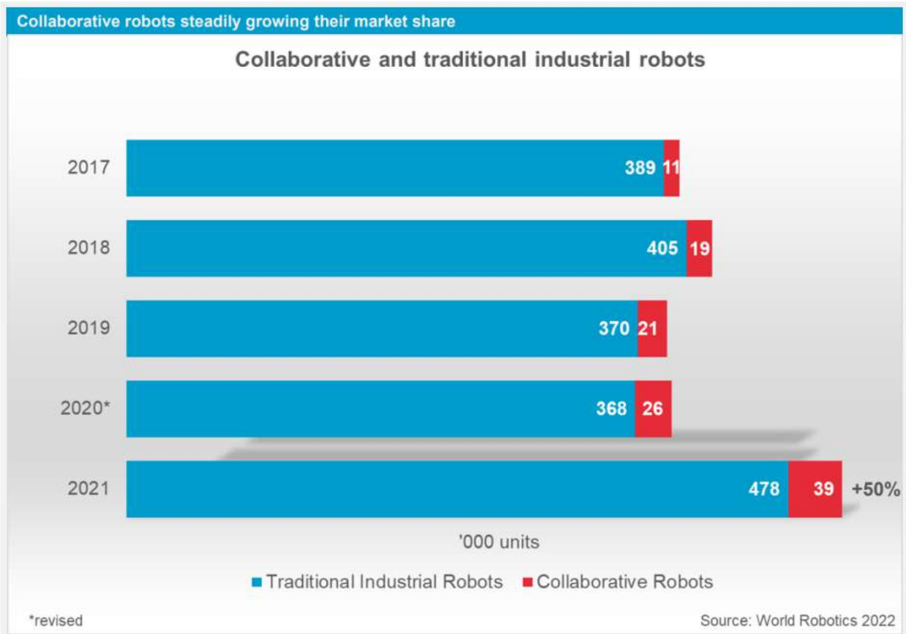



Figure 3: Sales of industrial robot vs collaborative robot [1]

## 2.2 Human-Robot Interaction (HRI)

Human-Robot Interaction (HRI) is a rapidly growing field that explores the integration of robots into human environments, particularly in the industrial setup. However, this is currently not limited to the industrial setup and many humanoid robots interact with humans in a more social gathering. As defined in [53], "*Human–robot interaction (HRI) is the interdisciplinary study of interaction dynamics between humans and robots. Researchers and practitioners specializing in HRI come from a variety of fields,* *including engineering (electrical, mechanical, industrial, and design), computer science (human–computer interaction, artificial intelligence, robotics, natural language understanding, and computer vision), social sciences (psychology, cognitive science, communications, anthropology, and human factors), and humanities (ethics and philosophy).”*

Human-Computer Interaction (HCI) is the parent field that encompasses Human-Robot Interaction (HRI). In the simplest terms, it is defined as the way the human and computer (machines) interact with each other. The literature defines HCI as *"Human–Computer Interaction (HCI) is the study of the way in which computer technology influences human work and activities." [5] "HCI is a discipline concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them."[50]*

To comprehend HCI, it is crucial to acknowledge that it extends beyond the design of human-computer interfaces and encompasses multiple interdisciplinary areas as comprehended nicely by Becker in [51]. The works highlights as HCI being an interdisciplinary field comprising of design and media, computer science and engineering, human factors and ergonomics, behavior science and psychology, other professionals including cultural anthropology and user research. The applications of HRI are seen in various fields such as industrial, medical, agricultural, service, and educational. It aims to combine the capabilities of robots with human skills to assist in precision, speed, force, experience, knowledge, intuition, and control strategies.

### 2.2.1 Types of Human Robot Interaction (HRI)

Bauer [44] have defined a classification based on the interaction between human and robot, where a distinction is made between the following five types as seen in Figure 4.

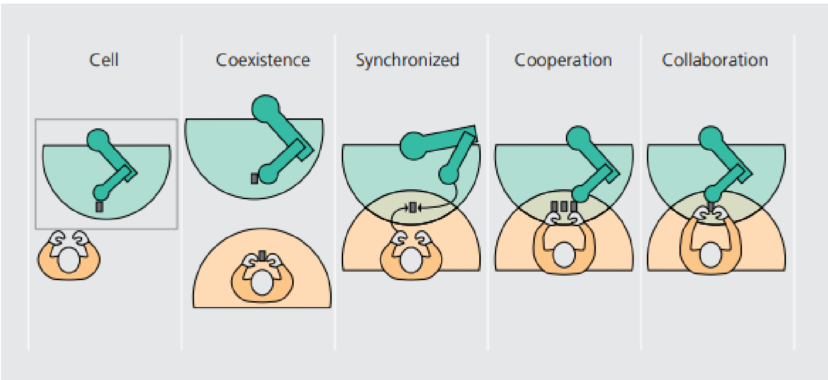



Figure 4: Various levels of interaction between human and robot [44]

i) Cell: In this scenario the robot and the human being work independent of each other. They have complete different workspaces of their own and are usually separated by a fence as seen in the first part of Figure 4.
ii) Coexistence: This scenario is like that of the cell, however, in this case the robot has no protective fence which allows for the human and robot to work together still in separate workspaces. The absence of fence in such a mode of interaction does call for the need of having safety regulations as the worker has free access to robot work area.
iii) Synchronized: In this type of interaction, both human and robot share the work-place. However, at a given time only one agent is active and works on the desired task either the robot or human.
iv) Cooperation: The "Cooperative" mode of interaction is like “Synchronized" as both the human and robot share the same workspace, however they work simultaneously on the desired task and are active at the same time. Nevertheless, the work is done by both the agents on different workpieces.
v) Collaboration: In this scenario, which represents the most flexible form of interaction, both the human and the robot work in the same workspace, on the same part and at the same time.

To understand this better, Wang [54] summarizes the features of each of these interaction types better as seen in Table 2.

| Feature | Cell | Co-existence | Synchornization | Cooperation | Collaboration |
|---|---|---|---|---|---|
| Open workspace | | ✓ | ✓ | ✓ | ✓ |
| Sgared workspace | | | ✓ | ✓ | ✓ |
| Direct contact | | | ✓ | | ✓ |
| Shared working tasks | | | ✓ | | ✓ |
| Shared resource | | | | ✓ | ✓ |
| Simultaneous process | ✓ | ✓ | | ✓ | ✓ |
| Seqeuntial process | | | ✓ | ✓ | |

Table 2: Human Robot interaction-based relationships [54]

In such a type of division between the forms of interaction, there exist some gaps which are identified majorly in the cooperation and collaboration mode as it is ambiguous if the interaction is dependent on each other. This is elaborated in the work by Chang Liu [55]. He divides the mode of interactions into two aspects:

i) Parallel HRI: In this kind of interaction, there exist a peer-to-peer interaction where the human and robot make their own decisions. In such a form of interaction, the agents either synchronize or asynchronize their actions. The synchronized form of action is called as synchronization as seen in the list by Bauer [44] and asynchronization is called as competition which is said to be a form in which the agents occupy the space in the workspace one at a time but have no dependency.

ii) Hierarchical HRI: Hierarchical interaction mode is where the robot is designed to operate in a hierarchical manner with respect to the human operator. In this approach, the robot has different levels of autonomy, with each level representing a different degree of interaction with the human.

### 2.2.2 Human Robot collaboration (HRC)

Human Robot Collaboration (HRC) is defined as *"the relationship between humans and robots aimed at achieving a mutual goal by sharing respective resources and intrinsic skills through joint action"* [54]. Collaboration is the highest form of interaction between humans and robots. In such collaborations, the strengths of both humans and robots are leveraged, with robots performing tasks that are repetitive, dangerous, or require high precision, while humans perform tasks that require complex decision-making or dexterity. HRC has the potential to increase productivity, improve product quality, and enhance workplace safety. However, it also poses challenges related to ensuring safety, designing effective communication interfaces, and managing the effective division of task between humans and robots.

#### 2.2.2.1.1 Types of Human Robot Collaboration

In the work by Beer [56], ten levels are used to describe the involvement of human and robot across three dimensions of sense, plan and act as shown in Figure 5. The framework explicitly addresses the sense, plan, and act dimensions attributed to the human and/or robot. However, the dimension of control is also relevant but not explicitly defined in the original work. The framework includes shared control with human initiative, where the human has the final say on actions and can continuously monitor the robot. In higher levels of robot autonomy, the robot has full control while the human has limited intervention and direction possibilities.

| Level of Robot Autonomy | Sense | Plan | Act | Description |
|---|---|---|---|---|
| Manual | H | H | H | The human performs all aspects of the task including sensing the environment, generating plans/options/goals, and implementing processes. |
| Tele-operation | H/R | H | H/R | The robot assists the human with action implementation. However, sensing and planning is allocated to the human. For example, a human may teleoperate a robot, but the human may choose to prompt the robot to assist with some aspects of a task (e.g. gripping objects). |
| Assisted Tele-operation | H/R | H | H/R | The human assists with all aspects of the task. However, the robot senses the environment and chooses to intervene with task. For example, if the user navigates the robot too close to an obstacle, the robot will automatically steer to avoid collision. |
| Batch Processing | H/R | H | R | Both the human and robot monitor and sense the environment. The human, however, determines the goals and plans of the task. The robot then implements th task. |
| Decision Support | H/R | H/R | R | Both the human and robot sense the environment and generate a task plan. Hoever, the human chooses the task plan and commands the robot to implement actions. |
| Shared Control With Human Initiative | H/R | H/R | R | The robot autonomously senses the environment, develops plans and goals, and implements actions. However, the human monitors the robot's progress and may intervene and influence the robot with new goals and plans if the robot is having difficulty. |
| Shared Control With Robot Initiative | H/R | H/R | R | The robot performs all apsects of the task (sense, plan, act). If the robot encounters difficulty, it can prompt the human for assistance in setting new goals and plans. |
| Executive Control | R | H/R | R | The human may give an abstract high-level goal (e.g., navigate in environment to a specified location). The robot autonomously senses environment, sets the plan, and implements action. |
| Supervisory Control | H/R | R | R | The robot performs all apsects of task, but the human continously monitors the robot, environment, and task. The human has override capability and may set a new goal and plan. In this case, the autonomy would shift to executive control, shared control, or decision support. |
| Full Autonomy | R | R | R | The robot performs all aspects of a task autonomously without human intervention with sensing, planning, or implementing action. |

Figure 5: Human Robot collaboration dimensions [56]

*H – Human, R- Robot*

The work by Zatari [58] summarizes four ways in which human and robot collaborate also considering the fact if the human and robot are working on the same piece.

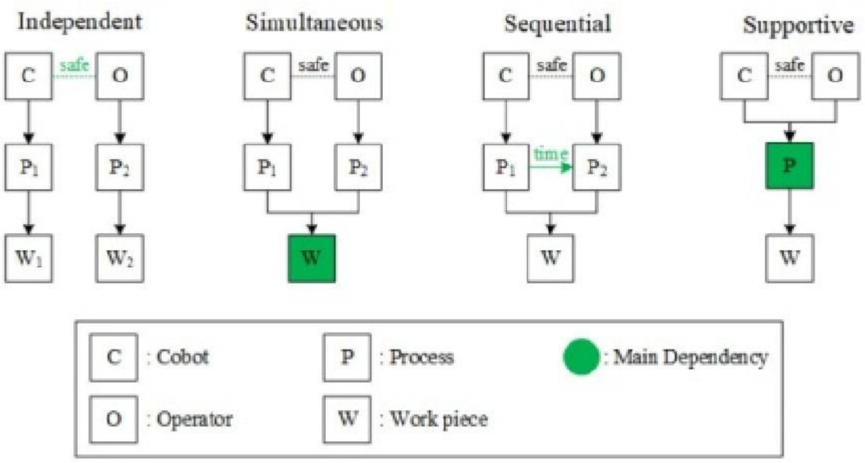



Figure 6: Types of Human-Robot collaboration by Zatari [58]

i) Independent: In this scenario the human and robot share the workspace but work on different workpieces.
ii) Simultaneous: In this case the human and robot work on the same workpiece with different processes.
iii) Sequential: This type of collaboration consists of a time dependent relation between human and robot as seen in process P1 and P2. A simple example

could be assembly operation where the robot picks up the part and provides it to the human for assembly operation.

iv) Supportive: In this type of collaboration, the human and robot work on the same workpiece and process together, a situation that can occur in assembly processes.

### 2.2.2.1.2 Safety in HRC

Ensuring physical safety in HRC is crucial for workplace design and practical implementation. The primary objective is to safeguard humans from the potential harm caused by unintended collisions between their body parts, robot systems, or workplace elements while simultaneously maintaining efficient production systems. As stated by Gualtieri et al. [59], the goal is to maintain proper performance while mitigating the consequences of such incidents.

Asimov laws since the origin in 1947, have been a footprint in robotic safety in the form of science fiction and now has become an unconscious choice of how robots should behave and exist [60]. However there have been multiple studies that have contradicted and debated on the background and the actual applicability of these laws in new-age robotics. One such is highlighted in [61] as law of *"Responsible robotics"* an extend or modified version of Asimov's laws as seen in Figure 7.

| | **Asimov's laws** | **Alternative laws** |
|---|---|---|
| 1 | A robot may not injure a human being or, through inaction, allow a human being to come to harm. | A human may not deploy a robot without the human–robot work system meeting the highest legal and professional standards of safety and ethics. |
| 2 | A robot must obey orders given to it by human beings, except where such orders would conflict with the first law. | A robot must respond to humans as appropriate for their roles. |
| 3 | A robot must protect its own existence as long as such protection does not conflict with the first or second law. | A robot must be endowed with sufficient situated autonomy to protect its own existence as long as such protection provides smooth transfer of control to other agents consistent the first and second laws. |

Figure 7: Alternative laws for "Responsible Robotics" [57]

Collaborative robots have given rise to specific ISO safety standards that highlight the need for limiting force applied, speed and safety features for the entire system as per the Machine Directive 2006/42/EC, 2016 which considers the collaborative robot, tool, fixtures, and physical components as an entire system [62]

In addition, the safety standards to be followed are as follows:

i) DIN ISO/TS 15066:2016 Robots and robotic devices - Collaborative robots [63]

ii) DIN EN ISO 10218-1:2020: Robotics – Safety requirements for robot systems in an industrial environment – Part 1: Robots (Draft) [64]

iii) DIN EN ISO 10218-2:2020: Robotics – Safety requirements for robot systems in an industrial environment – Part 2: Robot systems, robot applications and robot cells integration (Draft) [65]

A classification of safety concepts for collaborative systems are elaborated in [64] are presented in Figure 8.

i) Safety-Monitored stop: This type of safety collaboration suggests that the collaborative robot stops working while humans enter the workspace.

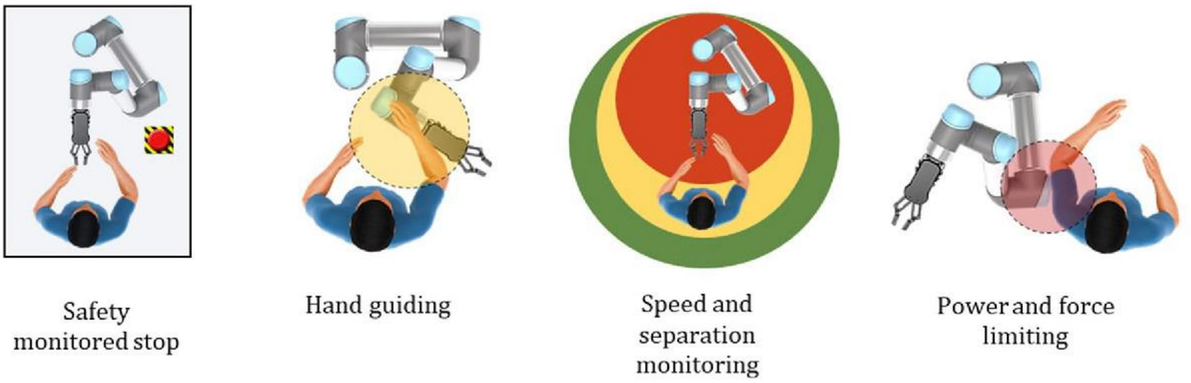



Figure 8:Human Robot Collaboration: Safety [64]

ii) Hand guiding: In this scenario, the robot is operated through a manual controller that is placed near the robot.
iii) Speed and Separation monitoring: In this type of collaboration safety, collaborative application can be witnessed where the human and robot work in the same workspace simultaneously, however keeping a required safe distance.
iv) Power and force limiting: In case of a collision that exists in collaboration between human and robot, the power and force with which must be under safety limits and norms to not hurt or injure the human worker.

### 2.2.3 Human centric design approach (HCD)

Human centric design of the workplace is a philosophy that prioritizes the well-being, productivity, and satisfaction of employees by creating environments that cater to their needs and preferences. This approach recognizes that the success of any organization relies heavily on its people and their ability to thrive in their work settings. The key principle and focus rely on comfort, flexibility, biophilic elements, inclusivity, and accessibility, resulting in better collaboration, productivity, creativity, and well-being.

### 2.2.4 Skills of Humans and Robots

Fitts List [11], popularized in the 1951 was a list of things *"men (human) do better than machines and vice versa"*. The list also allocated what is called the Human are better at/Machine are better at (HABA-MABA) approach for function allocation [66]. The original Fitts list highlighted the supremacy of humans over machines in flexibility, judgement, dexterity and have long term memory as summarized below [66].

**Human strengths:**

i) Good at making complex decisions based on incomplete or ambiguous information

ii) Skilled at adapting to changing situations

iii) Capable of handling multiple tasks simultaneously

iv) Able to learn from experience and improve performance over time

v) Can be creative and generate new ideas

**Machine strengths:**

i) Highly accurate and consistent in performing repetitive tasks

ii) Capable of performing tasks that are dangerous or difficult for humans

iii) Can operate in environments that are hazardous or inaccessible to humans

iv) Can perform tasks that require great physical strength or speed

v) Can process and analyse large amounts of data quickly and accurately

Traditionally, the HABA-MABA approach has inclined research programs to partition work responsibilities between humans and machines, without due consideration for their potential collaborative interaction. This approach was deemed acceptable, provided the machines were straightforward. However, with advancements in automation technologies, the nature of human-robot interaction has undergone significant transformation, prompting the need for more sophisticated and nuanced approaches to address complex interaction dynamics [66]. This gave rise to the need to study the same approach for the present-day advanced machines as compared to the ones in 1951.

In a survey conducted in Delft University of Technology (TU Delft, Netherlands), 2016 [68], revealed that current day machines outsmart the humans in the areas of detection, perception and long-term memory as opposed to the Fitts list [11]. It also discusses that the trends and development in sensor technology, artificial intelligence and computer processing and storage capabilities have seen this shift. While there have been technological advances, humans still hold an upper hand over machines in creativity, analytical thinking, resilience, flexibility and agility, talent management and technology design and formulation [69].

Nevertheless, with the aim of increasing collaboration between human and robots and not competing against one another, it is necessary to focus on how a human-robot teamwork can together with maximum efficiency and safety. To leverage on the strengths of both, Woods [68] presents what is surprisingly called an 'Un-Fitts list' that fills the gap and comprehends a list for the new age machines and human-robot teams in Figure 9.

| Machines | |
|---|---|
| **Are constrained in that** | **Need people to** |
| Sensitivity to context is low and is ontology-limited | Keep them aligned to the context |
| Sensitivity to change is low and recognition of anomaly is ontology-limited | Keep them stable given the variability and change inherent in the world |
| Adaptability to change is low and is ontology-limited | Repair their ontologies |
| They are not "aware" of the fact that the model of the world is itself in the world | Keep the model aligned with the world |
| **People** | |
| **Are not limited in that** | **Yet they create machines to** |
| Sensitivity to context is high and is knowledge- and attention-driven | Help them stay informed of ongoing events |
| Sensitivity to change is high and is driven by the recognition of anomaly | Help them align and repair their perceptions because they rely on mediated stimuli |
| Adaptability to change is high and is goal-driven | Affect positive change following situation change |
| They are aware of the fact that the model of the world is itself in the world | Computationally instantiate their models of the world |

Figure 9: The "Un-Fitts List" [68][69]

The "Un-Fitts List" provides a comprehensive perspective that does not solely focus on human limitations. The list, presented in Figure 9, highlights human strengths and how they leverage technology to amplify their abilities. One example of this is the development of algorithms that are well-suited for confined scenarios, which helps to counterbalance human limitations in getting trapped in localized viewpoints and action patterns. By prioritizing human capabilities and understanding the contexts in which machines can support them, the Un-Fitts List offers a promising approach to human-robot interaction design [66]. It encourages designers to consider the ways in which robots can complement and enhance human abilities, rather than replacing or minimizing them. This perspective not only benefits humans, but it also leads to more effective and efficient robot performance in various domains. Therefore, this approach promotes a symbiotic relationship between humans and machines, which can lead to improved collaboration and productivity.

## 2.3 Human Factors and Ergonomics (HFE)

Human factors and ergonomics (HFE) play a critical role in the industrial context today. With the advent of advanced technologies and automation, it has become increasingly important to ensure that the workplace is designed to optimize human performance, safety, and comfort. This is particularly important as many industrial processes require repetitive and physically demanding tasks that can lead to musculoskeletal disorders and other health issues. The word HFE is synonymous with ergonomics and is often used interchangeably. The goal of HFE is to make human interaction with systems error free, safe, comfortable and enhance productivity [70]. HFE deals with developing tools and workspaces in a way to achieve these goals as seen in Figure 10.

The cycle highlights five major factors in the improvement cycle for human factors namely: *Environment, Tasks, Equipment Design, Selection* and *Training.*

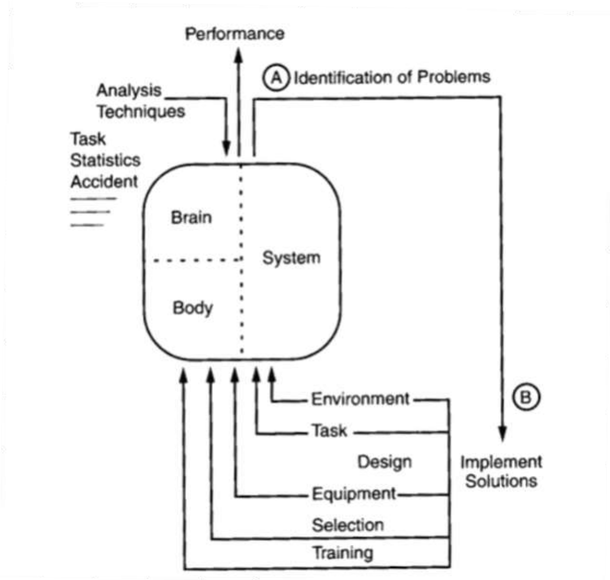



Figure 10: Cycle of Human Factors [72]

It shows that various approaches can be used to address and improve system problems, and after applying these approaches, performance can be assessed to ensure success. However, the focus of our discussion has been on fixing deficient systems (Point A). It is essential to note that good human factors practices are not only relevant to fixing deficient systems but also to designing effective systems. Anticipating human factors deficiencies before they arise and incorporating human factors early in the design process (Point B) can lead to significant cost savings and prevent human suffering. Therefore, the role of human factors in the design process is critical and should be considered early in the design stage.

### 2.3.1 Ergonomics and Types

According to the International Ergonomics Association (IEA,2000) [71], ergonomics is defined as *“the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimize human well-being and overall system performance”.* Historically, ergonomics is defined as the *“study of work”* [71] or *“science of work” [66],* with the Greek works *ergon (work)* + *nomos (laws).* Ergonomics is usually considered as a design related concept in which the methods and ways of interactions between human and machine (robot) is designed to be more flexible, safe, and efficient. Kawoski [73], defines ergonomics as an inter-disciplinary field that encompasses a variety of fields across the natural, artificial products processes and surrounding environments as seen in Figure 11. Each of these aspects plays an essential role in creating an ergonomically sound environment that promotes safety, productivity, and overall well-being [72].

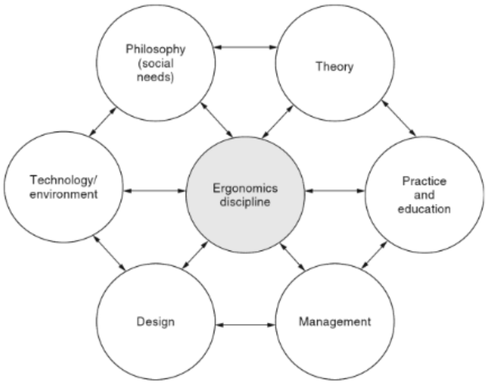



Figure 11: General dimensions of Ergonomics discipline [72]

#### 2.3.1.1 Types of ergonomics

In the broader spectrum ergonomics as a domain is classified as *Micro, Macro and Meso Ergonomics* [77]. These are classified based on the level implement site, decision making output, users' organizational level, type of applications, size of involvement, scope of workspace, area of work [72].

Micro Ergonomics deals with the design of an overall work system which poses a broader scope including the Organization design (OD). It designs the structure of organization and the relation between the elements in this structure. The major features scoped under this type are human-machine relationships, displays and workspace settings, work system optimization and macro work system design.

Macro Ergonomics is the traditional and the most perceived idea of ergonomics. It deals with the analyses of worker movements, postures, designing work tools to improve worker posture, enhance workspaces to meet ergonomic needs. It more specifically works on design of work systems in a way to provide flexibility and enhance human working capabilities. On the other hand, Meso Ergonomics is an area in ergonomics that lies between both micro and macro ergonomics, with very bleak boundaries. It caresses the relationship between human, OD, and sociotechnical systems [78]. It considers the human as in focus and works around HCD and processes.

Physical and cognitive workloads are most majorly studied as a part of these ergonomic methods. Physical workload comprises of all and any aspects that adversely affect the working health of the human. These include factors pertaining to the physical environment, working postures, materials handling, repetitive movements, work-related musculoskeletal disorders, safety, and health. These also include the robot related parameters such as type, automation level and adaptability [72].

| Dimension | Macro Ergonomics | Meso Ergonomics | Micro Ergonomics |
|---|---|---|---|
| Level of implementation | Organizational | Multilevel:Organization-Group-Individual | Work station |
| Decision making output | Decision making and policy | Decision making | Design work procedure and methods |
| Users (Organizational level) | Top management | Middle management | Operational workers |
| Types of Applications | Decision making | System creation | Work system improvement |
| Size of involvement | Organizational | Group/Department | Individual |
| Scope of workspace | Compmay wide | Individual and socio-technical | Individual workstation |
| Area of work | Environment and social relation in OD | Group and Human-Machine relation | Workstructure and workflow |
| Tools | Organizational work design system | Interface and software | Kaizen , SMED |

Table 3: Types of Ergonomics as per desired work level dimensions [77]

Similarly cognitive loads refer to the stress, mental or emotional processes that impact humans internally. Mental stress can have a significant impact on work performance, both in the short and long term. When workers are experiencing high levels of stress, they may have difficulty concentrating, making decisions, and completing tasks efficiently. This can lead to decreased productivity, errors, and lower quality work. Chronic stress can also have more serious long-term effects on workers' physical and mental health. Prolonged exposure to stress hormones can weaken the immune system, increase the risk of cardiovascular disease, and contribute to mental health conditions such as anxiety and depression.

### 2.3.2 Ergonomic assessment methodologies

Ergonomic assessment aims at measuring various aspects of the workplace environment depending on the type of ergonomics at focus. The most common agenda of the assessment is to gauge the physical and cognitive factors including, but not limited to mental workload, climate/environment (internal and external), work postures, repetition, cycle duration, etc. The aim of these assessment methods is to identify the loopholes in the form of bad conditions and/or practices and eliminate or improve them to improve safety, reduce errors and improve system performance. In the perspective of users and workers, it is necessary to improve the working environment, aesthetics, ease of use and more specifically the user acceptance [79], to achieve the desired tangible outputs needed for company performance discussed earlier. It is with this aim that the evaluation methods are designed that use either subjective judgement (self-questionnaires filled by the workers), systematic observations (collected by visual inspection on-site or via video recordings), or actual physical measurements (performed on site or via virtual simulations) [72][79].

#### 2.3.2.1 Subjective Judgement

The most common methods for evaluation used are in the form of checklists, surveys, questionnaires, forms etc. These aim at understanding both the physical and cognitive/mental workload on the worker. Physical load addresses the workload on human body due to stress, discomfort, muscle activity, repetition, force, duration of exposure and posture.

**I. Physical ergonomics**

i) Body mapping

Body mapping behaves as a questionnaire or checklist filled by workers themselves to highlight their area of discomfort [81]. The checklist aims at understanding the specific body part which is facing major discomfort alongside the discomfort level: "*Just noticeable, Moderate and Intolerable".* In granularity, it also understands the kind of discomfort being felt ranging from "*Aching, Burning, Paining, Itching, Swelling and/or Weakness"* amongst others.

ii) Rating scales

As the name suggest, rating scales is a generic method working on scales defined by the examiner per basis depending on the application, it can range from 1-10, with 1 being no discomfort and 10 being more discomfort to be more granular in the approach and have a scale from 1-5, as the need of the application be. An assessment of chair in terms of ergonomic was done in [82], where the authors defined the scale of 1-5 defined as: "*Perfectly comfortable, quite comfortable, barely comfortable, uncomfortable, restless and fidgety"*. A similar descriptive approach was followed in [83], to assess the impact of noise and vibration in the atmosphere as an impact. It was also discussed that such a method poses a disadvantage in understanding the ratings around the boundaries of these ratings and fire can make it difficult and sometimes even misunderstood in making decisions.

iii) Checklist

Checklists serve as the simplest way of understanding the ergonomic situation and condition of the worker in the workplace (industrial setup or office setup) based on a range of questions to understand their working condition, duration of prolonged work, weight (physical load) dealt with, posture, force, etc. [84]. However, the method is still highly subjective and does not help in any concrete findings that can be utilized to enhance further on the workplace conditions.

iv) NASA-TLX

The NASA Task Load Index (TLX) is a pen and paper [5] based questionnaire developed by NASA Ames Research Centre's (ARC) Sandra Hart in 1980 [85]. This method is used to evaluate both the physical and cognitive load across six dimensions as summarized in Figure 12. The users rate each of these dimensions in the form of a scale rating shown below or in some methods give a numeric rating between 1-100. After the ratings are completed, a weighted average score is calculated, which provides an overall workload score.

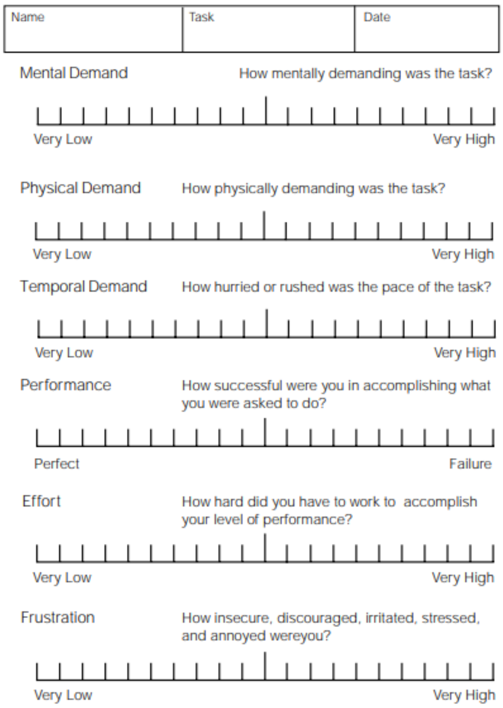



Figure 12: NASA Task load Index: Paper/Pencil Version [85]

## II. Cognitive ergonomics

Cognitive or mental workload refers to the level of cognitive processing and demand imposed on an individual while performing a task. It can affect various aspects of work performance, such as attention, decision-making, and memory. Thus, it is essential to assess cognitive workload levels to ensure that work demands do not exceed the individual cognitive capacity [86]. There are several methods available for cognitive workload assessment, including subjective, objective, and physiological measures.

[5] The method is called as pen- paper as it was initially originated as a method that required hand-written assessment, however now the digital version is available.

Subjective measures include self-reporting and rating scales, where individuals report their perceived level of cognitive workload. Objective measures include task performance, reaction time, and error rates, where performance is analyzed to determine workload.

i) Subjective Workload Assessment Technique (SWAT)

Subjective Workload Assessment Technique (SWAT) is an assessment technique developed specifically to evaluate the mental workload. It divides the assessment into three factors: *Time Load, Mental effort Load and Psychological Load.* The levels are described by descriptors indicating the lowest (level 1) and the highest (level 3) mental workload for each dimension. During the task scoring procedure, participants rank the cards in order from the one that represents the lowest mental workload to the one that represents the highest [87][88].

a) Time Load: Operationally time load takes into consideration the time available and the time overlap [87]. A worker is under “Time-Load” when the time taken to perform a task exceeds the total available time. According to [87], the sub-factors of this dimension are *Time Required, Time Available, Time Required/Time available (divide) and Time stress.*
b) Mental Effort Load: The second dimension comprises of task factors like difficulty, complexity and level of effort needed. It comprises of aspects like reasoning, cognitive thinking, problem solving, reasoning, memory retrieval, including but not limited to performing calculations, paying attention to information sources, and retrieving information. Hence the sub-factors were then named as *Task Complexity, Perceived Difficulty, Effort, Expenditure of Energy, Interrelating Expenses, and Information input* [87].
*c)* Psychological Stress Load: Stress seemed to affect the workers motivation, enthusiasm, health, fatigue, inquisitiveness, and emotional state. This includes but is not limited to external factors like physical harm, organizational culture and environment and internal factors such as fear of failure, tension, personal life conditions. Hence this dimension takes into consideration anything that adds to the stress, fatigue, anxiety, frustration, and mood of the worker. The subfactors in [87] were then called *Psychological Stress, Fatigue, Motivation, Emotional Stress, Stress, Uncertainty of Risk, Probability of Failure, Tension and Task Performance.*

ii) Cognitive Load Assessment for Manufacturing (CLAM)

The CLAM approach is an assessment technique that is primarily intended for proactive evaluation and design of workstations. It is designed to quickly evaluate cognitive workload associated with tasks and workstation design, with the goal of identifying relevant issues proactively, and facilitating efficient and effective changes in the manufacturing environment. The overarching aim of the CLAM method is to adopt a cost-efficient and holistic perspective, encompassing the entire workstation and work task, and saving time and resources when evaluating the cognitive workload of assembly workers in a manufacturing setting [89][87]. The CLAM Assessment method consists of 11 factors across the domain of task based and workstation-based factors as summarized in Table 4 [90].

| Task Based Factors | Description |
|---|---|
| Saturation | Amount of work planned on a workstation |
| Variant Flora | The variety of product mix |
| Level of difficulty | How difficult is the task? |
| Production awareness | Focused attention needed on the task by the worker (depends on the routine work) |
| Difficulty of tool use | Is complex tools needed for the task? |
| Workstation Factors | Description |
| Number of tools available | Number of tools used in the workstation |
| Mapping of Workstation | How well does the workstation comply with the assembly sequence? |
| Parts identification | What is the method used for part identification? |
| Quality of instructions | Focused on the readability and visibility of the instructions |
| Information cost | How much effort is needed to utilize the information (physical and cognitive) |
| Poke-a-yoke constraints | Are there any error-proofing solutions implemented? |

Table 4: CLAM Assessment: Factors and Description [90]

Each of the factors described in Table 4 are rated and weighted to find a final score in the CLAM Assessment. The rating scale for CLAM ranges from Level 0-8, the scale from 0-2 indicate very low, 2-4 indicate low, 4-6 indicate moderate and 6-8 indicate high [90]. Each of these factors also have corresponding weights that are used while calculating the weighted average in the final score.

#### 2.3.2.2 Systematic Observations

Systematic observation is an ergonomic assessment method that involves the structured and methodical collection of data through direct observations of tasks and work environments. It is a qualitative method that helps ergonomists understand how workers interact with their work environment and identify potential ergonomic risk factors that may contribute to discomfort, pain, or injury. The data collected through systematic observation can include information about postures, movements, tools, and equipment used, environmental factors such as lighting and noise, and the frequency and duration of task performance. The assessment is carried out normally using either on-site observations or via a video of the process.

### i) Ovako Working Posture Assessment System (OWAS)

OWAS was developed in Finland in a steel company, Ovako Oy, in 1973 to describe the workload in the overhauling of iron smelting ovens. It identifies the most common postures for the back (4 postures), arms (3 postures), and legs (7 postures). The OWAS assessment sheet comprises four main sections: task identification and time proportion determination, back posture evaluation (straight, bent, twisted, or a combination), assessment of arm postures (below shoulder level, above shoulder level, or a combination), and evaluation of leg postures (sitting, standing, squatting, or walking) as seen in Figure 13. It also considers load weight (less than 10 kg, 10-20 kg, or over 20 kg) and assigns a code, categorizing the action needed based on the assessment into four categories: no special attention required, postures requiring further examination, examinations needed soon, or urgent and immediate re-examination and modification.

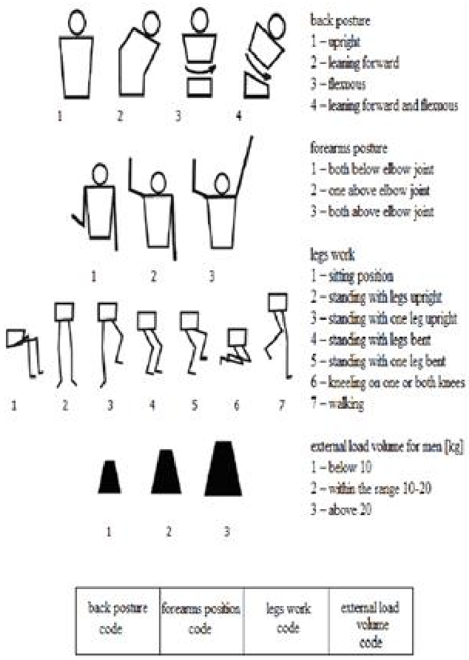



Figure 13: IOSH OAWS Assessment sheet [91]

### ii) Rapid Upper Limb Assessment (RULA)

Rapid Upper Limb Assessment (RULA) is an ergonomic tool used to swiftly evaluate musculoskeletal risks in the upper limbs and neck at work. It assesses postures, muscle exertion, and loads. RULA assessment process involves three parts: evaluating arm and wrist positions, scoring, and analyzing neck, leg, and trunk positions. In Part A, upper arm and wrist angles are measured, adjustments made for deviations. Muscle exertion and force are assessed. The final score categorizes risk into four levels: acceptable, further investigation, changes needed soon, and changes needed now as seen in Figure 14. This approach provides a quick and clear understanding of posture-related risks and the urgency for addressing them.

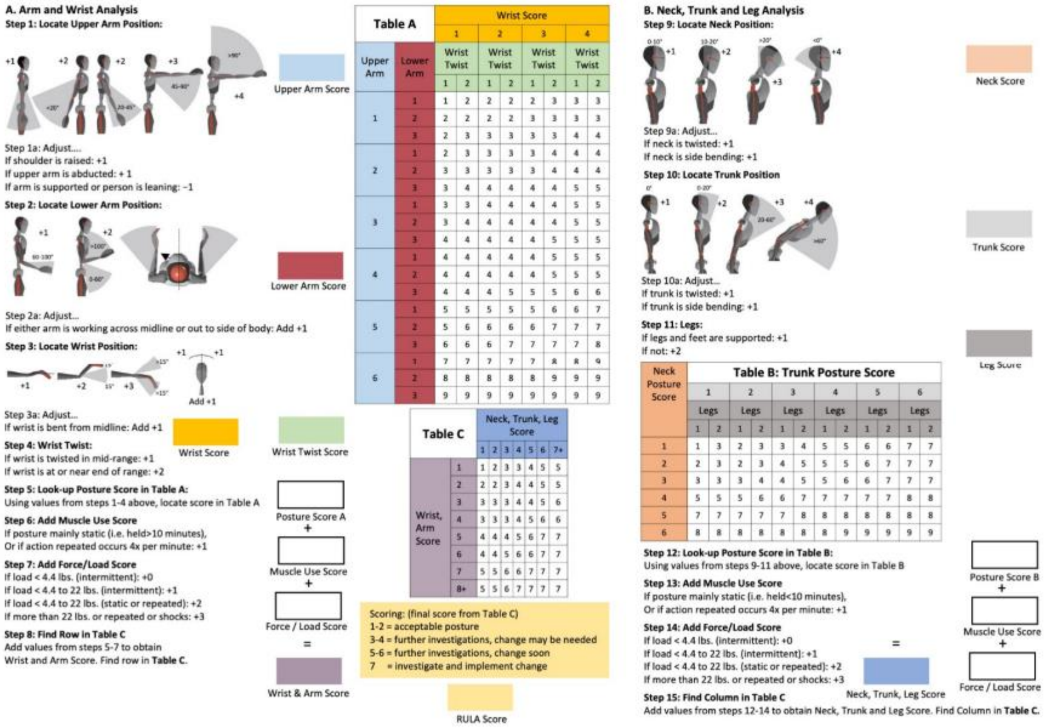


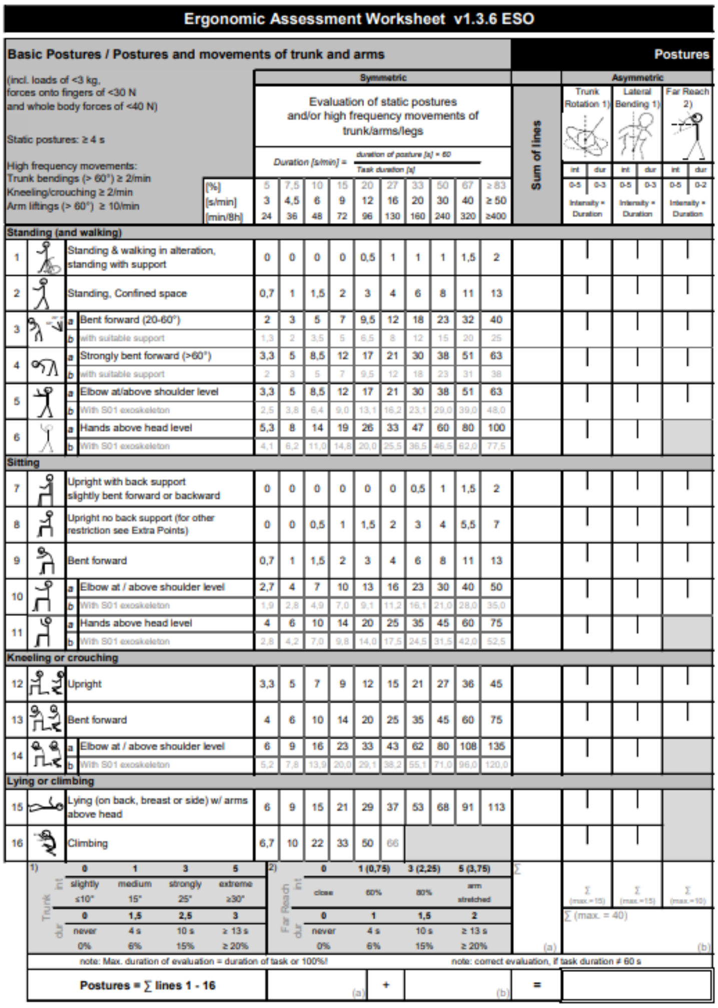

Figure 14: RULA Assessment sheet [92]

iii) Rapid Entire Body Assessment (REBA)

Rapid Entire Body Assessment (REBA) is an ergonomic tool designed to evaluate musculoskeletal risks in workplace tasks. It considers factors like posture, force exertion, repetition, and exertion level. REBA divides the body into segments and assigns scores (1-3) based on musculoskeletal risk severity. Posture and load handling are evaluated, and coupling (beyond hands) is considered. Scores are totaled to calculate a final score (1-15), categorized into low to very high risk. Higher scores indicate greater risk. Based on the score, appropriate actions are determined, potentially involving changes in the work environment, equipment, or practices. REBA offers a comprehensive assessment of posture-related risks, aiding in risk mitigation [94][95].

iv) European Assembly Worksheet or Ergonomic Assessment Worksheet (EAWS):

The Ergonomic Assessment Worksheet (EAWS) is a comprehensive tool designed to assess manual load handling in the workplace. It considers key factors like strength, posture, force, load, and repetition. The assessment sheet is organized into sections: worker information, task details, body part analysis (including upper limbs, lower limbs, trunk, and neck), risk level assessment, and recommended actions. During the assessment, the posture and movements of the worker are evaluated, and each body part is assigned a score reflecting its ergonomic risk level. These scores are then combined to determine an overall risk level for the worker and task, which is plotted on a risk matrix. Based on the identified risk level, the EAWS provides tailored recommendations for mitigating ergonomic risks, potentially involving adjustments to the work environment, equipment, or processes. The EAWS score ranged from a scale of 0 to infinity; points between 0-25 are classified in the green zone where no action is needed, between 25-50 is the yellow zone where there is a possible risk, and points above 50 depict the red zone suggesting action must be taken to reduce the risk.



Ergonomic Assessment Worksheet v1.3.6 ESO

Basic Postures / Postures and movements of trunk and arms

(incl. loads of <3 kg, forces onto fingers of <30 N and whole body forces of <40 N)

Static postures: ≥ 4 s

High frequency movements: Trunk bendings (> 60°) ≥ 2/min; Kneeling/crouching ≥ 2/min; Arm liftings (> 60°) ≥ 10/min

Symmetric: Evaluation of static postures and/or high frequency movements of trunk/arms/legs

Duration [s/min] = duration of posture [s] * 60 / Task duration [s]

| No. | Posture | [%] 5 / [s/min] 3 / [min/8h] 24 | 7,5 / 4,5 / 36 | 10 / 6 / 48 | 15 / 9 / 72 | 20 / 12 / 96 | 27 / 16 / 130 | 33 / 20 / 160 | 50 / 30 / 240 | 67 / 40 / 320 | ≥ 83 / ≥ 50 / ≥400 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Standing (and walking)** | | | | | | | | | | | |
| 1 | Standing & walking in alteration, standing with support | 0 | 0 | 0 | 0 | 0,5 | 1 | 1 | 1 | 1,5 | 2 |
| 2 | Standing, Confined space | 0,7 | 1 | 1,5 | 2 | 3 | 4 | 6 | 8 | 11 | 13 |
| 3 a | Bent forward (20-60°) | 2 | 3 | 5 | 7 | 9,5 | 12 | 18 | 23 | 32 | 40 |
| 3 b | with suitable support | 1,3 | 2 | 3,5 | 5 | 6,5 | 8 | 12 | 15 | 20 | 25 |
| 4 a | Strongly bent forward (>60°) | 3,3 | 5 | 8,5 | 12 | 17 | 21 | 30 | 38 | 51 | 63 |
| 4 b | with suitable support | 2 | 3 | 5 | 7 | 9,5 | 12 | 18 | 23 | 31 | 38 |
| 5 a | Elbow at/above shoulder level | 3,3 | 5 | 8,5 | 12 | 17 | 21 | 30 | 38 | 51 | 63 |
| 5 b | With S01 exoskeleton | 2,5 | 3,8 | 6,4 | 9,0 | 13,1 | 16,2 | 23,1 | 29,0 | 39,0 | 48,0 |
| 6 a | Hands above head level | 5,3 | 8 | 14 | 19 | 26 | 33 | 47 | 60 | 80 | 100 |
| 6 b | With S01 exoskeleton | 4,1 | 6,2 | 11,0 | 14,8 | 20,0 | 25,5 | 36,5 | 46,5 | 62,0 | 77,5 |
| **Sitting** | | | | | | | | | | | |
| 7 | Upright with back support slightly bent forward or backward | 0 | 0 | 0 | 0 | 0 | 0 | 0,5 | 1 | 1,5 | 2 |
| 8 | Upright no back support (for other restriction see Extra Points) | 0 | 0 | 0,5 | 1 | 1,5 | 2 | 3 | 4 | 5,5 | 7 |
| 9 | Bent forward | 0,7 | 1 | 1,5 | 2 | 3 | 4 | 6 | 8 | 11 | 13 |
| 10 a | Elbow at / above shoulder level | 2,7 | 4 | 7 | 10 | 13 | 16 | 23 | 30 | 40 | 50 |
| 10 b | With S01 exoskeleton | 1,9 | 2,8 | 4,9 | 7,0 | 9,1 | 11,2 | 16,1 | 21,0 | 28,0 | 35,0 |
| 11 a | Hands above head level | 4 | 6 | 10 | 14 | 20 | 25 | 35 | 45 | 60 | 75 |
| 11 b | With S01 exoskeleton | 2,8 | 4,2 | 7,0 | 9,8 | 14,0 | 17,5 | 24,5 | 31,5 | 42,0 | 52,5 |
| **Kneeling or crouching** | | | | | | | | | | | |
| 12 | Upright | 3,3 | 5 | 7 | 9 | 12 | 15 | 21 | 27 | 36 | 45 |
| 13 | Bent forward | 4 | 6 | 10 | 14 | 20 | 25 | 35 | 45 | 60 | 75 |
| 14 a | Elbow at / above shoulder level | 6 | 9 | 16 | 23 | 33 | 43 | 62 | 80 | 108 | 135 |
| 14 b | With S01 exoskeleton | 5,2 | 7,8 | 13,9 | 20,0 | 29,1 | 38,2 | 55,1 | 71,0 | 96,0 | 120,0 |
| **Lying or climbing** | | | | | | | | | | | |
| 15 | Lying (on back, breast or side) w/ arms above head | 6 | 9 | 15 | 21 | 29 | 37 | 53 | 68 | 91 | 113 |
| 16 | Climbing | 6,7 | 10 | 22 | 33 | 50 | 66 | | | | |

Sum of lines

Asymmetric: Trunk Rotation 1) | Lateral Bending 1) | Far Reach 2) — int / dur: 0-5 / 0-3 | 0-5 / 0-3 | 0-5 / 0-2 — Intensity * Duration

| 1) Trunk | 0 | 1 | 3 | 5 |
|---|---|---|---|---|
| int | slightly ≤10° | medium 15° | strongly 25° | extreme ≥30° |
| | 0 | 1,5 | 2,5 | 3 |
| dur | never 0% | 4 s 6% | 10 s 15% | ≥ 13 s ≥ 20% |

| 2) Far Reach | 0 | 1 (0,75) | 3 (2,25) | 5 (3,75) |
|---|---|---|---|---|
| int | close | 60% | 80% | arm stretched |
| | 0 | 1 | 1,5 | 2 |
| dur | never 0% | 4 s 6% | 10 s 15% | ≥ 13 s ≥ 20% |

Σ (a) — Σ (max.=15) | Σ (max.=15) | Σ (max.=10) — Σ (max. = 40) (b)

note: Max. duration of evaluation = duration of task or 100%!

note: correct evaluation, if task duration ≠ 60 s

Postures = Σ lines 1 - 16 (a) + (b) =

Figure 15: Ergonomic assessment worksheet [96]

## v) Quick Exposure Check (QEC)

The Quick Exposure Check (QEC) is a method developed by the UK's Health and Safety Executive (HSE) to address manual handling risks and prevent musculoskeletal disorders (MSDs) at workplaces. Introduced in 1999, it focuses on identifying disorders and pain in areas like the neck, shoulders, back, wrists, hands, and arms. The assessment involves both the practitioner and the task performer and examines physical and psychosocial aspects of the work environment. The QEC questionnaire covers various risk factors such as weight and force of the load, posture and movement, task duration and frequency, and environmental conditions. Each question is scored to gauge risk, and the cumulative score indicates the overall risk level of the task, aiding prioritization for further intervention [97]. Other methods, such as the National Institute for Occupational health and safety (NIOSH) Lifting Equation for back injury risk and the Strain Index (SI) for repetitive hand-intensive tasks, also contribute to ergonomic assessment and control in the workplace [98].

#### 2.3.2.3 Direct measurements and Virtual evaluation

Direct ergonomic measurement methods encompass various quantitative approaches to assessing physical ergonomics. Anthropometry involves measuring human body dimensions and characteristics to inform workstation and equipment design. Biomechanical analysis quantifies forces, torques, and movements exerted on the body during tasks using techniques like electromyography (EMG) and motion capture [99]. Inclinometry measures angles and postures of body segments, aiding in identifying poor postures and the need for ergonomic adjustments. Force measurement assesses grip strength, push/pull forces, and forces applied to objects, providing insights into ergonomic risks related to force exertion [100]. Vibration analysis quantifies whole-body or hand-arm vibrations, guiding the implementation of control measures. Postural analysis evaluates body postures during tasks, employing observational techniques, motion capture, or wearable sensors to identify postural issues and aid in ergonomic improvements [101]. These direct ergonomic measurement methods offer objective data to assess ergonomic risks, optimize the work environment, and promote employee health and safety.

##### 2.3.2.3.1 Computer Aided Ergonomics

Incorporating human factors in workplace design and engineering has been an area of major concern and importance lately. One of the ways of getting this done is the use of Digital Human Models (DHM) that replicate human characteristics for simulation and analysis. DHM involves the creation and manipulation of computer-generated human models to simulate human anthropometry, movements, and capabilities. It is a valuable tool used in ergonomics and human factors research to evaluate and optimize the design of workspaces, products, and environments. Human models designed as computer aided drawing (CAD) models help in simulating the real-life interaction of the human in the workplace environment and enables a reduction in the design time, cost, labor hours and improves quality, efficiency, and productivity [102][101].

DHM incorporates multiple data and functions to model, simulate and gather data for the ergonomic evaluation of the worker in the environment [102]. Firstly, it incorporates anthropometric data, encompassing body measurements and characteristics, ensuring accurate representation of diverse populations. Secondly, DHM employs biomechanics to mimic human movements and assess ergonomic aspects like posture and muscle activity. Thirdly, cognitive factors, including workload and attention, are considered to gauge the impact of design on human cognition. Fourthly, ergonomics and workstation design are analyzed to optimize physical work environments. DHM also addresses HCI principles for assessing digital interfaces and usability. Lastly, user preferences and demographics are factored in to customize models, catering to individual needs and diverse user groups effectively. This holistic approach aids in designing products and environments that better suit human capabilities and preferences.

These factors are bucketed into three main functions viz, manipulation functions, analysing functions and output functions as seen in Figure 16. By incorporating these various components and human factors, DHM aims to create realistic representations of human characteristics, movements, and interactions in virtual environments. This comprehensive approach helps evaluate and optimize designs from multiple perspectives, considering physical, cognitive, and ergonomic factors to enhance user comfort, performance, and overall satisfaction.

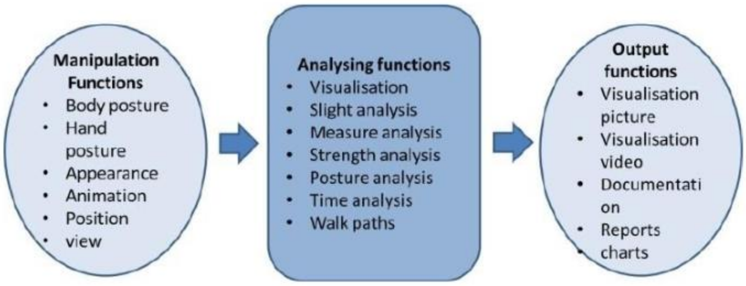



Figure 16: Functions of DHM [102]

DHM software empowers the creation of virtual human models that faithfully replicate the diversity of human populations, encompassing body dimensions, movements, and capabilities to accommodate a wide spectrum of individuals. Prominent DHM platforms include Siemens' Jack, renowned for its ergonomic analysis and simulation capabilities, Human Solutions' RAMSIS, notably used in the automotive industry for ergonomic evaluations, Dassault Systems' CATIA Human Builder, facilitating ergonomic analysis and virtual human modeling, the AnyBody Modeling System, a robust DHM tool for biomechanical analysis, and SIMULIA's ManneQuinPRO, designed for ergonomic analysis and simulation [103][105]. The most prevalent DHM models encompass CATIA's Human Builder, Siemens' Jack/Jill, and Human Solutions' RAMSIS, with numerous other models available to cater to various needs. These DHM platforms, illustrated in Figure 17, empower professionals to evaluate and enhance ergonomic aspects effectively, contributing to improved product designs and work environments. Jack, Human Builder, and RAMSIS are widely embraced platforms offering extensive tools for simulating human attributes, movements, and interactions, enabling the evaluation and optimization of ergonomic elements across diverse industries.

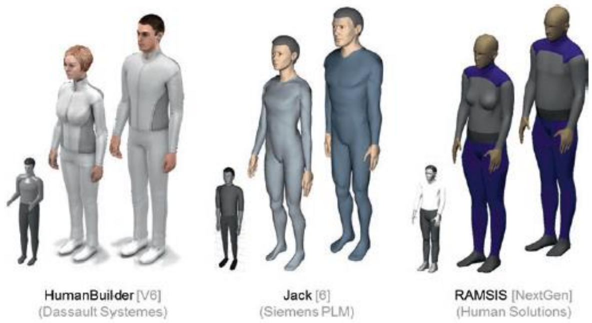



Figure 17: DHM Human Builder, Jack and RAMSIS [104]

While all three platforms share the common goal of improving ergonomics, they differ in terms of features, capabilities, and target industries. Table 5 summarizes the major capabilities of these human models.

| Function to be analyzed | Human Builder | Jack/Jill | RAMSIS |
|---|---|---|---|
| Load accessibility | ✓ | ✓ | |
| Posture | ✓ | | |
| Biomechanics | ✓ | | |
| Fatigue analysis | | ✓ | |
| Time analysis | | ✓ | |
| Forces | | | ✓ |

Table 5: Usability of Human Builder, Jac/Jill and RAMSIS (Own table)

# 3 State of the art / literature analysis

This chapter provides an overview of the state of the art in the field of human-robot task allocation, with a specific focus on ergonomics. The primary objective of this section is to gain a comprehensive understanding of the existing research and methodologies related to task allocation. To achieve this, the work will address the following research question *“How can task allocation algorithms in human-robot collaboration be optimized for ergonomics?”*. This will be divided into sub-sections each to answer and throw light on the sub-research questions highlighted in Section 1.2.

The first section summarizes the methods and quantitative results of the literature review and identifies relevant research work. The second section qualitatively evaluates the studied literature. The first part will explore existing task allocation methods that are widely used and researched in task sharing in human and robot teams. The second section will investigate the role of human factors in task allocation methods, recognizing the importance of considering human capabilities, limitations, and preferences. In this context, the various tools and frameworks used for modeling and visualizing ergonomics in task allocation scenarios will also be discussed. It will delve into the modeling and visualization aspects of task allocation, particularly in relation to ergonomics. The question of how the task allocation methods can be effectively modeled and visualized for ergonomic considerations will be thoroughly examined. Tools and techniques available for representing and assessing the ergonomic aspects of task allocation will be addressed. Lastly, the evaluation methods for task allocation approaches in the context of ergonomics. This section will delve into the different techniques and metrics used to assess the ergonomic performance of task allocation methods. By thoroughly investigating these research questions, the work in this thesis aims to provide a comprehensive understanding of the current landscape of human-robot task allocation, with a specific focus on ergonomics.

## 3.1 Literature Review

### 3.1.1 Structured Literature Review (SLR)

Structured Literature Review is a comprehensive analysis on the existing literature aimed at organizing the findings from the existing work in relation to the topic. The methodology is used from the works of Okoli [106]. According to Okoli, there is a comprehensive methodology to conduct a systematic literature review with includes identifying and structuring the purpose of the study, conduct a literature search using databases, extracting the data, synthesizing the data extract, and writing a summarized review. The literature review is carried out to answer the research questions formulated in this study. The databases utilized for the literature investigation were IEEE Xplore®, Scopus and SpringerLink.

Each of the databases were searched with a specific set of keywords and the results were exported into a 'csv'[6] file. The basic sanity checks on the results included checking the available information like the author names, publication data (title, date, and link) and abstract. The results were then scrutinized at a first level for the relevance of the title to the topic and were filtered out for non-relevant topics. The filtered results were examined by proofreading the abstract to gain the primary essence of the work in the literature and non-relevant works were eliminated from the review.

First the IEEE Xplore®[7] database was searched for keywords "human-robot" AND "task allocation". These keywords were used specifically to be able to satisfy the first sub-research question to investigate the existing methods of task allocation. This search resulted in 78 results. Of the total results, only 30 were found with the appropriate title while 6 search results either had multi or swarm robotics involved which was then removed from scope. The other titles either dealt with human robot teams and safety and trust in their collaboration but did not address the task allocation algorithms. Some titles also catered to the applications in social robotics and settings such as shopping malls, elderly care homes and banks, therefore limiting the scope to manufacturing and assembly, these were removed. About 5 results were not categorized and approved publications due to lack of further detailed information like authors, topics or abstract itself. On a careful consideration and proofreading the abstracts, only a total of 19 were found relevant for the topic since they delved in m: n[8] human-robot teams, methods of reducing or allocating task to reduce human idle times, or load balancing and scheduling problems with focus on high robot utilization.

The Scopus database[9] was queried using the keywords "human-robot" AND "task allocation" AND "ergonomics" AND NOT "mobile robot" AND NOT "Swarm" AND NOT "multi". This search resulted in 58 searches. A scrutiny on the title of the results had 24 relevant results with appropriate titles. The results consisted mostly of work in the field of ergonomic designs for workstations, several works also devised ergonomic stations for the inclusivity and accessibility of partially or completely disabled workers. Prominent results were seen around improving human robot collaboration with the aim of efficiency and productivity improvement. A total of 17 studies had a suitable abstract as the rest focused on either one robot interacting with multiple heterogenous robots

[6] Csv stands for comma-separated values, a file type that stores information in more than one field separated by comma.
[7] The search on IEEE Xplore® was conducted on 2023/05/08.
[8] M: n is a terminology that depicts the relationship between multiple entities in this case multiple humans to multiple robot teams.
[9] The search on Scopus was conducted on 2023/05/15.

or on tracking human motions to aid in improving cognitive load and therefore exploring the task scheduling issue.

The Springer Link[10] database was reviewed with the input “Human-robot AND task-allocation AND ergonomics” which resulted in 73 searches; however, only 15 were found relevant in their titles. A further deep dive in the abstract revealed a relevance of 11 studies in total as summarized in the Figure 18.

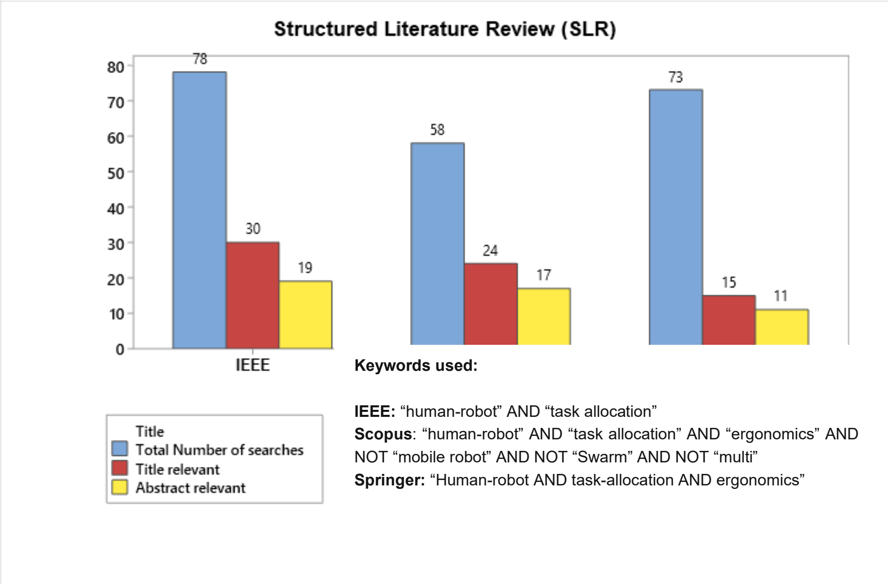



Figure 18: Quantitative Results of Structured Literature Review

Finally, after removing the duplicates across the databases about 48 papers were shortlisted as relevant in the domain of human robot task allocation.

### 3.1.2 Meta Analysis

The 48 pertinent publications were studied and scrutinized in the context of ergonomics in task allocation. The work from these publications were further bifurcated into three major buckets: Human Factors, Productivity and Empirical work.

i) Human Factors: Physical, cognitive and/or psychological factors considered as primarily important for improvising on the workplace design and/or task allocation
ii) Productivity: Reduction in assembly/production times and in addition in some cases improving quality and addressing load balancing problem between the human and robot
iii) Empirical: Mathematical development in efficient task allocation (might or might not integrate ergonomics)

[10] The search on Springer Link was conducted on 2023/05/20.

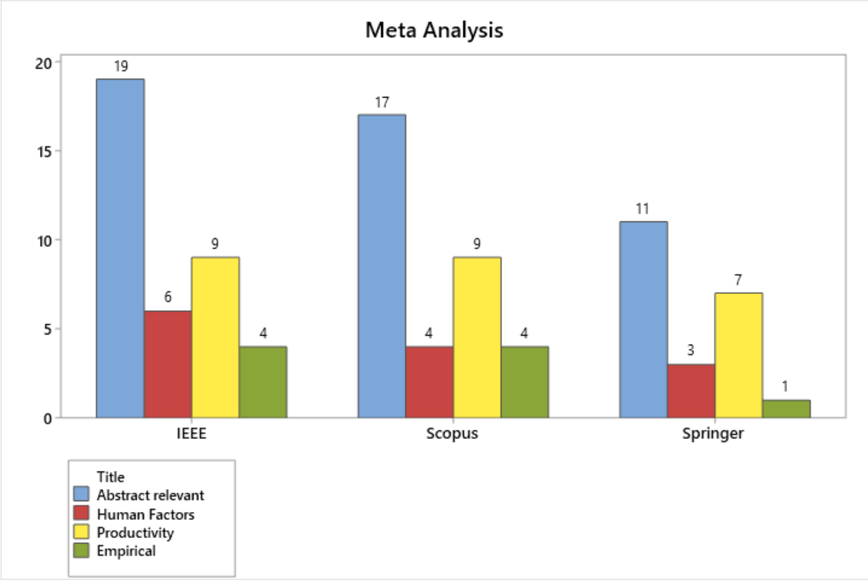



Figure 19: Results of Meta Analysis

In summary to literature is identified to answer the sub-research questions as follows:

i) Task allocation methods: 68.1% of the total literature dealt with improving the task allocation methods from static and fixed to online and dynamic, or improving strategies of task distribution to enhance automation
ii) Modelling and visualization: It comprise of the publications that aimed at devising a graphical or numerical algorithms related to task allocation between human and robots and comprised of 25.5% of the literature analyzed
iii) Evaluation for Ergonomics: Ergonomic evaluation in task allocation is a scarce topic in literature and hence comprised of only 6.5% of the total scrutinized work (48)

## 3.2 Human Robot task allocation

The field of human-robot task allocation has witnessed significant evolution over the years, driven by advancements in robotics, artificial intelligence, and human-robot interaction. Early approaches focused on predefined task assignments, where humans and robots were assigned, fixed roles based on their capabilities. However, as the complexity of tasks and the capabilities of robots increased, more sophisticated methods emerged. These methods incorporated human preferences, skills, and expertise into the allocation process, aiming to optimize the overall team performance. Recent developments have also explored collaborative approaches, where humans and robots work together in a symbiotic manner, leveraging the strengths of each team member. This evolution has led to more adaptive, efficient, and flexible task allocation methods that can cater to diverse application domains, from manufacturing and healthcare to search and rescue missions.

Task sharing between human and robot in a team consists of two major aspects, task analysis and allocation to make sure a suitable task is allocated to the most appropriate agent in the team. There are several methods studied from the existing literature described in the following sub-sections.

## I. Task analysis

### i) AND/OR Graphs

In task allocation, an AND/OR graph represents the relationship between tasks and their dependencies. Nodes in the graph represent individual tasks performed by either the human or robot, and edges represent the relationships between them which can share either an AND or OR type relationship. AND/OR graphs are widely used representation for task allocation between human and robots. In the simplest form shown in Figure 20, AND OR graphs comprise of a final task called $T_m$ which has a series of tasks that must be carried out to complete the final task categorized as $T_1$, $T_2$, $T_3$, $T_4$, $T_5$, $T_6$ and $T_7$.

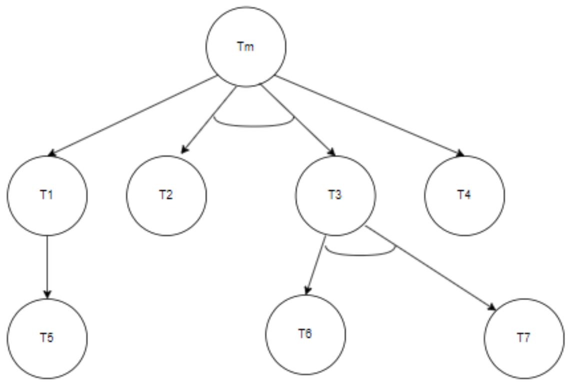



Figure 20: AND/OR graph nodal representation [107]

The node ($T_1$ to $T_7$) represents the individual tasks to be completed by either of the agents, the arcs seen between $T_2$ and $T_3$ depict the relationships between some tasks. It illustrates that these tasks are dependent and related to each other in nature. AND dependency depicts that one task must be completed before the other begins. For example, Task $T_1$ must be completed for $T_5$ to be executed. OR dependency (not illustrated in Figure 20) is normally depicted using a dotted line showing that a 100% dependency does not exist on the preceding task.

Most of the algorithms optimizing task allocation use AND/OR graphs in conjunction with either a best first or breadth first search method to optimize the overall cost incurred in the combinations of task sharing thereby improving productivity. The work presented by Merlo in [107] is an example of using AND/OR graph with A* search algorithm for online task allocation. Similar approaches have also been adopted in the works [108][109].In a similar approach, Johannsmeier and Haddadin [110] integrated the disparities between humans and robots by incorporating them into cost functions, thereby treating humans and robots as equivalent resources. They formulated cost functions based on workload and ergonomic factors to ensure fair allocation of tasks using such representations.

ii) A* graph search algorithms

A* algorithm is a popular path finding algorithm that has been adopted to the field of human robot task allocation in many literatures. Briefly, the A* algorithm defines a task graph consisting of each task node and defines heuristic values for each of the tasks which helps in estimating the cost of the heuristic function. The cost assigned depends and is based on the capabilities and considerations taken in the study. The algorithm then does a search across the nodes and selects the node with the lowest cost.

Tom and Murthy [111] in their work addresses the problem of optimal task allocation in a distributed computing system. Two models are considered: one with communicating tasks but no precedence relations, and another model with both communicating tasks and precedence relations. The focus is on finding an optimal allocation without assuming any specific connection structure for the processors. Gombolay in his series of works [129][130] has devised task allocation frameworks in human robot teams that consider the preference of human in task allocation algorithms. Johannsmeier and Haddadin [110] also deployed an A* algorithm for the defining the cost function which resulted in intuitiveness of use.

iii) Assembly Sequence graphs

Assembly process graphs are a generic way of visualizing tasks and exchanging information about the task details. One such method is also called Business process modelling and notation (BPMN) widely used for task visualization in granular ways. Petzoldt et al. [112] effectively makes use of assembly sequence graphs to visualize the difference in static and dynamic task allocation methods as seen in Figure 21 for a cardboard and few block assembly sequence. Similar analysis is researched in [66] to use BPMN as a way of dynamically allocating tasks between human robot teams online.

## II. Task allocation

Task allocation algorithms in human robot teams have been a topic of prevalent research in recent years. Task allocation algorithms follow multiple approaches and methods including but not limited to skill-based allocation, capability-based task allocation, agent-based decision-making task allocations, heuristic approaches, deterministic approaches as well as static and dynamic.

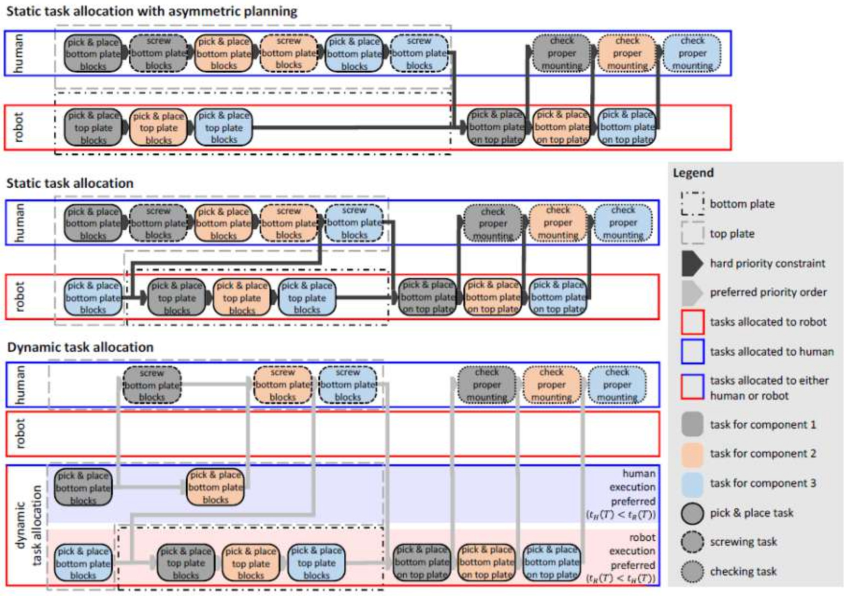


Figure 21: Assembly sequence graphs [112]

Deterministic task allocation algorithms utilize predefined rules and optimization techniques to allocate tasks. They consider factors such as task complexity, resource availability, and individual capabilities to determine the most efficient and optimal task assignment strategy. Heuristic task allocation algorithms, on the other hand, rely on practical and intuitive strategies for task allocation. These algorithms may use rules of thumb, simple decision-making processes, or prioritization criteria to assign tasks.

Ranz et al. [113] introduced a compensating strategy for task distribution which at first separated the procedure into several related steps. Then, "variable tasks," or tasks that could be completed by either agent, were assessed using capability indicators such process time, additional investment, and process quality. The human capability indicator was estimated by the authors as the average of these three criteria, and the robot capability indicator was obtained by deducting one from the human capability indicator.

A similar compensatory approach was also adopted by Müller et al. [114] for-manufacturing processes. They examined the product specifications as well as human and robot skills. The authors emphasized the variations in human attention and performance throughout the day compared to robots as one example of how people and robots differ from one another. While acknowledging the excellent precision and lifting capacity of robots, they also addressed the benefits of humans in terms of touch sensitivity, mobility, adaptability, and visual inspection capabilities. The distribution of tasks considered factors like difficult-to-reach places, intricate part designs, and the length of time required for robot programming.

Modular capability-aware strategy for work allocation between a cobot and a human in quickly reconfigurable industrial contexts was proposed by Lamon et al.[115]. in their study. Agent, team, and assembly levels were chosen as the three layers they would use to model the issue. To illustrate the assembly plan, AND/OR graphs were used to coordinate the assignment of assembly tasks at the assembly layer. Task distribution decisions were greatly influenced by the physical capabilities of the agents, considering elements like task difficulty, agent dexterity or kinematic reachability, agent effort or human and robot weariness.

A dynamic task allocation technique using a tree structure with sequential, non-ordering, and alternate execution routes was proposed by Anima et al. [124] in their work. To coordinate task distribution, the robot tracked the human movement hand-by-hand and developed a recognition model. A continuous message was transferred between the task representations to enhance cooperation and prevent the human and robot from working on the same task component at the same time.

The work from [110] represents a footprint in planning human robot interaction across three layers: team level, agent level and finally execution level. The overall objective of the framework using A* was to reduce the cost function considering the overall execution time, resource cost, process interruptions and pickup. To optimize task allocation, Fechter et al. [125] took into account multiple resources that could satisfy the needs of a certain product, process, or resource. They investigated two strategies: a heuristic search algorithm with a fitness function targeted at reducing cycle time, and full combination using Cartesian product. A greedy algorithm and a hybrid technique combining simulated annealing and evolutionary algorithm were used in the search algorithm. According to experimental findings, the single-crossover hybrid algorithm excelled in a condensed example use-case.

Machine learning approaches have also been used in many literatures. Machine learning approaches offer adaptability to dynamic environments, optimization for improved resource utilization, handling complex problems, decision-making under uncertainty, and learning from experience for continuous improvement. Wu et al. [126] presented a method for modeling human trust using a Markov Decision Process (MDP) algorithm in their study. Markov Decision Process is a mathematical framework used in machine learning algorithms for decision-making under uncertainty, involving states, actions, and transition probabilities to optimize choices based on expected rewards or costs. The MDP architecture considered probable robot malfunctions as well as unpredictability in human worker responses, including weariness and trust. The aim of optimal task allocation was to maximize the chance of satisfying linear temporal logic using linear temporal logic, a frequently used logic, to express the necessary system features in HRI.

Roncone et al. [127] used an automated method to transform low-level partially observable MDP from hierarchical task models. It showed through their evaluation that shorter completion times and less cognitive work were required of individuals. In addition, Srivastava et al. [128] research also used the MDP framework and a dynamic queuing system that took latency penalties into account. The authors also offered performance constraints for their system and offered tips for deciding on the queues mean arrival rate.

## 3.3 Ergonomics in Task allocation

Given that they cover a wide range of elements relating to human capacities, preferences, and constraints, human factors are important in job allocation. In order to achieve effective and efficient job distribution in human-robot teams, human considerations must be taken into account. When assigning tasks, considerations including human capacities, knowledge, cognitive capabilities, physical constraints, and workload capacity must be made. Including ergonomic considerations into task design and minimizing physical stress and exhaustion can improve worker safety and wellbeing. Therefore, a comprehensive understanding of human factors is vital for developing task allocation methods that optimize both human and robot performance, while also promoting human-centric considerations in the allocation process.

### 3.3.1 Human Factor Analysis

As summarized by the IEA in [71], human factors in three forms are the most important when designing work tasks: Physical ergonomics, Cognitive ergonomics, and Organizational ergonomics. Physical factors are mainly concerned about human body anthropometric details, postures, handling workload which trace to the attributes of a physical activity. Cognitive factors deal more with the mental aspects of human thinking, decision making, processing information and mental workload. Similarly, organization factors correspond to the external environment, management, policies at work as comprehensively elaborated in Section 2.3.1.1. [73][74] A detailed study on these three types of ergonomics revealed the factors that are to be considered in task allocation considering the focus on ergonomics as summarized in Table 6.

| Physical Ergonomics | Cognitive ergonomics | Organizational ergonomics |
|---|---|---|
| Repetitive movements | Mental workload | Communication |
| Loads and duration of load | Stress | Resource management |
| Working posture | Decision making | Work design |
| Material handling | Work fatique | Task complexity |
| Workplace layout | Work instructions | Task type |

Table 6: Ergonomic factors impacting task allocation (Adapted from [73] , [75] and [76])

Furthermore, studies from [75][76] summarized that each of these ergonomic factors are contributed to be by either the human agent or its counterpart robot agent related. Hancock et al. [75] in his work considered factors like worker demographics, self-confidence, work experience, workload as some human related factors that impact ergonomics. Parameters like robot anthropomorphism[11], level of automation, configuration, failure rate and alarms as robot related factors that impact the collaboration [75]. In the study by Ogorodnikova, she classified human factors into three buckets that impact ergonomics in workplace: Information processing (hinting towards cognitive ergonomics), Human error and physical ergonomics [76].

### 3.3.2 Physical ergonomics in task allocation

Physical ergonomics is a topic of research and highlight over the past years due to the increase injuries because of MSDs at workplace. Physical ergonomics that encompasses the likes of posture, load carried, frequency of movements and material handling as summarized in Table 6. Maurice et al. [116] tabulates an approach to address the MSDs issue to focus on ergonomics while sharing space with collaborative robots. The human factors in this study are segregated according to constraint and goal-oriented indicators. Constrained oriented indicators highlight the joint, position, velocity constraints whereas the goal-oriented constraints focus on the balance, vision, force of the digital human model in simulation.

Busch et al. [117] describes a postural optimization framework by considering task constraints for reducing MSDs. The methodology implies a motion and posture tracking mechanism which evaluates the current posture based on a cost function find the most safe and suited posture. Similar works are also seen by Sisbot et al. [119] and Suay et al. [120].Colim et al. [118] proposes an algorithm to alter the workstation attributes based on the anthropometric data of the workers performing the task.

Borges et al. [131] develops a dynamics-based model for designing feedback mechanisms in HRC systems. It designs a close loop diagram-based model to understand the physical workload on the human worker. Similar is the study by Petzoldt et al. [111] which considers the physical workload on the human as a method to devise task allocation routines.

### 3.3.3 Cognitive ergonomics in task allocation

As described in Table 5, cognitive ergonomics deals with decision making, analyzing and stress due to workload. Neerincx [121] in his work describes a comprehensive 3D cube model that describe the impact of level of information to be processes, task

[11] Anthropomorphism in the context of robotics, generalizes a robot that resemble the shape and construct of a human body.

rotation, and time taken as three important factors that describe the overall cognitive load that ranges from underload, vigilance, lock up and overload.

Wolter et al. [122] in their work emphasize on the cognitive demands needed from workers during performing their tasks and how these impact their performance at their workplace. The major demands are time related, decision making related, task complexity related and the external environment. In the survey conducted in this study, it was found that workers who had clock ticking to complete their tasks or difficult and complex assemblies to do in a defined space and time ended up making more errors and loosing focus impacting their efficiency negatively.

Papantonopoulos and Selvandy [123] in their work propose a framework for cognitive task allocation which define a framework to identify the task, cognitive process needed in completing the task (memorizing, visualizing, logical reasoning, information sequencing, mathematical reasoning), describe the performance criteria and define the final task allocation to an agent (human, robot or a human/robot controller).

In addition, more general methods are also used to measure the cognitive load of the human worker subjectively and therefore consider task sharing. It involves techniques such as interviews, observations, and protocol analysis to uncover the underlying cognitive activities, decision-making strategies, and mental models used by individuals. Cognitive task analysis therefore provides insights into how people think, solve problems, and make decisions, which can inform the design of training programs and decision support systems [134]. Situation Awareness Global Assessment Technique (SAGAT) is another method used to measure situation awareness, which is the understanding of the current situation and the ability to anticipate future events as used in the study in [135]. It involves presenting participants with a series of scenarios and assessing their ability to detect changes, make predictions, and maintain situational awareness. The method helps evaluate the effectiveness of information displays, training programs, and decision support systems in enhancing situation awareness [136]. Multiple methods to capture the motions, sensation and emotions of the worker have been proposed in studies to study and detect the mental load and fatigue of the worker. Eye tracking mechanisms, automatic emotion recognition [137], expression synthesis [138], mental load fluctuation via the electroencephalogram (EEG) [139] , has also been under implementation.

Longo et al. [164], summarizes how cognitive workload has been defined across literatures as an index comprising of multiple factors. Hancock and Caird [165], define mental load as a characteristic defined by the demands of the task being carried out. A similar definition was also put forward by Byrne [166] and in addition it also highlights the factor of the level of performance of the operator. According to the cognitive load theory, the working memory plays a major role in the overall mental workload on the human counterparts. The amount of information processing, memorizing and decision making are factors that are owed to the working memory. Stuiver et al. [167] and Wilson and Eggemeier [168], agree to consideration of the level of information-processing as an important factor in completing the task at hand. Another highlighted factor in literature is the level of performance required to complete the task in time. It is the amount of energy one puts in performing the task to a desired level in desired time [169][170]. Lin et al. [171] interestingly posts as the lack of resources within the existing and desired capabilities is what contributes to higher mental workload. Similar theories describing the level of processing capabilities, level of mental and physical resources and workers capabilities to do the task is described in [172][173][174]. Level of attention, decision making and time are another important factor that are considered in describing the mental workload [175][176][177][178].

## 3.4 Evaluation of ergonomics in task allocation

Several ergonomic evaluation based techniques are discussed in Section 2.3.2. These methods assess factors like posture, load handling, biomechanics, cognitive workload, and task constraints to determine ergonomic suitability, both physical and cognitive ergonomics. The ergonomic evaluation methods consider a single or multiple criteria of human factors when evaluating task allocation methods for ergonomics. In addition, task allocation algorithms as per the legacy methods are mostly pen and paper based. Physical ergonomic evaluation methods like EAWS, RULA, REBA are traditionally pen-paper based methods. Similarly, cognitive evaluation methods such as CLAT and SAGAT are questionnaires filled using user input via handwritten input. However, lately there has been a paradigm shift and there have been multiple platforms that support digital simulation and evaluation for ergonomics as discussed in the section earlier.

### 3.4.1 Single Factor Evaluation

Study conducted by Colim et al. [118] is to apply a human-centered approach to the design of a collaborative robotics workstation in order to minimize the musculoskeletal risk associated with a manual assembly task in industrial furniture manufacturing. The study aims to identify workers' complaints and risk factors that can be mitigated with future implementations of human-robot collaboration. The authors use Strain index and RULA for evaluation of ergonomics. The work only considers the use of worker postures for the evaluation of ergonomic condition.

Yetkin and Ultutas [140] present a consolidated review of the literature addressing ergonomics in human robot collaboration. It points out literature that deals with designing the workspace and workstation to improve the physical ergonomics of the human agent. Tsarouchi et al. [141] in their work develop a decision-making framework using a simulation and mathematical framework to design the workstation in a way that is ergonomically safe and feasible for the human counterpart. The model uses the strain index percentage from the worker muscle activity to evaluate and alter the model accordingly. The model was also used to evaluate the task allocation framework where the algorithm tests all possible alternatives suitable for task allocated to human or robot. However, the ergonomic aspect in the allocation framework was highly limited and the major focus was paid to productivity and cycle time in the task allocation.

While most of the single criteria studies consider human posture for an optimal ergonomic design, the study by Cherubini et al. [142] considers the load of the workpieces in developing an ergonomic workstation design. The study aimed to develop a collaborative human robot manufacturing cell for homokinetic joint assembly that considers ergonomics. The article discusses how the robot alternates between active and passive behaviors to assist the operator and comply with their needs. The goal is to reduce the workload on the operator and decrease the risk of strain injuries.

### 3.4.2 Multi-factor Evaluation

The online role allocation strategy proposed in the study by Merlo et al. [143] assigns actions among the agents of a human robot team according to the physical human-worker status. It is based on an adapted AND/OR graph that models all the possible assembly sequences of an assembly task. The evaluation for ergonomics is conducted using the RULA technique. The main contribution of the method is the integration of a human joint-level status indicator, which they call kinematic wear, that can account for the usage of each joint during the execution of an assembly task of lightweight pieces.

A more granular is the approach followed by Petzoldt et al. [112] with considers multiple factors and evaluation methods for overall productivity and user experience improvement (inclusive of ergonomics). Process effectiveness, process efficiency, HRC process efficiency, workload, worker satisfaction, user preference. Rather subjective evaluation methods such as the System Usability Scale (SUS) and NASA-TLX score. The study also compares the difference in task allocation with static and dynamic task allocation using assembly sequence graphs.

Similarly, Pearce et al. [144] develops an optimization framework for integrating collaborative robots into manufacturing processes. It considers the improvement in both cycle time and ergonomics by generating task assignments and schedules for human robot teams. The SI is estimated from video data and reviewed with experienced job analysts. The duration of the task is also considered, and the optimizer uses a time-index approach. The authors use the SI method to quantify human physical stress and create a set of solutions with assigned priorities on each goal.

### 3.4.3 Digital Methods

Digital evaluation methods offer significant benefits in the consideration of ergonomic factors during human-robot task allocation. These methods enable objective assessments, facilitate simulation and visualization, support iterative design and optimization, enhance cost, and time efficiency, and enable predictive analysis. Several digital tools are readily available to be able to use in the context of process visualization for ergonomics and add-in evaluation for ergonomics as discussed in Chapter 4.

The focus of the study by Rinaldi et al. [145] is to investigate the ergonomic risk of a manual assembly station, changing the anthropometric characteristics of the worker. The study proposes a new approach to improve a real system and reduce the ergonomic risk among operators. Different potential workers with different anthropometric characteristics have been tested, and the critical situations have been identified and solved proposing different job rotation solutions. The simulation results confirm that job rotation is a good approach to reduce the ergonomic risk and they provide practical guidelines for task allocation. The authors do not explicitly mention the simulation tool used and the OWAS ergonomic evaluation method is used.

Another study by Messeri et al. [146] focuses on a dynamic task allocation strategy to mitigate human physical fatigue in collaborative robotics. The study proposes a novel digital evaluation using OpenSim dynamic musculoskeletal model of the entire human upper body, which is used to collect offline data encoding the complex mapping between human motions and muscle activations using a deep neural network (DNN). The DNN learns mapping and to predict online how the muscles activate during the workers motions to dynamically allocate the task activities to human and robot. The study includes experimental validation and evaluation using the RULA methodology, and the results show the effectiveness of the proposed strategy in mitigating human physical fatigue in collaborative robotics.

The simulation study by Borges et al. [131] aimed to improve ergonomics and productivity in assembly workstations by simulating HRC. The authors compared two workstations, one with a human robot simulated scenario and the other replicating the current situation. The results showed that the robot-simulated scenario led to increased productivity, reduced posture exposure time, decreased overall workload, and provided insights for better understanding the system. The work mentions the use of Xsens MVN software to capture the motions of workers during the study and apply the RULA algorithm to assess physical workload.

## 3.5 Summary

After conducting a thorough review of the results from the SLR and conducting a forward and backward search of more related literature. Overall, the most relevant ones are summarized in Table 7. 71.93% of the literature summarized was a part of the original literature review.

| Sr No | Author | Year | Task allocation | Ergonomic design | Ergonomic Evaluation | Digital ergonomics | Part of SLR |
|---|---|---|---|---|---|---|---|
| 1 | Merlo | 2022 | x | | x | | Y |
| 2 | Alirezazadeh | 2022 | x | | | | Y |
| 3 | Messeri | 2022 | | | x | x | Y |
| 4 | Li | 2022 | | x | | | Y |
| 5 | Malik | 2019 | x | | | | Y |
| 6 | Merlo | 2023 | | | x | | Y |
| 7 | Colim | 2020 | | x | | | Y |
| 8 | Euchner | 2023 | x | | | | Y |
| 9 | Yetkin | 2022 | x | x | x | | Y |
| 10 | Rücker | 2018 | | | | | Y |
| 11 | Borges | 2022 | | x | x | x | Y |
| 12 | Borges | 2021 | | x | x | | Y |
| 13 | Murali | 2020 | x | | | | N |
| 14 | Karami | 2020 | | | | | N |
| 15 | Johannsmeier | 2016 | x | | | | N |
| 16 | Ajith | 1999 | x | | | | N |
| 17 | Ranz | 2017 | x | x | | | Y |
| 18 | Müller | 2017 | x | x | | | Y |
| 19 | Lamon | 2019 | x | x | | | Y |
| 20 | Anima | 2019 | x | x | | | N |
| 21 | Fechter | 2019 | x | x | | | N |
| 22 | Wu | 2017 | | x | x | | N |
| 23 | Roncone | 2017 | x | | | | Y |
| 24 | Karwowski | 2005 | | x | | | N |
| 25 | Srivastava | 2014 | | x | | | N |
| 26 | Gombolay | 2015 | | x | | | Y |
| 27 | Gombolay | 2013 | | x | | | Y |
| 28 | Clark | 2008 | | x | | | N |
| 29 | Endsley | 1988 | | x | | | N |
| 30 | Roy | 2020 | | x | | | N |
| 31 | Kliensmith | 2013 | | x | | | N |
| 32 | Tsarouchi | 2017 | | | x | | N |
| 33 | Colim | 2021 | | | x | x | Y |
| 34 | Liu | 2022 | x | x | | | Y |
| 35 | Tram | 2020 | x | | | | Y |
| 36 | Izghouti | 2022 | x | | | | Y |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 37 | Makrini | 2022 | x | | | | Y |
| 38 | Schmidbauer | 2020 | x | | | | Y |
| 39 | Schmidbauer | 2023 | x | | | | Y |
| 40 | Monguzzi | 2022 | x | | | | Y |
| 41 | Cai | 2022 | x | | x | | Y |
| 42 | Pearce | 2018 | | | x | | N |
| 43 | Noormohamadi | 2022 | x | | | | Y |
| 44 | Badiloa | 2022 | x | | | | Y |
| 45 | Pupa | 2021 | x | x | | | Y |
| 46 | Chen | 2013 | x | | | | Y |
| 47 | Schmidbauer | 2021 | x | | | | Y |
| 48 | Petzoldt | 2022 | x | | x | | Y |
| 49 | Makrini | 2019 | x | x | | | Y |
| 50 | Faccio | 2023 | x | x | | | Y |
| 51 | Castro | 2019 | | x | | | Y |
| 52 | Yuan | 2021 | x | | | | Y |
| 53 | Kousi | 2022 | x | | | | Y |
| 54 | Sheikh | 2022 | | x | | | Y |
| 55 | Linsinger | 2018 | x | | | | Y |
| 56 | Markis | 2021 | x | | | | Y |
| 57 | Cherubini | 2016 | | x | x | | N |

Table 7: Summary of Literature review

## 3.6 Research gap

From the literature summarized in Table 6, most of the literature (59.65%) focused on ways of allocating task using static or dynamic methods based on human capabilities and human preference. Of this, only 29.44% (10/34) considered ergonomic conditions mainly focused on workstation and organizational design. However, there were only three literatures (5.26%) that dealt with using digital ergonomic visualization and evaluation techniques.

Cobots for their adaptivity and intuitiveness are slowly becoming the choice of the industry [9]. Integrated with lean manufacturing, human robot collaboration is a popular topic with high focus on operator well-being, which is believed to be achieved using cobots [10]. When interacting with cobot, trust, safety and ergonomics play a major role in the performance of the team. While research in the field of task allocation has been prevalent, ergonomics has been in the light for quite some years. Literature over the past years is adapting to focus on ergonomics but still, very few exploit the digital resources available for ergonomic visualization and evaluation. To address this, the research focuses on answering the question:

***How can task allocation algorithms in human-robot collaboration be optimized for ergonomics?***

# 4 Methodology

Chapter 4 describes the detailed analysis of the factors that are selected for the task analysis and the evaluation methods. The first section will deal with the analysis of the task and elaborate in depth each of the factors and the usability in task allocation in human robot teams. This section is aimed at answering the sub-research question *"What are the various methods for task allocation that can be analysed?"* The second section will delve into the visualization methods available in the form of digital tools to visualize the situation for ergonomics and evaluate the ergonomic score based on the methodology described in Section 1 for task allocation using digital evaluation methods and will answer the following sub-research questions *"How will the task allocation method be modelled and visualized for ergonomics?"* and *"How can task allocation methods be evaluated for ergonomics?"*

## 4.1 Task analysis and assignment

Initially, the process is divided into sub tasks each consisting of basic assembly operations. Each of these subtasks then based on the criteria are evaluated for feasibility for allocation to either of the agents (human or robot). The cost for allocation of the task is then computed and final task allocation is carried out.

### 4.1.1 Human task analysis

Since the focus of the work is mainly on ergonomics, task allocation for human counterparts will be matched for feasibility checking the physical, cognitive, and organizational factors described in upcoming sections.

#### I) Physical Ergonomics

Physical factors in ergonomics define the physical capabilities and limitations of individuals. It involves the study of how people interact with their work environment, tools, and equipment to optimize productivity, efficiency, and safety. Studies highlight the ergonomic modelling for physical factors should consider the anthropometric data, biomechanical models and entail the concept of DHM [132]. Human posture, load handled, duration of load handling are widely described factors in literature [149][150][151][152] and will be considered as important factors in understanding the physical comfort of the worker while carrying out the desired work.

Load handling limit as per the NIOSH for humans in standing position is 15kg [155]. However, it is important to understand that the repetition of this load handling (frequency) is an important factor in conjunction, hence the final product is two-fold. If the weight of part (Load, *l*) is greater than the maximum specified load as per the law in country ($l_{max}$), it is directly to be allocated to the robot (R) counterpart. However, when the load is less than the limit, the frequency (Frequency, *f*) of handling the load must be considered. If weight is less than $l_{max}$, but the frequency of handling is less than once per minute [156], then either the human (H) should be allocated the task or option of sharing the task (S) should be explored. These conditions can be put forward as:

IF $(l >= l_{max})$

THEN R

ELSE IF ($l < l_{max}$ AND $f < 1$/min)

THEN S or H

ELSE R

END

These conditions are answered in the form of binary answers to questions: *“Is the load of the part* > $l_{max}$*?”* and *“Is the number of times to handle the load in 1 min greater than 1?”.* The answers of Yes (1) to these questions hint that the task is allocated to R, else if No (0) then, S or H.

In addition, static loads are highly harmful for muscle contraction and aggravating the MSD risk, hence task requiring handling static loads for greater than 1 min [152] are not suitable for human, hinting at the duration (Duration, *d*) of static load handling.

IF ($d > 1$ min)

THEN R

ELSE S or H

END

This condition answers the *question “Is the duration of handling the static load > 1 min?”*, if answer is Yes (1), task is allocated to R, else S or H.

Posture remains one of the most important factors in describing the physical discomfort, hence the major factors indicating towards posture are described via the question, *“Is the material outside the span of human reach?” (Reach of human,* $r_h$*). If* the answer to this question is Yes (1), indicate task to be allocated directly to R, else S or H.

Finally, the evaluation criteria also include the scores from ergonomic assessment scales of EAWS. EAWS defines the scores as green (0-25 points; no action needed), orange (25-50 points; possible risk, take measures) and red (>50 points, high risk, immediate action needed).

### II) Cognitive Factors

Cognitive factors focus on optimizing the interaction between humans and cognitive processes in various tasks and work environments. It involves studying how individuals perceive, process, and comprehend information, make decisions, solve problems, and allocate their attention and mental resources. Cognitive factors modelled in the form of questionnaires are rather subjective based on once capabilities and conditions. Nevertheless, use of measurement sensors such as EEG, EMG described in Section 3.3 address this and aim at making the measurement and evaluation more stand alone. It is therefore important to factor them correctly in the task assignment model. Cognitive ergonomics encompass the factors of user, task and the environment surrounding them [157]. Valery et al. [158] discuss how cognitive load is a function of the work efficiency the work strategy and the way human interact with the socio-technical systems in the vicinity. The quality of HRC/HCI plays a very important role in the overall cognitive load of the human in interacting with the system. The needs, abilities, and limitations of the skills of the human is also to be considered for cognitive analysis [159].

Task variety, diversity and worker preference are considered as major factors in assigning task to human-robot teams [66]. Similarly, the HABA-MABA and Fitts List discussed earlier also describe how at certain cognitive tasks the human counterpart supersedes the robot agent in the team and hence should be allocated to them. Gualtieri et al. [160] describes factors such as trust, usability, frustration, perceived enjoyment, acceptance, stress, and cognitive workload as important factors while assessing cognitive ergonomic in task allocation in human robot teams.

Considering the work described, the following questions are understood before task allocation:

i) *Is the task mentally challenging? (Mental demand, $m_d$)*
ii) *Carrying out the task is unpleasant? (Acceptance, $u_a$)*
iii) *Do you have to memorize steps or work instructions? (Work Instructions, $w_i$)*
iv) *The task is frustrating. (Frustration, $u_f$)*
v) *There is no variety in the current task assigned? (Task variety, $t_v$)*

Answers to these questions as Yes (1) directly assign the task to R, else can be S or H.

### III) Organizational Factors

Organizational ergonomics aims to create work environments that promote effective communication, collaboration, and coordination, while minimizing stress, burnout, and organizational constraints. Organizational ergonomics plays a crucial role in creating healthy and high-performing work systems. Organizational factors such as organizational structuring and stakeholder environment are difficult to model in empirical algorithms. Dul et al [161] discussed theoretical methodologies to add ergonomic principles into the strategic business functions and in conclusion intercepted the improvement in efficiency. They discussed how product design, marketing, and communication can be improved with ergonomic fundamentals. However, another aspect of organizational factors are the surrounding environmental conditions such as lighting, noise, temperature and working conditions such as workspace layout, worktable and resources provided as aid to complete the work.

Optimal external environmental conditions are a work right for people and hence it is assumed the environmental conditions are perfect and not considered as factors in task allocation in human robot teams. The organizational factors mainly considered in this work will deal with availability of human resources, robot and task switching abilities. The following questions are therefore considered for task assignment:

*i) Task switching is not possible in the current scenario? (Task switching, $t_s$)*
*ii) Robot is available at least 90% of the work shift and functions well? (Robot mechanical function, $av_r$)*
*iii) Human handles two workstations at the same time? (No of workstation, $n_w$)*

Answers to these questions as Yes (1) directly assign the task to R, else can be S or H depending on the task allocation process later. Table 8 provides a summary of the factors considered in human task analysis.

### 4.1.2 Robot task analysis

Similar to some hard-coded areas where tasks are always allocated to the robot, it is necessary to consider the feasibility of the robot factors in deciding task allocation as well. These factors range from the mechanical, operational, safety and economic perspective of using the robot. As described by Schmidbauer [66], reachability (r), critical issues (u), robot payload (p) and risk of collision (c) are considered in this work. These factors are formed as questions as below:

*i) Is the part to be manipulated within the robot workspace? (Reachability, r)*
*ii) There are no critical issues in the mechanical functioning of the robot (Critical issues, u)*

iii) *Is the load to be handled less than the maximum payload of the robot? (Payload, p)*

iv) *In any position the robot does not collide with either any surrounding part of human counterpart? (Risk of collision, c)*

| Sr No | Factor | Notation | Unit | Type | Score |
|---|---|---|---|---|---|
| 1 | Load | *l* | kg | Physical | 1 (>15 kg - R) , 0 ( S or H) |
| 2 | Frequency | *f* | constant | Physical | 1 (>1/min - R) , 0 (S or H) |
| 3 | Duration | *d* | min | Physical | 1 (>1 min - R) , 0 (S or H) |
| 4 | Reach | $r_h$ | m | Physical | 1 (Yes (out of reach) - H) , 0 (R) |
| 5 | Ergonomic Score | $E_s$ | constant | Physical | EAWS (>50) ; RULA (>5) |
| 6 | Mental demand | $m_d$ | - | Cognitive | 1 (Yes - R) , 0 (No , S or H) |
| 7 | Acceptance | $u_a$ | - | Cognitive | 1 (Yes - R) , 0 (No , S or H) |
| 8 | Work instruction/ Assistance | $w_i$ | - | Cognitive | 1 (Yes - R) , 0 (No , S or H) |
| 9 | Frustation | $u_f$ | - | Cognitive | 1 (Yes - R) , 0 (No , S or H) |
| 10 | Task Variety | $t_v$ | - | Cognitive | 1 (Yes - R) , 0 (No , S or H) |
| 11 | Task switching | ts | - | Organizational | 1 (Yes - R) , 0 (No , S or H) |
| 12 | Robot mechanical | $a_{vr}$ | - | Organizational | 1 (Yes - R) , 0 (No , S or H) |
| 13 | Workstation handled | $n_w$ | - | Organizational | 1 (Yes - R) , 0 (No , S or H) |

Table 8: Summary of human task analysis factors and assignment criteria

In addition to the above questions, it is important to consider that the robot does not reach singularity while dealing with any of the parts in the nearby position which is considered as a part of the collision factor discussed above.

| Sr No | Factor | Notation | Score |
|---|---|---|---|
| 1 | Reachability | r | 1 (Yes - R) , 0 (No , S or H) |
| 2 | Critical issues | u | 1 (Yes - R) , 0 (No , S or H) |
| 3 | Palyload | p | 1 (Yes - R) , 0 (No , S or H) |
| 4 | Risk of collision | c | 1 (Yes - R) , 0 (No , S or H) |

Table 9: Summary of robot task analysis factors and assignment criteria

### 4.1.3 Part and process analysis

In many cases the task to be carried out also depends on the nature, value and expected result of the final assembly. In this case, as discussed by Schmidbauer [66], stickiness, grasping of parts, gluing is some of part related characteristics that are to be considered. However, there can be extended considerations to understand the final product expectations as described in detail in the following questions.

i) *Is the part to be handled hazardous (i.e., does it classify as a hazmat part? (Hamzat, $p_h$)*
ii) *Is the part usual and can be grasped and handled by the robot (e.g., not sharp, small, uneven, sticky, etc)? (Part nature, $p_n$)*
iii) *Is the part to be handled not of high retail value? (Retail value, hrv)*
iv) *The task requires high accuracy and precision? (Accuracy, $p_a$)*

Like the other factors, the answers Yes (1) to the questions suggest that the task is to be allocated to the Robot, and otherwise be considered for sharing or allocation to Human agent.

| Sr No | Factor | Notation | Score |
|---|---|---|---|
| 1 | Hazmat | $p_h$ | 1 (Yes - R) , 0 (No , S or H) |
| 2 | Part nature | $p_n$ | 1 (Yes - R) , 0 (No , S or H) |
| 3 | Retail Value | hrv | 1 (Yes - R) , 0 (No , S or H) |
| 4 | Accuracy | $p_a$ | 1 (Yes - R) , 0 (No , S or H) |

Table 10: Summary of part and process factors

One of the important factors also considered by Schmidbauer [66], is also the learning factor which represents that in case a worker is new and in the learning curve and have not reached the desired learning break even representing that the task will be allocated to the human.

## 4.2 Visualization

Based on the analysis conducted using the factors described in Section 4.1, the scenario is then visualized using either traditional or digital methods and further evaluated. This work focuses on digital visualization and evaluation and hence these methods are discussed in the upcoming sections.

### 4.2.1 Digital Simulation

Process simulation tools for ergonomics offer several advantages in evaluating and optimizing ergonomic factors within industrial settings. These tools provide a digital representation of the production processes, allowing for a comprehensive analysis of human interactions, movements, and work conditions. By integrating ergonomics into process simulation, it becomes possible to assess the impact of various factors on worker comfort, safety, and efficiency. Process simulation tools help evaluate alternative process designs, identify potential bottlenecks, and assess the impact of process changes on ergonomics, productivity, and overall operational efficiency. Some of the popular platforms used are Technomatix Process Simulate by Siemens, DELMIA by Dassualt systems and Ema Work and Plant designer by imk Automotive GMBH.

### I. Technomatix Process Simulate

Process Simulate, developed by Siemens, is a digital ergonomic simulation platform focused on industrial manufacturing processes. It allows for the simulation and analysis of human tasks and interactions within a virtual production environment. Process Simulate enables users to optimize ergonomic conditions and ensure efficient and safe manufacturing operations. Process Simulate uses the Jack and Jill digital human models. By utilizing a broad set of international anthropometric databases, these tools can effectively incorporate body dimensions and proportions specific to different regions and demographics, ensuring a comprehensive analysis [153].

These platforms help identify potential risks associated with awkward postures, excessive exertion, or repetitive movements, leading to informed design decisions and interventions to mitigate ergonomic issues as seen in Figure 22.

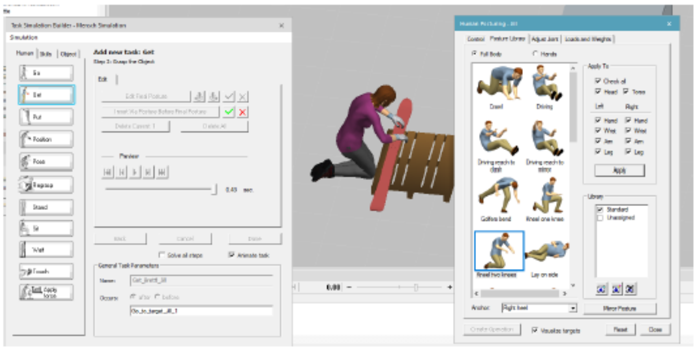


Figure 22:Posture selection for human model [72]

Process simulate uses RULA for the ergonomic assessment. Its analyses the upper limb for each of the posture and gives a specific score divided into the left and right limb ranging from 0-6 (0 being lowest and 6 being highest). It also represents the torso flexion as seen in red, alerting the high flex in torso which is unergonomic.

### II. DELMIA

The platform DELMIA by CATIA is an integrated platform that allows the 3D CAD models built using CATIA to be used for DELMIA simulation platform. It provides tools and analysis techniques to assess factors like reach, vision, clearance, and space, enabling designers to optimize workstations and ensure optimal human-machine interactions. The software also facilitates the reduction of physical prototypes by enabling virtual validation of worker interactions within the work cell, saving time and costs. Its enhanced ease of use ensures rapid deployment, making it accessible and efficient for ergonomic analysis. It has the feature to dive deep and conduct an ergonomic assessment of each of body parts giving a detailed analysis as seen in Figure 23, an analysis for the forearm is being done.

Figure 23: Ergonomic analysis in DELMIA [72]

### III. Ema Work Designer

EMA Work Designer by IMK Automotive GmbH offers a comprehensive solution for designing and optimizing workstations and assembly lines with a focus on ergonomics. By leveraging digital design, ergonomic analysis, virtual validation, and collaboration features, the platform aims to enhance worker well-being, productivity, and overall operational efficiency. It allows flexibility in choosing various anthropometric data as seen in Figure 24.

Figure 24: Human model selection in Ema Work designer (Own figure)

Once the environment and activity description have been created, the scenario can be simulated. The simulation utilizes the user input to generate a 3D simulation of the planned workflow and generates motion sequences for the avatars involved. Additionally, complex dependencies such as time synchronization and human-machine interactions are accurately represented, facilitating better planning. It helps in understanding the postures in a detailed analysis and uses EAWS and NIOSH method for ergonomic assessment.

The digital simulation and evaluation platform used in this work will be the Ema Work designer due to the available license and prior experience in using the platform. In addition, EAWS will serve as an apt evaluation considering the factors identified for physical ergonomics.

## 4.3 Evaluation

The evaluation for ergonomics will be conducted across two ways, one using the digital evaluation tools using ema Work designer with EAWS and the empirical evaluation using developed evaluation index. In addition to the physical ergonomic evaluation, the cognitive load will be evaluated based on factors defined and enumerated. The detailed description of these methods is described in Section 2.3.

Ema Work designer uses the EAWS methodology for ergonomic evaluation and supports cycle time analysis using spaghetti diagram. The EAWS evaluation as shown in Figure 25 considers the points of the posture, forces, and load handling.

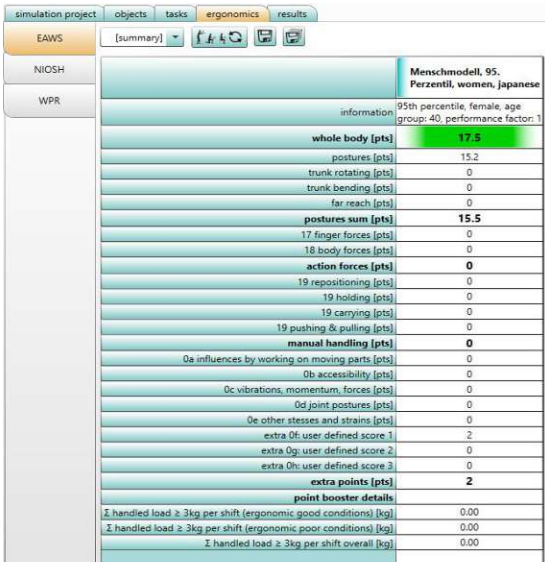



Figure 25:Sample EAWS Ergonomic assessment in Ema Work designer (Own figure)

The cognitive ergonomic evaluation is considered by computing the Mental Workload Index (MWLI). Strain index (SI) is a common method to evaluate the ergonomic workload including the workload, forces, postures, and strain on the muscles of the worker performing tasks [162]. A similar evaluation is also conducted by using the CLAM methodology for cognitive load assessment [163]. However, this works deal with improvising and optimizing the make span, energy, time taken and mental workload. However, the term mental workload in this work is left ambiguous and does not define the sub-factors impacting or affecting the mental workload. Based on the factors discussed in Section 3.3 the MWLI is defined as a product of mainly five factors as described in Table 11.

| Factor | Notation | Scale | Description |
|---|---|---|---|
| Task demand | $T_d$ | 1-5 | 1 – Task is not mentally demanding<br>5 - Task is highly demanding |
| Level of performance | $L_p$ | 1-5 | 1 – No extra effort needed to keep up to the expected performance<br>5- Very high effort needed to reach the level of performance |
| Level of resources | $L_r$ | 1-5 | 1 – No extra resources needed to complete the task in the desired level and time<br>5 – Most resources to bridge the gap in performance |
| Level of information processing | $L_i$ | 1-5 | 1 – No information processing or acquiring needed to complete the task<br>5 – Task requires high level of information acquiring and processing |
| Level of decision making | $L_d$ | 1-5 | 1 – No decision making required in the process<br>5 – Frequent decision making required |

Table 11: Cognitive evaluation factors (Own table)

### *i) Task Demand ($T_d$)*

Task demand is the ask or insistent request of the task that requires cognitive interference by human. ElMaraghy et al. [180] models empirically the task complexity in engineering design, product development and manufacturing processes. They describe the nature of static and dynamic complexity in tasks. Task demand is highly dependent on the complexity of the task and assembly at hand. For instance, screwing task would not be considered highly demanding, however fixing solar cells in a panel could be more demanding. The irony here still being that the demand is highly subjective in nature. It is dependent on factors like the learning curve/level, experience of the worker in the same process as well as attributes to some extent on the personal/organizational circumstances.

Jang and Park [181] describe and evaluate the task complexity measurement metric (TACOM) as a function of the task scope, structure, and uncertainty. They consider each of these metrics as a dependent score based on the weighted summation of information, number of actions, sequence of actions, knowledge, and the overall resources. These factors encompass accurately the cognitive portfolio and the task demand based on complexity of the task. The TACOM adopted from [181] is described as

Equation 1

$$TACOM = \sqrt{(0.621{T_s}^2) + (0.239{T_{st}}^2) + (0.14{T_u}^2)}$$

$T_s$ = 0.284 * Number of Actions (N) + 0.716 * Level of information processing ($L_i$)

$T_{st}$ = 0.109 * Learning level (α) + 0.891 * logical sequence of actions ($s_a$)

$T_u$ = Level of predictability/confidence in a task

Learning level (α) is defined as a gap of the current learning level with respect to the desired company and/or task specific learning level. Schmidbauer [66] as shown in Figure 26, extrapolates a desired reference value xc necessary to be obtained and defined by individual task and the initial execution time $t_1$.

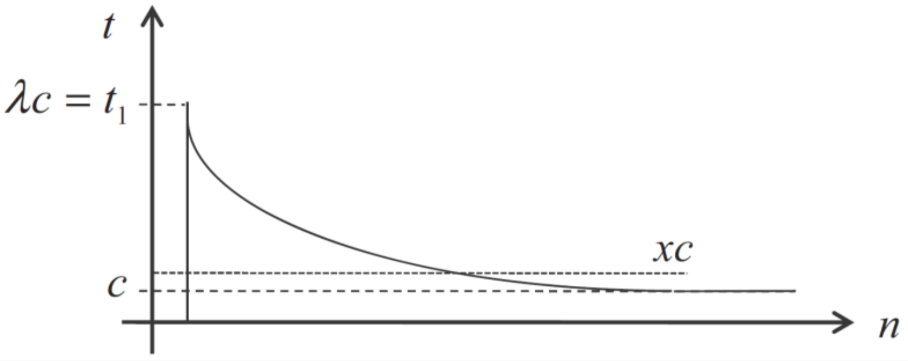



Figure 26: Learning curve [66]

$T_u$ the level of confidence is defined using the confidence probability curve for conducting the task at hand without exerting more time in thinking or perceiving any aspect of the task. The basic concept of confidence curve is adopted using the probability of successful decision making that results in higher level of confidence and hence cognitive load [186].

In [181] , the overall TACOM score is compared with the probability of an unsafe act, however in this work we will relate the TACOM score to the overall cognitive load. The TACOM scale is defined from 0 - 4.5 with an interval of 0.5 in the analysis by Jang and Park [181]. In consideration for cognitive load assessment the scale will be related to the evaluation in Table 10 as described below in Table 12.

| TACOM Score | Task Demand Score |
|---|---|
| 0 – 2.5 | 1 |
| 2.5 – 3.0 | 2 |
| 3.0 – 3.5 | 3 |
| 3.5 – 4.0 | 4 |
| 4.0 – 4.5 | 5 |

Table 12: Task demand cognitive score

*ii) Level of performance ($L_p$)*

Level of performance correspond to the *"extra cognitive effort"* needed to keep up with the desired level of performance. In more ways than one, the extra effort needed to keep up with the level of performance is governed by the task demand, nature of task and hence the task complexity. Mental effort is a highly broad and subjective term and Steele in his work in [182] rhetorically questions if at all mental effort is quantifiable. He also describes *"Given how widely effort as a concept is employed in the cognitive sciences it seems that there should be interest in more precisely defining it, and as such improving the ability to consider how appropriate proposed."* Effort as an abstract concept is the gap between capacity and demand and can be modelled as a function of Capacity (C), Demand (D), for a task $P_n$, in time (t) such that $E_n$ ($P_n$, $t_n$, $C_n$, $D_n$). Effort is most frequently scoped as a percentage numerically to bridge the gap between the Capacity and demand.

Equation 2

$$E_n = \frac{D_n}{C_n} * 100\ \%$$

The Rasch model has been highly popular in empirically defining the demand and capacity as a logarithmic relation [182][185]. According to Rasch's model

Equation 3

$$P_s = \frac{e^{(C_n - D_n)}}{1 + e^{(C_n - D_n)}}$$

$P_s$ is the probability of taking the correct decision as a logistic function of capacity and demand. This however defines the probability of carrying out a task successively which is highly dependent on the factor representing $C_n$ – $D_n$, which is closely defined as the cognitive effort. The higher the difference between the capability and demand, the higher the effort needed to complete the task and the lower the probability of successive decision making and vice versa. Hence capacity and demand highly and closely relate to the overall cognitive effort and decision-making success. The scores obtained from Equation 2 are then normalized to the cognitive score as in Table 13.

| Score (%) | Level of performance Score |
|---|---|
| 0 – 50 | 1 |
| 50 - 100 | 2 |
| 100 - 150 | 3 |
| 150 - 200 | 4 |
| >200 | 5 |

Table 13: Level of performance (Lp) score

The percentage score represents the ratio of $E_n$ in percentage. For instance, a score of 150% suggests that 1.5 times the current effort is needed to meet the desired process demand, incurring higher cognitive load.

*iii) Level of resources ($L_r$)*

Level of resources links back to the training needed. This metric emphasizes on the need of extra cognitive resource mainly in the form of training to meet the desired level of performance. Level of resources directly link to the training level as described in Task demand and Figure 26.

*iv) Level of information processing ($L_i$)*

Level of information processing suggests the use of working memory[12] to memorize the sequence of actions, or any extra information needed to complete the task. According to the Cognitive Load theory, the working memory would decay over time unless repetitive attention is enforced [183]. Oberauer and Lewandowsky [187] define that the cognitive load is a factor of time-based information processing represented as a ratio of the duration of attention, number of times it is needed and the overall available time to achieve the level of performance. The level of information processing relates to the working memory and the number of times information processing was needed in the task represented by Equation 4.

[12] Working memory is defined as the limited capacity cognitive system that enables temporary storage for limited information to perform complex cognitive tasks such as learning and reasoning [183].

Equation 4

$$L_i = \frac{t_a * N}{T}$$

Where $t_a$ represents the time duration for which attention is needed to process the information, N the number of times information processing is needed in the overall process and T being the total demanded time to complete the task. The scores obtained are normalized as seen in Table 14 to meet a scale range of 1-5.

| Score (%) | Level of information Score |
|---|---|
| 0 – 20 | 1 |
| 20 – 40 | 2 |
| 40 – 70 | 3 |
| 70 – 85 | 4 |
| 85 – 100 | 5 |

Table 14: Level of information (Li) score

*v) Level of decision making ($L_d$)*

Some process has sub tasks that require decision making irrespective if the task is done by human or the robot counterpart. Increased frequency of decision making requires higher cognitive attention exerting higher cognitive load. Any et al. [184] describes entropy as a method in describing the cognitive model. Similar thought is also raised in [66].Computing the task demand and level of performance already describe the decision-making metric as an important one in measuring the overall cognitive load. Number of times decision making occurs is directly found proportional to the overall cognitive load. However, decision making also impacts the cognitive load based on the level of information processing needed in working memory, task demand and cognitive effort added. Overall load based on decision making is defined as

Equation 5

$$L_{di} = N_d \text{ ; such that } N_d > 0$$

$$\text{If } N_d = 0, L_{di} = 0$$

Where $N_d$ represents the number of times decision making is needed in the overall process. However, the cognitive load is not only a function of the number of times decision making is done but also a function of the successful decision making over time. Therefore, Equation 6

$$L_{di} = P(i) = N_d \sum_i P_i$$

Where $N_d$ is the number of decisions and $P_i$ is the probability of successful decision taken [182].The final $L_d$ score for overall cognitive evaluation is then summarized as seen in Table 15.

| Score (%) | Level of decision-making Score |
|---|---|
| 0 – 20 | 1 |
| 20 – 40 | 2 |
| 40 – 70 | 3 |
| 70 – 85 | 4 |
| 85 – 100 | 5 |

Table 15: Level of decision making (Ld) score

The raw score is calculated considering the overall percentage of the score from the maximum possible score. The max score is calculated based on the number of times decision making is done ($N_d$) as a share of the total number of steps in the task ($N_t$), considering successful decision making each time and the $N_d$ is based on the duration of entire shift.

# 5 Implementation and evaluation

The use case considered in this work is for the assembly of a ski board. The assembly consists of the ski board, the brackets (2 pairs of 2 types) and screws to fix the brackets and complete the ski assembly. The assembly steps of the application are described in the modified Event-driven process chain diagram (EPC) described in Figure 27.

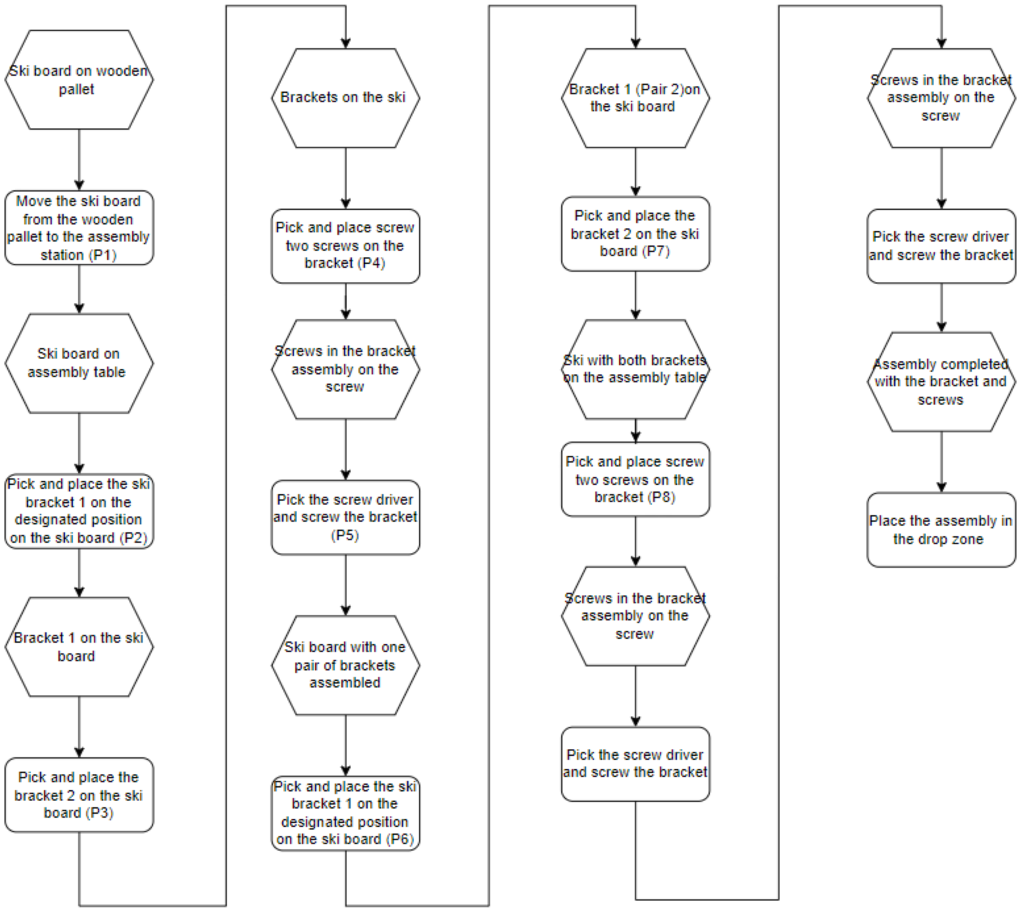



Figure 27: Event-driven process chain diagram (AS-IS) (Own figure)

Based on the designed process map the task is given the nomenclature from P1 – P11 as summarized below in Table 16. The following factors for the task analysis are assumed.

i) The weight of the ski board is considered as 3 kg and the bindings as 2 kg, with a total weight of the assembled ski as 5 kg [179]

ii) Number of ski's assembled in a day are assumed to be 100 as it is seasonal in nature

iii) Average hourly wage in Austria as € 28 for skilled workforce [193]

iv) The cost of cobot is assumed to be € 25000, cost of peripherals as €10000, installation and software cost as € 3000.

| Number | Task |
| --- | --- |
| P1 | Pick and place up the ski board on the assembly table |
| P2 | Pick and place the Binding 1 on the ski board |
| P3 | Pick and place the Binding 2 on the ski board |
| P4 | Pick and place screws on the slots in the bracket |
| P5 | Pick the screw driver and screw the brackets on the ski board |
| P6 | Pick and place second pair of Binding 1 on the ski board |
| P7 | Pick and place second pair of Binding 2 on the ski board |
| P8 | Pick and place screws on the slots in the bracket |
| P9 | Pick the screw driver and screw the bindings on the ski board |
| P10 | Inspecting the assembly for any loose brackets or screws |
| P11 | Place the assembled ski board on the drop area |

Table 16: Task summary and nomenclature for task allocation

## 5.1 Task analysis and allocation

Considering the factors analyzed and designed in Section 4.1, the tasks from P1 to P11 will be allocated. The task analysis is carried out based on the human factors, robot analysis, part and process analysis and efficiency analysis and finally summarized with the values.

### 5.1.1 Human Task analysis

The human factors are analyzed based on the physical, cognitive, and organizational ergonomic factors described in the earlier section. Considering these factors, the analyzed factors are summarized in Table 17.

| Factor | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Load | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Frequency | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Duration | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Reach | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Action | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

Table 17: Human Task analysis

### 5.1.2 Robot task analysis

Robot task analysis revolves around four aspects of reachability, critical issues, payload, and collision risk. Based on these factors, the analysis for each of the task is carried out in Table 18.

| Factors | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Reachability | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Critical issues | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Payload | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Collision | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |

Table 18: Robot task analysis

### 5.1.3 Part and process analysis

Considering the inherit nature of the part to be handled and the retail value including the outcome of the product is important in deciding the task allocation to either human or the robot agent. Based on these criteria, the task analysis for the example of Ski assembly is summarized in Table 19.

| Factors | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Hazmat | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Part nature | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 |
| Retail value | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Accuracy | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |

Table 19: Part and process task analysis

### 5.1.4 Task assignment

The task assignment based on the criteria discussed in Section 5.1 is evaluated in the upcoming sections under two scenarios. The use case of ski assembly for this work does not have flexible sequence of options for showcasing multiple alternatives and their impact. Considering the boundaries of the capabilities, for instance the robot is fix mounted and hence the tasks of picking placing the ski from an area outside of its reach is not interchangeable and has to be done by a human agent (can be replace by automation, however that is not the scope of this work) and therefore the task allocation will be considered fixed.

*I. Scenario 1*

Considering the task analysis and factors discussed in the previous sections, it is highly evident that task P1, P10 and P11, cannot be performed by the robot agent due to the reachability and existing capabilities available.

| Agent | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Human | x | | | x | x | | | x | x | x | x |
| Robot | | x | x | | | x | x | | | | |

Table 20: Task assignment Scenario 1

In the task assignment hinted in Table 20, Task P4 and P5 hint at the possibility of a shared task. The first scenario deals with the use case of conducting the screwing application by the human and the robot agent picking and placing the brackets, this is further visualized and evaluated in Section 5.2 and 5.3 respectively under title Scenario 1.

***II. Scenario 2***

Considering the limited flexibility, and exorbitant boundaries of the task analysis, Scenario 2 will only have the scope to explore the task switching opportunity of having the robot conduct the screwing application and the pick and place of ski bindings via the human. However, to have the robot to do only the screwing operation would require extended screw head that feeds screw and conducts the screwing operation [192]. Based on this, the task assignment for Scenario 2, will be changed as seen in Table 21.

| Agent | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Human | x | x | x | | | x | x | | | x | x |
| Robot | | | | x | x | | | x | x | | |

Table 21: Task assignment Scenario 2

## 5.2 Task visualization

***I. Scenario 1***

The task visualization is carried out using the Ema Work Designer which enables to design, simulate and closely replicate scenarios for the assembly process considering both productivity and ergonomics. The layout of the simulated process is shown in Figure 28.


Figure 28: Task visualization Scenario 1 (Own figure)

The use case is directly adopted from the theoretical use case as a part of the Digital Simulation of Ergonomics and Robotics (DSER) course at TU Wien. In this use case, the human model used is a 50th percentile, German female (Aged 40 years). The anthropometric data at the 50th percentile is used to establish the median values within a normal distribution, providing a comprehensive representation of the entire range of values. As a result, these data are regarded as a suitable choice for estimation. Initially the task is directly visualized as the initial scenario. No improvements in any aspects are simulated. On completing and running the simulation, the work designer provides an overall ergonomic score as well as spaghetti chart and time analysis as seen in Figure 29. The overall cycle time includes the sequence without any improvements in the design layout or workplace and workstation design. 74.3 seconds was taken to complete the entire sequence of one assembly with an overall ergonomic score of 44 as seen in Figure 32 as discussed in the further section.

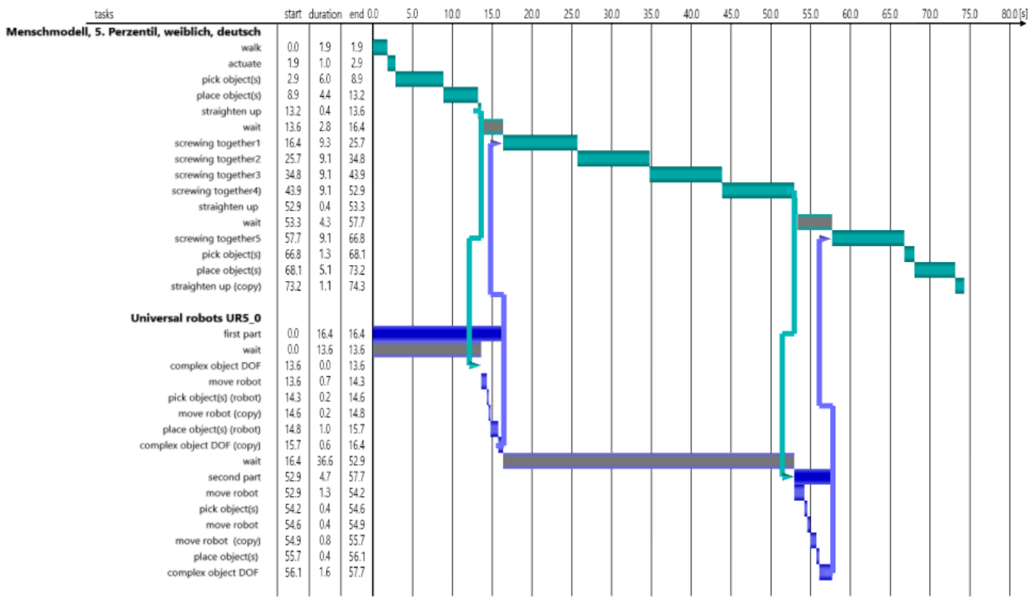



Figure 29: Overall time analysis of the task – Scenario 1 (Own figure)

### *II. Scenario 2*

In this scenario, the visualization involved a human performing the task of picking up and placing the two ski binding brackets, while the robot handled the screwing task. Figure 25 depicts how the human picks and places the ski binding on the ski marking area.

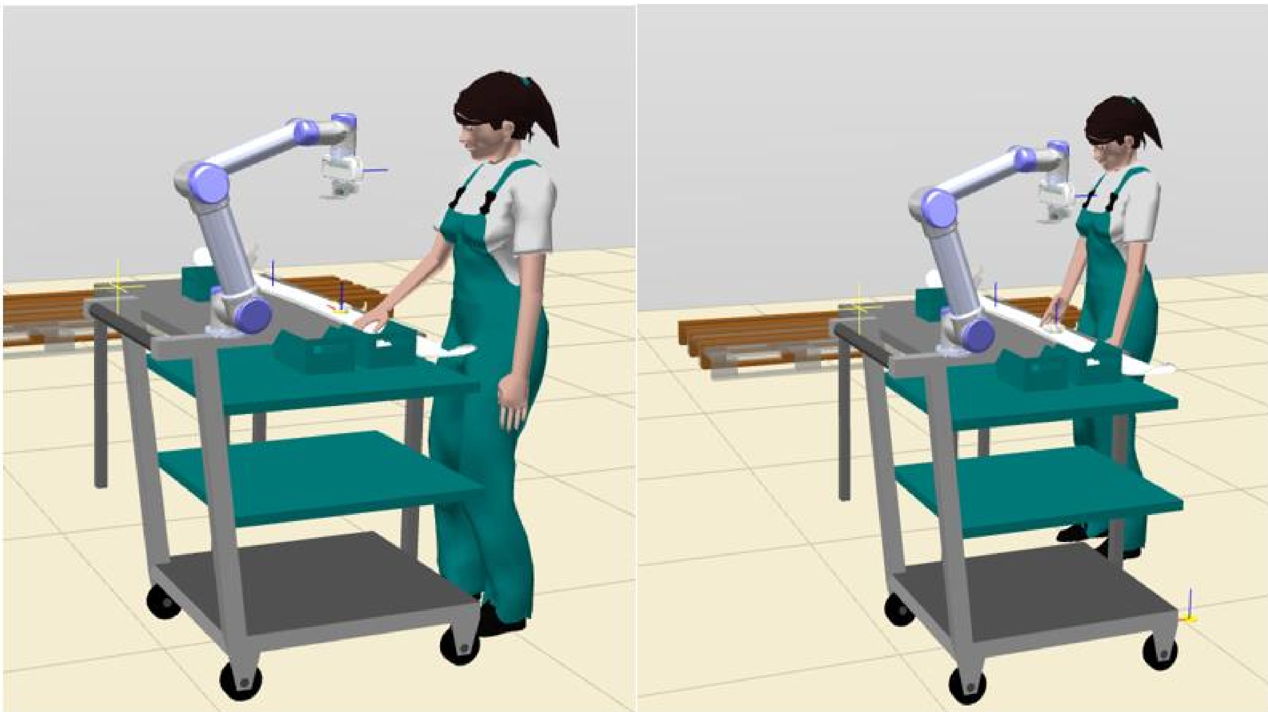


Figure 30: Task visualization Scenario 2 (Left: Pick Binding; Right: Place Binding) (own figure)

The simulation was then monitored for the cycle time and ergonomic aspects (discussed in Section 5.3). Overall, the cycle time reduced by 19.25% in comparison to scenario 1 from 74.3 seconds to 60 seconds per ski assembly as seen in Figure 31. However, there are certain consequences for cost and minor impact on ergonomics as discussed further.

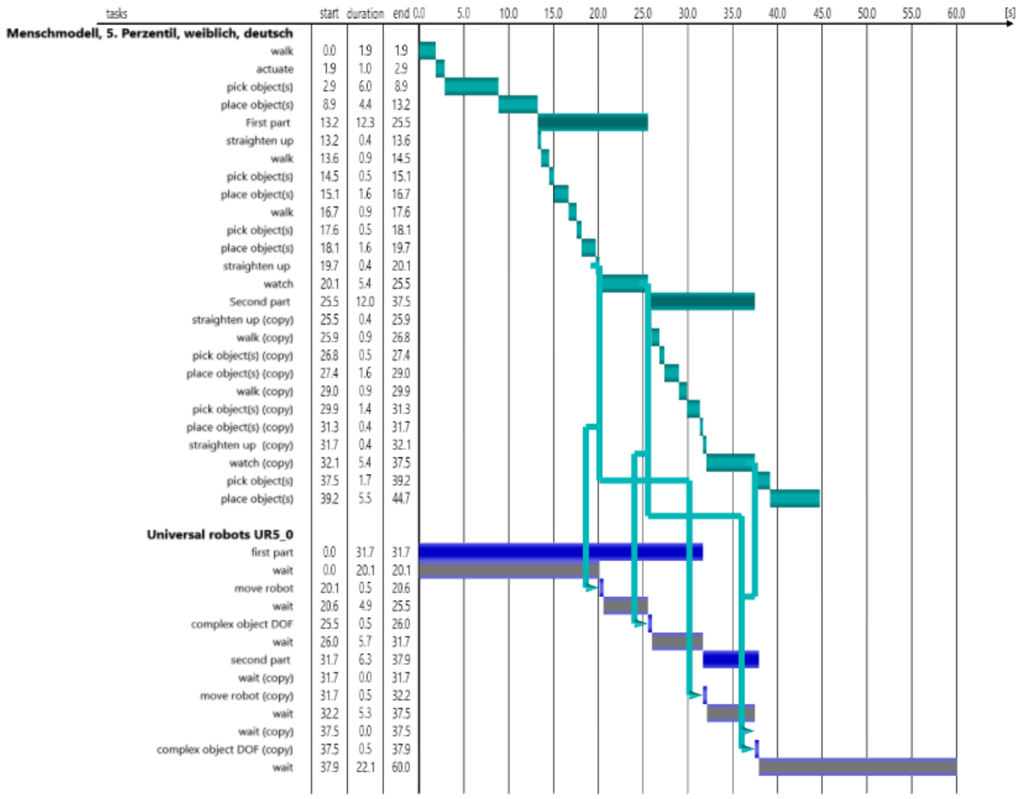



Figure 31: Overall time analysis of the task – Scenario 2 (Own figure)

## 5.3 Evaluation

### *I. Scenario 1*

The evaluation is conducted for physical and cognitive ergonomics following the methodology described in Chapter 4. Physical ergonomics is directly supported using the EAWS score provided by the simulation tool as seen in Figure 32. The score of 44 does not belong to the red zone, but there is some scope of possible improvements. The high score is constituted by the repositioning score. This score is related to the need for adjustments in hand postures and handling techniques when retrieving the ski from the euro pallet. Furthermore, points are attributed to posture-related issues, particularly related to the act of kneeling when picking up and placing the pallet. To address these concerns, modifications were made, including altering the orientation of the ski and adjusting the height of the table or pallet from which the ski is retrieved and placed. These changes are depicted in Figure 32 and have led to an improved physical ergonomic score of 22.5, which falls within the green zone.

| | Menschmodell, 5. Perzentil, weiblich, deutsch |
|---|---|
| information | 50th percentile, female, age group: 40, performance factor: 1 |
| **whole body [pts]** | **44** |
| postures [pts] | 2.7 |
| trunk rotating [pts] | 0 |
| trunk bending [pts] | 0 |
| far reach [pts] | 0 |
| **postures sum [pts]** | **3** |
| 17 finger forces [pts] | 0 |
| 18 body forces [pts] | 0 |
| **action forces [pts]** | **0** |
| 19 repositioning [pts] | 39 |
| 19 holding [pts] | 0 |
| 19 carrying [pts] | 0 |
| 19 pushing & pulling [pts] | 0 |
| **manual handling [pts]** | **39** |
| 0a influences by working on moving parts [pts] | 0 |
| 0b accessibility [pts] | 0 |
| 0c vibrations, momentum, forces [pts] | 0 |
| 0d joint postures [pts] | 0 |
| 0e other stesses and strains [pts] | 0 |
| extra 0f: user defined score 1 | 2 |
| extra 0g: user defined score 2 | 0 |
| extra 0h: user defined score 3 | 0 |
| **extra points [pts]** | **2** |

| | Menschmodell, 5. Perzentil, weiblich, deutsch |
|---|---|
| information | 50th percentile, female, age group: 40, performance factor: 1 |
| **whole body [pts]** | **23.5** |
| postures [pts] | 2 |
| trunk rotating [pts] | 0 |
| trunk bending [pts] | 0 |
| far reach [pts] | 0 |
| **postures sum [pts]** | **2** |
| 17 finger forces [pts] | 0 |
| 18 body forces [pts] | 0 |
| **action forces [pts]** | **0** |
| 19 repositioning [pts] | 19.5 |
| 19 holding [pts] | 0 |
| 19 carrying [pts] | 0 |
| 19 pushing & pulling [pts] | 0 |
| **manual handling [pts]** | **19.5** |
| 0a influences by working on moving parts [pts] | 0 |
| 0b accessibility [pts] | 0 |
| 0c vibrations, momentum, forces [pts] | 0 |
| 0d joint postures [pts] | 0 |
| 0e other stesses and strains [pts] | 0 |
| extra 0f: user defined score 1 | 2 |
| extra 0g: user defined score 2 | 0 |
| extra 0h: user defined score 3 | 0 |
| **extra points [pts]** | **2** |

Figure 32: EAWS score: Before (Left) and After (Right) for Scenario 1

Cognitive ergonomics is evaluated based on the factors of Task demand ($T_d$), level of performance ($L_p$), Level of resources ($L_r$), Level of information processing ($L_i$) and Level of decision making ($L_d$) as discussed in Section 4.3. Working backwards on the cognitive evaluation, the $L_i$ is defined first.

The tasks in the sequence do not require any information processing since the comprise of basic actions except for P10, where the human should inspect the final assembly for quality checks. The overall cycle time of task P10 is 2.8 seconds ($t_a$) hence from the Equation 4,

$$L_i = \frac{t_a * N}{T}$$

$$= \frac{2.8 * 1}{70.4}$$

$$L_i = 0.039 = 3.9\%$$

A total of 3.9% of the time stringent information processing is needed in the task which is considered normal and has an overall rating of 1. Similarly, the decision making is only required in task P10, and since the level of decision making is also dependent on the probability of successful decision making, it is considered that it is successful at least 85% of the time. The calculation is considered using the data from [187] and considering a growth of 6% year over year and hence manufacturing about maximum of 150 ski boards per shift per station. The overall cognitive load based on decision making will be cumulated over time across the shift and hence it is important to consider the number of times the decision making is needed in the shift. However, it is also important to consider this as a ratio of the total duration for which the work is done, the decision making is needed in P10 which has a duration of 2.8 seconds (total of 420 seconds)

$$L_{di} = N_d * \sum_i P_i$$

$$= 150 * 150$$

$$L_{di} = 22500$$

The score is scaled using the guidance shown in Table 15, and therefore the final normalized score for $L_d$ is 1. The maximum possible score for $L_{di}$ is 2,47,500 (150 *11*150), therefore the obtained $L_{di}$ is 9.09% which equals a score of 1. Since the task does not have sub tasks that require high skill or learning level, it is considered that the cognitive load due to the level of resources will be considered theoretically nil. The learning curve is reached for the associates doing the task, hence $L_r$ is considered as 1.

The level of performance ($L_p$) as described is highly described as the effort needed to gap the demand considering the existing capacity. As described, the ski industry is slowly rising at a rate of 6% at least, hence as opposed to the current demand of 136 ski per shift per station, the rise as considered earlier is 150 skis, therefore the extra cognitive effort is enumerated as

$$E_n = \frac{D_n}{C_n} * 100\ \%$$

$$= \frac{150}{136} * 100\ \%$$

$$E_n = 110.29\%$$

This score than suggests that extra efforts must be put in to keep up the demand, and as hinted in Table 13 and the final score is considered as 3.

Finally, the Task demand, TACOM is measured using the formula described in Equation 1.

$$TACOM = \sqrt{\left(0.621{T_s}^2\right) + \left(0.239{T_{st}}^2\right) + \left(0.14{T_u}^2\right)}$$

Where

$T_s$ = 0.284 * Number of Actions (N) + 0.716 * Level of information processing ($L_i$)

$T_{st}$ = 0.109 * Learning level (α) + 0.891 * logical sequence of actions ($s_a$)

$T_u$ = Level of predictability/confidence in a task

The level of confidence in conducting the task is highly dependent on the learning level (α). As described in Figure 33, assuming that the ideal learning level is 85% and is achieved, therefore $T_u$ is 0.85. Another variable, $s_a$ describes abstractly on the percentage of task that are sequenced that can be altered, if for instance 20% of the tasks can be re-shifted, then $s_a$ is 80%. In the two scenarios explore in this work 4 of 11 tasks are switched in the two scenarios hence 36% of the task can be shifted , making $s_a$ as 64%. Using this information,

$$T_s = (0.284 * 6) + (0.716 * 0.039) = 1.73$$

$$T_{st} = (0.109 * 0.85) + (0.891 * 0.64) = 0.66$$

$$TACOM = \sqrt{(0.621 * 1.73^2) + (0.239 * 0.66^2) + (0.14 * 0.85^{\,2})}$$

$$TACOM = 1.4$$

The score of 1.4 in the TACOM corresponds to an overall score of task demand ($T_d$) as 1. Overall, the MWLI is then defined as an average of these scores as in Equation 7.

Equation 7

$$MWLI = \frac{T_d + L_p + L_r + L_i + L_d}{5}$$

$$MWLI = 1.48$$

An overall cognitive score of 1.48 suggest being in the green zone (Green: <2, Amber 2 – 3, Red >3).

The evaluation for ergonomics overall considered the physical, cognitive, and organizational ergonomic aspects discussed in Section 3.3, Table 9.

The primary aim of the work in this thesis is the inclusion of human factors impacting ergonomics into task allocation framework. However, it is equally important to consider the consequences of the same on efficiency and economical analysis. While considering efficiency the major factors considered are time and cost invested in performing and completing a task, and a similar approach will be followed for this study. The time and cost for both the human and robot will be calculated to do a particular task and the agent with the least cost and time will be selected.

Human Cost ($C_h$) is considered as the product of time taken by the human in seconds ($T_h$) and the cost per labor hour (CPLH) of the labor. It is identified as the cost the human takes to complete the task as demonstrated in Equation 8.

Equation 8

$$C_h = \frac{T_h * CPLH}{3600}$$

Similarly calculating the cost for a robot to conduct will give a comparison between the overall economic picture of conducting an action. However, there are multiple factors to be considered when considering the cost for robots ($C_r$) ranging from setup to installation cost. There the basic cost will be calculated in a similar manner to human cost considering the Time taken ($T_r$) and Cost per robot hour (CRPH). Cost per robot hours is calculated considering the cost of setup, auxiliaries, installation and required peripherals. The cost of each of these aspects is calculated per part based on the processed volume in ways summarized below.

Equation 9

$$CRPH = \frac{Robot\ Cost + Installation\ cost + Cost\ of\ peripherals + System\ integration\ cost}{Maximum\ volume\ throughput\ per\ hour}$$

Based on the CRPH, the robot cost is calculated as,

Equation 10

$$C_{r=} \frac{T_r * CPRH}{3600}$$

In order to conduct the efficiency and economical analysis, the initial system and labor costs are already considered assumptions in the beginning of the section, however comparing the cycle time of doing the task is necessary. Based on these the time and cost for each of the tasks is summarized in Table 20 using Equations 1, 2 and 3 for Scenario 1. The time to complete the task is calculated using the MTM-UAS[13] readings available in Ema Work designer. These costs depict the cost of a single cycle, since the maximum expected throughput is considered as 150 skis per shift, the total score is multiplied to 150.

[13] MTM stands for the Methods-Time Measurement, which is a standard technique used to analyse times required to perform a task. MTM-UAS is an extended standard of MTM used specifically for Europe [194]

| Factor | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $T_h$ | 10.4 | - | - | 18.4 | | - | - | 18.2 | | 2.8 | 4.9 |
| $C_h$ | 0.08 | - | - | 0.14 | | - | - | 0.14 | | 0.02 | 0.04 |
| $T_r$ | - | 2.8 | 4.7 | - | - | 2.8 | 4.7 | - | - | - | - |
| $C_r$ | - | 0.02 | 0.04 | - | - | 0.02 | 0.04 | - | - | - | - |

Table 22: Efficiency analysis for Scenario 1

Based on Equation 2, the CPRH is calculated as:

$$CRPH = \frac{Robot\ Cost\ +\ Installation\ cost\ +\ Cost\ of\ peripherals\ +\ System\ integration\ cost}{Maximum\ volume\ throughput\ per\ hour}$$

$$= \frac{25000 + 10000 + 3000}{17}$$

$$CRPH = 2235\ Euros$$

In 2021, Austria manufactured 2.02 million ski boards [188]. Atomic, Fischer, Blizzard, Head and Kneissl represent the five market players [189][190] with largest share in ski market. It is assumed that 10% of the share is held by other players and on average each of these holds 18% of the market share, therefore manufacturing approximately 350,000 skis a year. Average working hours per year as 2080 hours (40 h/week * 52 weeks/year) and there are at least 10 assembly stations.

Considering that the volume of the production and that ski is a seasonal product, it is beneficial to consider that the robot is employed as a service following the concept of Robot as a service (RaaS). Though Ai.nl [191] explain that the robot as a service cost about $8 per hour, for this use case we would still consider that the overall cost of the labor per hour and the robot per hour is the same.

### *II. Scenario 2*

In comparison to scenario 1 for physical ergonomics, the EAWS score is 49.5 in the yellow zone with similar areas of high score as for the first scenario for positioning and handling of the parts. In this case since the human is now picking extra parts (ski bindings) it can be fairly said that the increase in the score is attributed to that. In this scenario, irrespective of the fact that the same improvements are done as in Scenario 1, the repositioning error still prevails forbidding the EAWS score to be in the green zone as the bindings are picked by the human agent (4 times) which induces the repositioning factor.

On the cognitive ergonomics aspect, just as the methodology is followed by Scenario 1. Cognitive ergonomics is evaluated based on the factors of Task demand ($T_d$), level of performance ($L_p$), Level of resources ($L_r$), Level of information processing ($L_i$) and Level of decision making ($L_d$).

In this scenario, the information processing is not majorly required. The inspection (P10) like in Scenario 1 is still considered to have some level of information processing. In addition, since the ski binding is now placed by the human, it has to be placed over dedicated place in the ski framework hence task P2 and P7 will also incur some amount of information processing and retrieving.

| | Menschmodell, 5. Perzentil, weiblich, deutsch | | Menschmodell, 5. Perzentil, weiblich, deutsch |
|---|---|---|---|
| information | 50th percentile, female, age group: 40, performance factor: 1 | information | 50th percentile, female, age group: 40, performance factor: 1 |
| **whole body [pts]** | **49.5** | **whole body [pts]** | **27.5** |
| postures [pts] | 2.7 | postures [pts] | 2 |
| trunk rotating [pts] | 0 | trunk rotating [pts] | 0 |
| trunk bending [pts] | 0 | trunk bending [pts] | 0 |
| far reach [pts] | 0 | far reach [pts] | 0 |
| **postures sum [pts]** | **3** | **postures sum [pts]** | **2** |
| 17 finger forces [pts] | 0 | 17 finger forces [pts] | 0 |
| 18 body forces [pts] | 0 | 18 body forces [pts] | 0 |
| **action forces [pts]** | **0** | **action forces [pts]** | **0** |
| 19 repositioning [pts] | 44.2 | 19 repositioning [pts] | 23.4 |
| 19 holding [pts] | 0 | 19 holding [pts] | 0 |
| 19 carrying [pts] | 0 | 19 carrying [pts] | 0 |
| 19 pushing & pulling [pts] | 0 | 19 pushing & pulling [pts] | 0 |
| **manual handling [pts]** | **44.5** | **manual handling [pts]** | **23.5** |
| 0a influences by working on moving parts [pts] | 0 | 0a influences by working on moving parts [pts] | 0 |
| 0b accessibility [pts] | 0 | 0b accessibility [pts] | 0 |
| 0c vibrations, momentum, forces [pts] | 0 | 0c vibrations, momentum, forces [pts] | 0 |
| 0d joint postures [pts] | 0 | 0d joint postures [pts] | 0 |
| 0e other stesses and strains [pts] | 0 | 0e other stesses and strains [pts] | 0 |
| extra 0f: user defined score 1 | 2 | extra 0f: user defined score 1 | 2 |
| extra 0g: user defined score 2 | 0 | extra 0g: user defined score 2 | 0 |
| extra 0h: user defined score 3 | 0 | extra 0h: user defined score 3 | 0 |
| **extra points [pts]** | **2** | **extra points [pts]** | **2** |

Figure 33: EAWS score: Before (Left) and After (Right) for Scenario 2

The overall cycle time of task P3, P6 and P10 is 9.2 seconds ($t_a$) hence from the Equation 7,

$$L_i = \frac{t_a * N}{T}$$

$$= \frac{9.2 * 3}{43.9}$$

$$L_i = 0.629 = 62.9\%$$

A total of 62.9% of the time some kind of information processing is needed in the task which is considered which has an overall rating of 3.

Similarly, the decision making is also required in task P3, P6 and P10, and since the level of decision making is also dependent on the probability of successful decision making, it is considered that it is successful at least 85% of the time as in Scenario 1. Assuming 150 skis as the production rate per shift per station for reasons discussed earlier and total duration $t_a$ of 9.2 seconds then $L_d$ is

$$L_d = N_d * \sum_i P_i$$

$$= 150 * 3 * 150$$

$$L_d = 67500$$

The score is scaled using the guidance shown in Scenario 1 and Table 14, therefore the final normalized score for $L_d$ is 2. Since the task does not have sub tasks that require high skill or learning level, it is considered that the cognitive load due to the level of resources will be considered theoretically nil. The learning curve is reached for the associates doing the task, hence $L_r$ is considered as 1.

The level of performance ($L_p$) as described is highly described as the effort needed to gap the demand considering the existing capacity. Considering the assumptions assimilated for Scenario 1, the $E_n$ will be considered similar as in Scenario 1

$$E_n = \frac{D_n}{C_n} * 100\ \%$$

$$= \frac{150}{136} * 100\ \%$$

$$E_n = 110.29\%$$

This score than suggests that extra efforts have to be put in to keep up the demand, and as hinted in Table 12 and the final score is considered as 3.

Finally, the Task demand, TACOM is measured using the formula described in Equation 1.

$$TACOM = \sqrt{\left(0.621{T_s}^2\right) + \left(0.239{T_{st}}^2\right) + \left(0.14{T_u}^2\right)}$$

Where

$T_s$ = 0.284 * Number of Actions (N) + 0.716 * Level of information processing ($L_i$)

$T_{st}$ = 0.109 * Learning level (α) + 0.891 * logical sequence of actions ($s_a$)

$T_u$ = Level of predictability/confidence in a task

The level of confidence in conducting the task is highly dependent on the learning level (α). As described in Figure 21, assuming that the ideal learning level is 85% and is achieved, therefore $T_u$ is 0.85. Another variable, $s_a$ is considered as 66% same as Scenario 1.

$$T_s = (0.284 * 6) + (0.716 * 0.629) = 2.15$$

$$T_{st} = (0.109 * 0.85) + (0.891 * 0.66) = 0.66$$

$$TACOM = \sqrt{(0.621 * 2.15^2) + (0.239 * 0.66^2) + (0.14 * 0.85^{\ 2})}$$

$$TACOM = 1.7$$

The score of 1.7 in the TACOM corresponds to an overall score of task demand ($T_d$) as 1. Overall, the MWLI is then defined as an average of these scores as in Equation 11.

Equation 11

$$MWLI = \frac{T_d + L_p + L_r + L_i + L_d}{5}$$

$$MWLI = 2.14$$

An overall cognitive score of 2.14 suggest being in the amber zone (Green: <2, Amber 2 – 3, Red >3). Though it is not necessary to consider immediate actions for improving the score, since it is impacting the overall cognitive score, it should be considered that changes be made for ease of mental demand.

Similar efficiency and ergonomic analysis are conducted for Scenario 2 as seen in Table 23.

| Factor | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $T_h$ | 10.4 | 3.0 | 5.0 | - | - | 3.0 | 5.0 | - | - | 2.8 | 4.9 |
| $C_h$ | 0.08 | 0.02 | 0.04 | - | - | 0.02 | 0.04 | - | - | 0.02 | 0.04 |
| $T_r$ | - | - | - | 8.7 | | - | - | 9.2 | | - | - |
| $C_r$ | - | - | - | 0.06 | | - | - | 0.07 | | - | - |

Table 23: Efficiency analysis in Scenario 2

## 5.4 Discussion

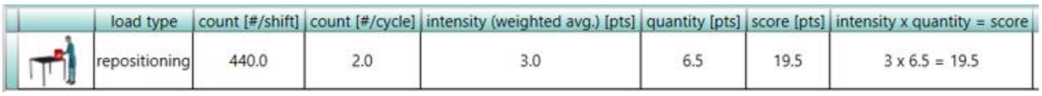
Two different scenarios were tested for overall feasibility of the devised algorithm. In both the scenarios, the ski assembly task involves fixed task allocation due to the limited reachability of robot, where certain tasks cannot be performed by the robot agent. In Scenario 1, the task of picking and placing the ski binding is assigned to the robot and in Scenario 2, the scope is to explore task switching opportunities with the robot conducting screwing operations and the human performing pick and place task of the ski binding. The evaluation is done through ergonomic aspects, considering physical and cognitive ergonomics and secondarily, the cycle time and efficiency are also compared.

In Scenario 1 and 2, the task analysis indicates that tasks of picking and placing the ski from another table (P1, P10, and P11) cannot be performed by the robot due to reachability limitations. Simulation results in Ema Work designer for Scenario 1 indicate an overall ergonomic score of 44, with an overall cycle time of 74.2 seconds for one assembly. Subsequent improvements in design, such as changing the orientation of the ski and adjusting table height, lead to a physical ergonomic score improvement to 22.5, indicating green zone status. On the other hand, Scenario 2 depicts an overall initial physical ergonomic score of 49.5 and cycle time of 60 seconds for one assembly. The cycle time reduces by 19.25% compared to Scenario 1. Same improvements in the design and layout for visualization conducted in Scenario 2 resulted an improvement of 27.5, with an amber status. Though the cycle time in Scenario 2 is less, the physical ergonomic score with EAWS remains in the amber zone. This is attributed to the allocation of pick and place of ski bindings (P2, P3, P6 and P7) to the human agent that requires them to walk, bend, twist, and handle load of the binding over a period of the entire shift. On the overall EAWS scale spectrum (0 - >50), the difference between 23.5 and 27.5 is not significantly high. In a deeper comparison between load and forces for physical ergonomics in both cases is summarized in Table 24.

| Factor | Scenario 1 | Scenario 2 |
|---|---|---|
| Posture score | 2 | 2 |
| Repositioning load | 19.5 | 23.5 |
| Shoulder raised | 2 | 2 |
| EAWS Score | 23.5 | 27.5 |

Table 24: EAWS Ergonomic score comparison

The difference between both the scores is caused by the repositioning load score. The repositioning score is calculated as a product of the average weight handled in the cycle and the average number of times the load must be handled. Between both the cases, since Scenario 2 assigns humans to pick and place the binding, additional weight is added to the overall cycle average weight as seen in Figure 34.



| | load type | count [#/shift] | count [#/cycle] | intensity (weighted avg.) [pts] | quantity [pts] | score [pts] | intensity x quantity = score |
|---|---|---|---|---|---|---|---|
| | repositioning | 440.0 | 2.0 | 3.0 | 6.5 | 19.5 | 3 x 6.5 = 19.5 |

| | load type | count [#/shift] | count [#/cycle] | intensity (weighted avg.) [pts] | quantity [pts] | score [pts] | intensity x quantity = score |
|---|---|---|---|---|---|---|---|
| | repositioning | 440.0 | 2.0 | 3.6 | 6.5 | 23.4 | 3.6 x 6.5 = 23.4 |

Figure 34: Repositioning load score: Scenario 1 (Top) and Scenario 2 (Bottom)

Cognitive ergonomics assessment is conducted based on factors like task demand, performance level, resources, information processing, and decision making mathematically computed for the MWLI. The resulting MWLI score is 1.48 on a scale of 1-5, indicating a green zone (<2) cognitive score in Scenario 1. However, in the case of Scenario 2, an overall MWLI score of 2.14 highlights the need to mitigate the risk by taking preventive measures. In comparison to Scenario 1, Scenario 2 results in a higher level of information processing ($L_i$) and decision making ($L_d$) due to the task of picking and placing the ski binding in the correct order at the dedicated place for accurate assembly. In addition to the ergonomic scores for Scenario 2, it is also important to consider the additional costs needed for the screw driving end effector head which will add to the CRPH. Additional cost for CE[14] certification of this setup individually and the application overall would increase the cost which is currently not considered in the analysis. Table 25 summarizes the overall difference in the two scenarios for Ergonomic factors.

| Factor | Scenario 1 | Scenario 2 |
|---|---|---|
| EAWS Score | 22.5 | 27.5 |
| Task Demand ($T_{d)}$ | 1.4 | 1.7 |
| Level of performance ($L_p$) | 3 | 3 |
| Level of resources ($L_r$) | 1 | 1 |
| Level of information processing ($L_i$) | 1 | 3 |
| Level of decision making ($L_d$) | 1 | 2 |
| MWLI | 1.48 | 2.14 |

Table 25: Evaluation summary

[14] CE mark on products and application signify that it meets the safety, health, and environment protection standards in the European Economic Area (EEA) [196]

The overall cost is also compared for both the scenarios, where Scenario 1 theoretically incurs more cost for the activities conducted by the human with 63.78[15] in comparison to 39 for Scenario 2, attributed to the additional time human takes for screwing together in comparison to the robot.



[15] The cost compared here is the cost of conducting the assigned activities based on the time taken for the whole shift. This does not indicate the cost of the labor or the cost for the assembly in monetary terms.

# 6 Conclusion and Outlook

This Chapter will summarize the work discussed in the thesis, with conclusions, possible extension of the work and answer each of the pre-defined research questions in Chapter 1.

## 6.1 Conclusion

The aim of this work is to present a methodology to incorporate ergonomic factors in the task allocation strategy between human and robot agent. It defines a detailed framework by analysing factors to analyse the task in the sequence, assign task based on certain pre-defined hardcoded guidance, visualize the task using digital tools and finally conduct the evaluation for ergonomics and re-iterate this process unless the best task allocation is found considering productivity, efficiency, economic factors with focus on ergonomics.

The framework is defined as a three-step paradigm including task analysis and assignment, task visualization and evaluation. Task analysis considers four major aspects in terms of defining hardcoded rules for task assignment viz, human factors, robot factors, part, and process factors and finally efficiency factors. On deciding the pre-assignment based on the hardcoded factors, the task is visualized using the digital simulation tool Ema Work designer. The evaluation framework then describes an evaluation score for physical ergonomics using the EAWS evaluation method and a cognitive and organizational ergonomics index to incorporate major factors discussed in Section 4.3.

The initial step of task analysis encompasses the discussion on analysing factors based on the aspects of human, robot, part, process, and efficiency. The requirement of the thesis stem from the need of incorporating and optimizing the way tasks are allocated also considering the well-being of the human counterpart, however it is also important to consider the overall limitations of the robot and process to meet the demands of production.

The following framework is tested on the Ski assembly use case demonstrated in the DSER course of TU Wien Institute of Management science course at TU Wien Pilot Factory, Industry 4.0. Implementing the framework on this use case demonstrates that the flexibility and agility of introducing ergonomic factors in the task allocation framework. It considers various factors for ergonomics across three domains of physical, cognitive, and organizational ergonomics.

The main research question of the thesis is addressed in the work by developing an overall ergonomic metric that help evaluating the overall efficacy of task allocation and follow the iteration process.

“***How can task allocation algorithms in human-robot collaboration be optimized for ergonomics?”***

The developed method incorporates the physical and mental (cognitive and organizational) load to alter and reinstate the task allocation which can be adaptive in nature and dynamic. Several task allocation strategies are discussed in Chapter 2 that provide a rather laid-back allocation methodology; this work delves into a rather flexible approach of considering human factors at the centre.

The initial work presented in Chapter 3, studied the literature that present task allocation algorithms, however a clear gap existed in task allocation since they were majorly focused on the overall cost of the allocation with minimal focus of HFE, which is addressed in this work. Task allocation methods including physical ergonomic evaluation using standard ergonomic evaluation tools have been discussed, however no work presented incorporated mental workload into the task allocation. Several factors impacting and affecting the overall mental workload have been studied and incorporated to form a Mental workload index that evaluates the potential mental workload.

In addition to this several sub research questions were laid down to understand more deeply how ergonomics can be allocated in the existing task allocation algorithms and what are the best ways to visualize these task sequences and allocation to get the best allocation results. The answers to these questions are described briefly in the upcoming text.

***I. What are the various methods for task allocation that can be analysed?***

Robotics and human-robot interaction improvements have all contributed to the evolution of human-robot job allocation. As jobs and robot capabilities got more complicated, sophisticated procedures started to take shape. Initially, fixed roles were allocated to people and robots based on their capacities. To improve team performance, these techniques considered human preferences, aptitudes, and experience. The use of collaborative methods that emphasize symbiotic human-robot interactions has grown in popularity. Task analysis and allocation are the two fundamental components of task allocation. Task analysis techniques include AND/OR graphs, A* graph search methods, and assembly sequence graphs. Deterministic and heuristic algorithms, compensating tactics, capability-aware strategies, and dynamic procedures utilizing tree structures are a few task allocation methodologies discussed in Chapter 3. Machine learning methods using MDP are also discussed in the literature for more real-time task allocation. The strategy of task allocation in this work stand alone does not represent the dynamic task allocation strategy, it resonates to the capability and HFE based task allocation describing and considering the limitations and pros of each agent for a given task in the sequence.

### II. How will the task allocation method be modelled and visualized for ergonomics?

Several works have been discussed in literature as highlighted in the state of the art that use A* graphs, precedence graphs, assembly graphs or even real time BPMN to visualize the task and assembly sequences. Task analysis strategies discussed in sub-research question I serve the purpose of visualizing the task allocation; however, they are not specifically meant for visualization for ergonomics. This work, however, deals with exploring and adopting the use of digital simulation tools. The simulation tool used in this case enables detailed analysis of physical ergonomics and addresses some aspects of organizational ergonomics related to workplace and task design. The tools discussed in the work are Ema Work designer, Technomatix Process Simulate and DELMIA. By simulating the planned workflow and generating motion sequences for DHM, Ema Work Designer accurately represents complex dependencies, and human-machine interactions, facilitating informed design decisions and interventions to mitigate ergonomic issues. This platform plays a crucial role in optimizing workstations and assembly lines, enhancing worker well-being, productivity, and overall operational efficiency.

### III. How can task allocation methods be evaluated for ergonomics?

In contrast to the existing methods discussed in the literature in Chapter 2 mostly use the cost of each allocation sequence. Basis the summary in Table 7, only 22.80% (13/57) of the literature studied evaluated ergonomics in their task allocation strategy, however none of them addressed the mental workload in their evaluation, they were majorly based on evaluation of physical factors. The evaluation method in this work adapts to the major factors of ergonomics discussed in Section 3.3. specifically focusing on digital evaluation tools using Ema Work Designer with the EAWS methodology. Additionally, the cognitive load is evaluated using MWLI based on various factors. Ema Work Designer uses the EAWS methodology for ergonomic evaluation and supports cycle time analysis using the spaghetti diagram. The EAWS evaluation considers posture, forces, and load handling points to assess ergonomic factors. The cognitive load is evaluated MWLI, which considers factors like task demand, level of performance, level of resources, level of information processing, and level of decision making. The overall MWLI index not only encompasses the cognitive factors and organizational factors. Task demand and sequence of actions represent the organizational factors. The hardcoded factors used in task analysis are also used for evaluating the overall task allocation strategy. The individual factors used to contribute to the MWLI can be considered during the design and allocation stage for allocating tasks incurring higher mental workload to the robot agent. Considering the bifurcation of ergonomic factors analyzed in Section 3.3, Table 26 summarizes the factors used in overall ergonomic evaluation discussed.

| Physical ergonomics | Cognitive ergonomics | Organizational ergonomics |
|---|---|---|
| Postures | Mental workload (MWLI) | Work design ($s_a$) |
| Load | Decision making ($L_d$) | Task Complexity ($T_d$) |
| Forces | Effort ($L_p$) | Task type ($L_i$) |
| Repetitive movements | Stress ($T_u$) | |
| Workplace layout | | |

Table 26: Summary of ergonomic evaluation factors

## 6.2 Outlook

This section on Outlook highlight and delve into the probable areas and points where the work can be extended. It gives guidelines for further enhancement and applicability of the designated framework.

To fully comprehend cognitive demands, mental workload evaluation in HCI uses both macro and micro methodologies. Macro methods evaluate the entire mental burden imposed by a system or task by considering task complexity overall, cognitive demands, and user experience. The user experience of cognitive burden is commonly captured by these assessments, which also frequently include user questionnaires, arbitrary ratings, and performance indicators. Micro methods, on the other hand, focus on more minute details, examining cognitive processes and brain responses using tools like eye tracking, EEG, EMG, and functional magnetic resonance imaging (fMRI). These techniques give light on how various design features and interactions affect mental burden, revealing insights into certain cognitive processes including attention, memory, and decision-making. Using both macro and micro perspectives allow for a complete strategy. The work presented in this thesis addresses the macro analysis of the mental load, however this can be extended and integrated to the micro techniques for a real time assessment and allow for dynamic task allocation.

In addition to the micro methods in cognitive load measurement, the framework described in the work can also be used to gain the real time micro measurements of physical factors such as posture, load handling and duration of load. Integrating wearable technologies here directly into the visualization and simulation platform will be able to integrate with utmost efficacy the real time scenario and therefore be integrated to a more flexible and adaptable task allocation in human robot teams.

The factors task demand, level of performance, level of resources, level of information processing, and level of decision making are used to compute the overall MWLI. However, there are several aspects of these factors and task sharing that would impact the overall evaluation and should be worked upon. Frequent task switching can have a significant impact on cognitive load, affecting both the human performance and their mental workload. When individuals switch between tasks frequently, they need to mentally disengage from one task and re-engage with another. This cognitive shifting requires attentional resources to process the information, which can lead to increased cognitive load.

The cognitive factors are interconnected and can influence each other. It is important to investigate how these factors overlap and interact, as their relationships can impact the overall cognitive load experienced by the human. This can be validated by exploring scenarios of optimizing one cognitive factor which may lead to a trade-off with another. For instance, achieving a high level of performance might require more information processing or decision-making, thereby increasing cognitive load. Correlations between different cognitive factors should also be analyzed to find, for example if higher task demand tends to be associated with increased decision-making requirements. It is also worthy to establish if there is a hierarchical relationship to establish which factors affect directly and via multiple layers to another factor.

Additionally, the assumption of equal weighing for all cognitive factors might not accurately represent their real-world influence on cognitive load. Assigning appropriate weights to these factors can lead to a more accurate assessment of cognitive load and better predictions of how changes in task allocation or sequence might affect the human. Some ways to delve into this would be to conduct subjective evaluations with human agents, quantitative analysis using statistical methods or machine learning techniques to determine data driven weights for the cognitive factors. However, it is also important to derive whether the importance of these factors varies dynamically based on the context. For instance, certain tasks or sequences might have higher demands for information processing compared to decision making.

Multiple factors like task demand ($T_d$) and level of resources ($L_r$) use the learning curve as their base for mathematical calculations. However, one important factor to be considered is the forgetting curve and its overall impact on the learning curve and vice versa. The forgetting curve greatly studied by Hermann Ebbinghaus, a German psychologist in the early 90's suggests that there are four phases of information acquisition and remembering. The initial learning phase helps us acquire information and strongly remember it, however there is a sharp decline in the retained memory level which is called the rapid forgetting phase. During the third phase called stable forgetting where the rate of memory loss slows down, and forgetting becomes more gradual. Ultimately, without reinforcement, memory retention reaches a memory plateau, where it stabilizes at a certain level, and any further forgetting occurs at a slower pace [197]. It would therefore be critical and hence important to consider the rate of forgetting while modelling the factors involving learning curve and formulate the impact of each over the other.

The framework of this work is tested end-to-end on one man team, though in the organizational factors summarized in Table 8 for human factors, there is a factor that considers human being allocated in a team with two robots, but the full potential of this condition is not explored in the use case demonstrated , however it can be extended not limited to the factor discussed but extending to the overall algorithm in terms of ergonomics to multi robot or human teams as this situation will impact ergonomics significantly.

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# 8 List of Figures

# 9 List of Formulas

# 10 List of Tables

# 11 List of abbreviations

| Abbreviation | Description |
|---|---|
| 3D | 3 Dimensional |
| ARC | Ames's Research Centre |
| BPMN | Business process modelling and notation |
| CAD | Computer Aided Drawing |
| CAGR | Compound Annual Growth Rate |
| CE | European Conformity |
| CERA | Composite ergonomic risk assessment |
| CLAM | Cognitive Load Assessment for Manufacturing |
| Cobot | Collaborative Robot |
| CPLH | Cost per Labor hour |
| CPRH | Cost per robot hour |
| DHM | Digital Human Models |
| DIN | Deutsches Institut für Normung |
| DNN | Deep Neural Network |
| DSER | Digital Simulation of Ergonomics and Robotics |
| EAWS | Ergonomic assessment worksheet / European Assembly Worksheet |
| EEA | European Economic Area |
| EEG | Electroencephalogram |
| EMG | Electromyography |
| EPC | Event driven Process Chain |
| EU | European Union |
| EU-OSHA | European Agency for Safety and Health at Work |
| fMRI | Functional magnetic resonance imaging |
| GM | General Motors |
| HABA-MABA | Humans are better at - Machine are better at |
| HAMA | Hand arm movement analysis |
| HCD | Human Centered Design |
| HCI | Human Computer Interaction |
| HFE | Human Factors Engineering |
| HMI | Human-Machine Interface |
| HRC | Human Robot Collaboration |
| HRI | Human Robot Interaction |
| HSE | Health and Safety Executive |
| IEA | International Ergonomics Association |
| IEEE | Institute of Electrical and Electronics Engineers |
| IFR | International Federation of Robotics |
| ISO | International Organization for Standardization |
| kg | Kilograms |
| KIM | Key Indicator method |
| m | Meter |
| MDP | Markov Decision Process |
| MFA | Muscle Fatigue analysis |

| | |
|---|---|
| min | minute |
| MSD | Musculoskeletal disorder |
| MTM | Methods Time Measurement |
| MWLI | Mental Workload Index |
| NASA | National Aeronautics and Space Administration |
| NIOSH | National Institute for Occupational Safety and Health |
| OD | Organization Design |
| OWAS | Ovako Working Posture Assessment System |
| OEM | Original Equipment Manufacturer |
| QES | Quick exposure check |
| RaaS | Robot as a service |
| REBA | Rapid Entire Body Assessment |
| ROI | Return on Investment |
| RULA | Rapid Upper Limb Assessment |
| SI | Strain Index |
| SLR | Structured Literature Review |
| SMEs | Small and medium sized enterprises |
| SUS | System Usability Scale |
| SWAT | Subjective Workload Assessment Technique |
| TACOM | Task complexity |
| TLX | Task Load Index |
| UK | United Kingdom |