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Proposal of a complexity model for human-robot collaboration assembly processes

Matteo Capponi, Riccardo Gervasi, Luca Mastrogiacomo, Fiorenzo Franceschini *

Politecnico di Torino, DIGEP (Department of Management and Production Engineering), Corso Duca degli Abruzzi 24, 10129, Torino, Italy

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A B S T R A C T

Assembly complexity in manual processes has been widely addressed over the years in manufacturing-related literature. The concept of complexity indeed is linked to the cognitive and physical effort required on behalf of the human operator in completing the assembly process and is directly linked to the occurrence of process failures and inefficiencies. In the light of the introduction of novel technologies such as collaborative robotics such paradigm should be revised. This paper presents a proposal for a complexity model, i.e., "C—HRC model", for Human-Robot Collaboration assembly processes. C—HRC model provides a multidimensional framework and a practical tool for analysing the complexity of collaborative assembly processes performed by humans supported by collaborative robots. In this situation, the collaboration with the robot may require an additional effort from the human operator, resulting in a more complex activity and thus more error prone. In this regard, the C—HRC model integrates insights from multiple disciplines to provide an overview of collaborative assembly complexity based on four layers: product complexity, assembly complexity, interaction complexity and collaboration complexity. The conceptual foundation of the C—HRC model is thoroughly detailed and supported by a review of the relevant literature. Hence, the paper uses the complexity formulation proposed by Samy and ElMaraghy as a basis to provide a quantitative approach. The model is then applied to practical case studies to demonstrate its application and illustrate how it can enhance the understanding of effective human-robot collaboration. This provides process designers with a practical tool to support design and improve collaborative assembly processes.

List of acronyms

HRC	Human-Robot Collaboration
HRI	Human-Robot Interaction
DFA	Design for Assembly
C—HRC	Complexity of Human-Robot Collaboration
DoIR	Density of Interaction Ratio
ToCR	Time of Collaboration Ratio

1. Introduction

In modern manufacturing, the integration of robots into assembly processes represents a significant shift towards more innovative and efficient production methods. Human-Robot collaboration ("HRC") indeed has widely spread in industrial environments in the last few years [1]. Specifically, this change enabled by the introduction of collaborative robots, i.e., robots capable of working closely with human operators commonly called cobots, marks a pivotal evolution in the industrial landscape [2–5]. Industry 5.0 seeks to harmonise the strengths of human creativity and intuition with the precision, consistency and repeatability of robotic systems, creating a collaborative environment where both agents contribute optimally [6]. However, this integration presents complex challenges that must be addressed in order to realise the full potential of such collaborations. Understanding and managing the complexity inherent in these interactions is a necessity for the development of efficient, adaptive and safe manufacturing systems. The literature on human-robot collaboration has focused primarily on optimising task allocation between humans and robots [7,8] and on ensuring safety protocols to facilitate effective human-robot teamwork [9,10]. However, plenty of other variables should be taken into account in the assessment of what the authors called "collaborative assembly complexity". The concept of complexity is common in assembly related literature [11,12]. This is a very broad concept involving all those aspects that may affect cognitive effort on behalf of the human operator in

* Corresponding author.
E-mail addresses: matteo.capponi@polito.it (M. Capponi), riccardo.gervasi@polito.it (R. Gervasi), luca.mastrogiacomo@polito.it (L. Mastrogiacomo), fiorenzo.franceschini@polito.it (F. Franceschini).

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performing an assembly process [13]: product characteristics, variety of parts, ergonomics, workstation layout are all potential influential aspects of assembly complexity [14–18]. Increased cognitive effort, indeed, may lead to a greater occurrence of errors and thus to inefficiencies in manufacturing. Given the spread of novel technologies like collaborative robots in manufacturing, there is a need for a comprehensive framework that can capture and analyse the diverse and dynamic elements of complexity in collaborative assembly processes. This study proposes the development of a model to evaluate complexity in Human-Robot Collaborative Assembly Processes (i.e., "C—HRC"). The model tries to identify the various levels of complexity and provide a quantitative approach to assess them. It identifies four layers of complexity: product complexity, assembly complexity, interaction and collaboration complexity. In addition, in this work the authors leveraged the mathematical formulation of assembly complexity developed by Samy and ElMaraghy [16] and adapted it to specifically assess collaborative assembly processes. The model is then exemplified through the analysis of a small case-study. The proposed C—HRC model introduces a novel conceptual framework that defines the various aspects of assembly complexity in human-robot collaboration. By providing designers with a practical and quantitative tool, this model can be further used for effective task allocation, error prediction and process optimisation, improving the efficiency and quality of HRC assembly processes. The paper is organised as follows: Section 2 presents a literature review on human-robot collaboration and assembly complexity. In Section 3 the collaborative assembly complexity is conceptually addressed and in Section 4 the proposed approach is described. Section 5 shows the implementation of the model to a small case study. Section 6 summarises the main contributions and limitations of the C—HRC model.

2. Literature review

The emergence of Industry 5.0 marks a significant evolution in the industrial landscape, shifting from Industry 4.0′s automation-centric focus to a more integrated, human-centric approach [19]. This new paradigm emphasises human-robot collaboration, i.e., that synergy between humans and robots aimed at creating a collaborative environment where both human workers and robots can contribute simultaneously with their unique capabilities [6]. Prior to examining the particulars of human-robot collaboration in manufacturing, it is important to introduce the concept of human-robot interaction (HRI). HRI encompasses the study and design of interactions between humans and robots, with the objective of developing systems that facilitate effective, efficient, and natural communication and cooperation between human users and robotic systems. Goodrich and Schulz's comprehensive review [20] identifies the main issues, key aspects and challenges of HRI. Their review provided a cohesive narrative of human-robot interaction bridging various applications and perspectives to promote a unified understanding of HRI. Bartneck et al. [21] highlighted the importance of standardized measurement instruments in HRI. They also focused on key concepts such as anthropomorphism, animacy, likeability, perceived intelligence, and safety. Leite et al. [22] explored the effects of long-term interactions between users and social robots. Their comprehensive review underscores the importance of sustained engagement in HRI, identifies key robot characteristics that facilitate these interactions, and summarises findings from existing long-term studies. Sheridan [23] examines the status quo of HRI, outlining the transition of robots from tools for handling hazardous materials to entities capable of working under human supervisory control in a variety of domains. By identifying key challenges for human factors research in HRI, Sheridan's reviewed the diverse applications of HRI, ranging from industrial tasks to social interactions. Generally, the principles of HRI represent also the basis of human-robot collaboration (HRC) in manufacturing, with the aim of integrating robots and human workers to enhance productivity, safety and efficiency. In human-robot collaboration human workers and robots share workspace and goals each contributing with their own skills [24]. One of the main challenges in implementing human-robot collaboration is developing technologies that enable smooth and natural interactions. Wang et al. [25] highlighted the importance of the communicative interface between robots and humans in achieving a symbiotic HRC. Inkulu et al. [26] outlined the prospects and key challenges associated with HRC. Integrating HRC into manufacturing requires the removal of traditional physical barriers separating human and robot workspaces. This makes safety a primary concern in this field. To overcome these issues, the introduction of standards such as ISO 10218-1, ISO 10218-2 and ISO/TS 15066 identified the main risks associated with the use of industrial robots in manufacturing environments and allowed for greater robot autonomy in close proximity to humans. These environments require sophisticated sensors and control algorithms to maintain safety and efficiency. Another common concept that is directly related to safety is trust [27]. Maurtua et al. [1] emphasised the need to develop trust between workers and robots to facilitate seamless collaboration. However, when dealing with HRC, focusing only on safety would result in a limited approach [4,28]. In pursuing a smooth collaboration between humans and robots, a lot of different aspects should be included and, thus, a more comprehensive analysis should be pursued [4]. To address this situation, in which so many different variables are involved, the authors used the concept of complexity. Assembly complexity is a very well-known concept in manufacturing, as many studies proved its relationship with process failures and product errors [11,12,29]. In the context of HRC, the complexity concept goes beyond traditional aspects of product and process defects to include the dynamics of human-robot collaboration [30–32]. This expanded view of complexity requires detailed exploration to fully understand its impact and to develop strategies for managing it.

2.1. Assembly complexity

Many quantitative models have been developed to objectively assess the complexity of assembly processes. A significant area of research relates assembly complexity directly to the complexity of the product itself, encompassing its dimensional, geometrical and structural attributes. Many of these models are based on design for assembly (DFA) principles, as highlighted in the work of Boothroyd and Alting [33] and of Boothroyd [34]. Hinckley's [35] pioneering work introduced a complexity factor based on product assembly times. Similarly, Shibata [36] and later Su et al. [37] associated assembly complexity to both physical product characteristics and to standard assembly times. More recently, Alkan [14] proposed a new method for measuring assembly complexity that combines standard assembly times with DFA theory, building on a more generalised product complexity model basing on the work by Sinha [38,39] which compares complexity of products to that of molecular structures. The relationship between product complexity and assembly times was also investigated by Verna et al. [18,40] and Sudhoff et al. [41] who further adapted these models and used them to predict product failures and establish a link between complexity measures and assembly times.

Another common way of assessing assembly complexity is to apply the principles of information theory [42] to products, production processes and systems. These approaches are based on the idea that complexity and challenges depend on the uncertainty in the assembly process. El-Maraghy and Urbanic [43,44] first introduced an entropy-based method, the "MCAT" (Manufacturing Complexity Assessment Tool), which links manufacturing complexity to the quantity, variety and content of information managed [45]. Fujimoto et al. [46] and Zhu et al. [47] also used information entropy to deal with manufacturing complexity arising from product variety. Ameri et al. [48] combined information and graph theories to assess product design complexity. MCAT was later combined with DFA principles for product assembly complexity assessment by Samy and ElMaraghy H. [16], and subsequently used for a comprehensive manufacturing system complexity metric [49,50]. Wang and Hu [51] developed a complexity metric that considers the uncertainty of operator choices in different assembly system configurations, which was later used to reduce complexity in mixed model assembly systems [52]. Zeltzer et al. [53] introduced an entropy-based complexity measure that accounts for the variability of task durations in mixed assembly lines. More recently, Liu et al. [54] developed an information entropy measure to optimise assembly line balancing in the face of demand uncertainty.

The complexity of assembly processes as perceived by humans can be influenced by various factors, such as knowledge, personal experience, required skills, and the cognitive and physical effort involved. In this regard a qualitative approach was followed by Mattsson et al. [55–57] who identified five primary factors that affect workers' perception of assembly complexity: product variants, layout, work content, tools, and information. The authors developed a series of statements related to each factor, which workers evaluated on a five-point scale. Similarly, Falck et al. [58] identified 16 fundamental complexity criteria that are further assessed by expert teams to provide a qualitative overall complexity rating on a five-level scale.

All the studies presented here provide a method to assess complexity in manual assembly processes. To the best of authors' knowledge, there is a lack of literature in the adaptation of these concepts in HRC assembly processes.

3. Conceptual definition of a collaborative assembly complexity model

In the changing landscape of Industry 5.0, the integration of collaborative robots requires a re-evaluation of traditional complexity models to account for the challenges and opportunities presented by human-robot collaboration. It's also worth underlining that complexity of assembly processes in manufacturing is significantly influenced by the inherent characteristics of both humans and robots. Human factors, divided into categories such as skill level, ergonomics, adaptability and psychological attitudes towards robots, play a crucial role in determining the complexity of these processes. Similarly, robot complexity, characterised by technical capabilities, sensing and perception systems, safety measures and integration capabilities, adds another layer of complexity to assembly operations. These aspects are essential to ensure efficient, safe and productive human-robot collaboration in manufacturing environments. However, such features will not be preliminarily addressed in this work.

The C—HRC Model underlines the need for a comprehensive approach to complexity by considering four critical layers: product complexity, assembly complexity, interaction complexity and collaboration complexity (see Fig. 1). These layers combined together lead to a structured concept of "collaborative assembly complexity". In detail:

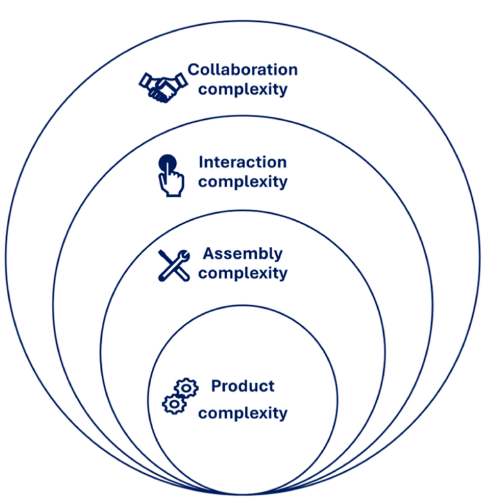

Fig. 1. The four layers of the C—HRC model.

- Product complexity refers to the features of the product itself, including the number and variety of components, their geometrical and dimensional features, the nature of their interconnections, and the degree of customisation required. This layer represents the foundation of the complexity model and reflects the fundamental challenges that must be addressed in any manufacturing process.
- Assembly complexity deals with the difficulties encountered during the actual assembly process. This includes factors such as the sequence of assembly, the precision required to join parts, the handling and positioning of components, and the overall efficiency of the assembly line. Assembly complexity is a critical layer that transforms product specifications into a functional entity.
- Interaction complexity refers to any scenario in which humans and robots interact, covering a wide range of interactions from simple one-way commands to complex two-way communication. It covers the fundamentals of how humans communicate, control and respond to robots in different environments, focusing on the interface and communication protocols used to facilitate these interactions [23].
- Collaboration complexity extends the previous concept of interaction complexity. It implies a more integrated and cooperative interaction, where both the human and the robot contribute with their unique capabilities to the task. Therefore it is characterised by shared goals, times and spaces that also lead to common decision making, adaptive roles and mutual adaptation of actions [24].

This model was developed through several focus groups with researchers specialising in human-robot collaboration in assembly. These discussions focused on identifying the key dimensions necessary to assess the complexity of HRC assembly. The model was also informed by insights gained from authors' previous experimental experience, where participants frequently highlighted the challenges faced when interacting and collaborating with cobots. The first two layers of the model (product and assembly complexity) have already been extensively studied in the literature on manual assembly. When the assembly process is carried out in collaboration with the robot, two further layers of interaction and collaboration complexity are added. The combination of these 4 layers leads to the concept of collaborative assembly complexity, as shown in Fig. 2.

3.1. Product complexity

In the context of collaborative assembly, product complexity strictly refers to the characteristics of the items being assembled [11,48,59]. This concept can be broken down into three main macro-features: design, variety, and materials. In detail they are:

- Design encompasses the fundamental architecture of a product, including the integration of its components. The design of a product drives its complexity through the number of parts, their interdependencies, as well as the shape and size of the parts. Therefore, complex designs with intricate geometries and tight tolerances necessitate precise assembly and coordination [16,34,37,40,60–62]
- The variety of a product refers to the range of options and variations available. High variability in design and components, including unique parts and customisation options, leads to a more complex assembly process. Therefore, greater variability leads to greater cognitive effort to complete successfully the assembly. In light of this, the process should be adaptable to manage these model variations and modular components, which heightens the potential for errors [16,46,63,64].
- Materials represent another crucial variable in product complexity. Complexity in this category relates to the fragility and weight of the materials. Delicate materials demand careful handling to avoid damage, which complicates the assembly task. Materials can also

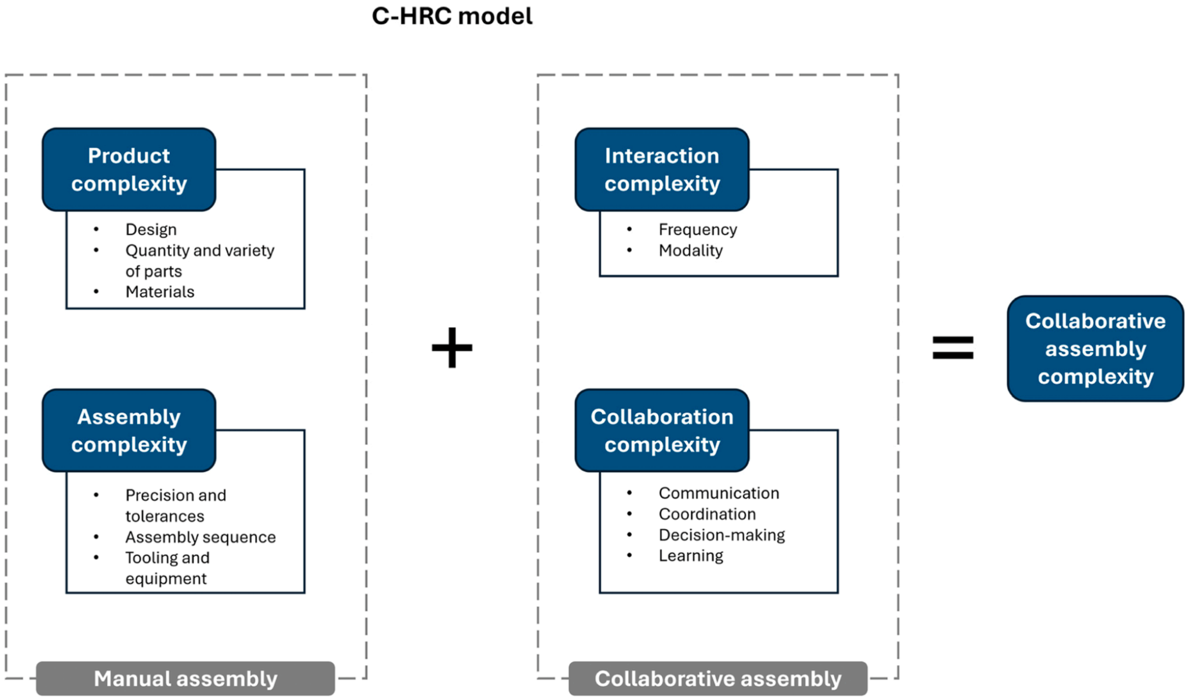

Fig. 2. A conceptual framework of the collaborative assembly complexity model (C—HRC model).

impose specific handling and joining requirements, like strict tolerances or the need for cleanroom conditions [16,34,65,66].

Hence, product complexity is a function of design aspects, the variety of components and customisation options, and the features of materials used. These factors can increase the risk of errors and influence the manufacturability of a product. Assembly strategies must therefore be specialised, possibly requiring sophisticated equipment or skilled labour. Understanding these complexity drivers is crucial for optimising manufacturing operations and enhancing product quality.

3.2. Assembly complexity

In the literature, assembly complexity is often associated with the cognitive and physical load on the agents involved while performing the assembly process [11,16,44,63,67]. In this work, assembly complexity specifically refers to the challenges faced by either a human or a robot during the assembly process. According to DFA (i.e., "Design For Assembly), an assembly process can be broken down into two major categories: handling and joining activities [16,34]. Handling in assembly processes is defined as the physical manipulation of parts or components within the manufacturing environment. This encompasses a range of activities, including picking, placing, sorting, and orienting items in preparation for the next stage of the assembly process. The precision and care required to avoid damage is often dependent on the characteristics of the parts themselves, such as their size, weight, and fragility. Joining refers to tasks in which two or more parts are put together to form a more complex unit and it encompasses a multitude of activities, including welding, soldering, gluing, screwing, and the assembly of parts using a variety of techniques. Hence, assembly complexity is strictly tied to product complexity. For example, greater variety of parts can increase the cognitive effort required by the operator, leading to more difficult and error-prone assembly processes [16]. In addition, it was assumed that complexity of an assembly process, regardless of the agent performing it, can be characterised by:

- Tolerances and precision requirements: Different parts may require precise alignment or special tools for joining, which can be complex when tolerances are tight. Hence, errors in meeting these tolerances can lead to product failures or to the need for rework [16,68].
- Assembly sequence and planning: The order in which components are assembled can have a significant impact on the difficulty of the process. An inadequate sequence can cause inefficiencies, increased labour or even the need to disassemble parts of the product to correct errors [12,64,69].
- Tooling and equipment: The variety and capacity of assembly tools and equipment available can introduce complexity. This includes the need for specialised tools for certain tasks and the efficiency with which they can be used [44,56,70].

3.3. Interaction complexity

In the field of collaborative assembly, human-robot interaction represents one of the central aspects. The research on human-robot interaction has seen significant advancements in the last years, especially in manufacturing [2,23]. From a technological point of view, many attempts have been made to make human-robot interaction smoother and intuitive. Currently, human and robots can interact in different ways [71]:

- Audio interfaces: based on verbal communication between humans and robots.
- Visual modality: the robot can interpret gestures or facial expressions.
- Haptic modality: the robot is able to react to touch and apply force to human operator.
- Kinesthetic modality: it refers to the ability of the robot to perceive movements and act consequently.

Audio modality provides a natural interaction but can be difficult to implement in noisy manufacturing environments. Visual modality, on the other hand, allows operators to direct robot actions using predefined movements, which can be intuitive but may require extensive training and precise motion tracking systems. Haptic feedback provides tactile cues to the operator during interaction but requires sophisticated hardware integration. In general, each of these techniques has its strengths and weaknesses, depending on the specific task to perform, the environmental conditions, and the operator's preference. In addition, it's also worth noting that the recent development of augmented reality ("AR") and mixed reality ("MR") devices represents an opportunity to enhance human-robot interaction [72]. Subramanian et al. [73] presented a framework that highlights the essential components of AR required to advance HRI. The framework also details effective strategies for the continuous evaluation of AR systems in the context of HRI. Tadeja et al. [74] implemented an AR-based solution to enhance communication between human operator and collaborative robot in performing an assembly process. Similarly, Hietanen et al. [75] proposed a depth sensor-based workspace monitoring model and an interactive augmented reality (AR) user interface designed to ensure safe human-robot collaboration (HRC). However, AR/MR technology, albeit promising, may not yet be mature enough to be used by operators in daily activities in real work scenarios.

In addition to technology, many tools have been also developed over the years to evaluate the effectiveness of human-robot interaction [76]. For example, Steinfeld et al. [77] developed a set of metrics to quantitatively assess human-robot interaction. All these metrics together can guide the design of efficient and effective human-robot interaction. Young et al. [78] presented a new view of social interaction with robots called the "holistic interaction experience" and introduced three key perspectives for examining these interactions: visceral factors, social mechanics, and social structures. Apraiz et al. [79] presented the HEUROBOX tool, a newly developed set of heuristics designed to assist practitioners and researchers in the evaluation of human-robot systems in industrial settings. The HEUROBOX tool organises design guidelines and methodologies into a logical list of heuristics for human-robot interaction, categorised into four key areas: safety, ergonomics, functionality and interfaces. In general, methodologies in the literature are often based on the use of numerous metrics, which are not always easy to calculate.

Understanding human-robot interaction thus is critical to analyse the dynamics of collaborative processes, which can significantly influence the overall complexity and efficiency of the assembly, resulting on greater cognitive effort on behalf of the human operator [30]. In this regard, the study of interaction processes - whether between humans or between humans and robots - reveals the pivotal role of both verbal and non-verbal communication [80,81]. Therefore, communication frequency and modality play a key role in interaction processes [82]. As technology advances, the field of Human-Robot Interaction (HRI) introduces additional complexities, particularly in terms of communication challenges [20].

Unlike human-human interaction, when interacting with a robot, one has to cope with the lack of shared social and cultural understanding.

Therefore, interaction complexity causing greater cognitive effort on the human operator may be due to:

- Frequency of interaction: regular and frequent interaction between humans and robots can increase cognitive load, especially when these interactions require constant attention. For example, in environments where robots provide updates or require instructions at a high frequency, humans need to maintain a high level of awareness and continuous engagement. This can be challenging and leading to cognitive fatigue [83]
- Modalities of interaction: the modalities of communication between humans and robots can be auditory, visual, haptic or a combination of these and they have a significant impact on cognitive effort. Complex modalities that require the interpretation of sophisticated signals or extensive input can increase the complexity of interactions. For example, a robot that communicates status updates through a complex dashboard requires users to interpret multiple streams of information simultaneously, increasing cognitive demands. Conversely, simplifying these modalities, such as using simple verbal commands or intuitive gestural interfaces, can help reduce cognitive load and make interactions more efficient [71,83]

In order to provide a first quantitative proxy of interaction complexity, the authors focused mainly on the frequency of interaction and developed a novel indicator called Density of Interaction Ratio.

3.3.1. Density of interaction ratio

Density of Interaction Ratio, henceforth referred as "*DoIR*", is based on the idea that the greater the number of interactions of a human operator with a robot, the greater the cognitive effort required. In this work, the number of interactions has been assessed with the number of "role-switching interactions". The concept of role switching in human-robot collaboration has been previously addressed by other studies [84,85] and it is related to the dynamics of task allocation in a collaborative process where humans and robots alternate as active agents in a process. The indicator proposed is based on the notion that each instance of required interaction, whether it involves physical actions like pressing a button or communication tasks such as signalling readiness, is integral to the continuation and effectiveness of the collaborative process. Hence, *DoIR* can be mathematically expressed as follows:

$$DoIR = \frac{n_{rs}}{N_t} \tag{1}$$

Where:

- $n_{rs} \in [0; N_t - 1]$ represents the numbers of role switching between human and robot and vice versa. If human and robot can perform two tasks in parallel, these will not be considered for the computation of *DoIR*.
- N_t represents the number of elementary tasks of the assembly process.

The mathematical codomain of this indicator is $\left[0, \frac{N_t-1}{N_t}\right]$, where 0 indicates a process totally performed by a single agent, while the maximum value (i.e., $\frac{N_t-1}{N_t} < 1$) represents a situation where there is a role switching between human and robot for each elementary task. As an example, suppose to have a collaborative assembly process composed of "pick and place" and "joining" tasks. The first refer to picking the correct component (C_i) and placing them in suitable positions for the subsequent joining tasks, e.g., screwing processes. Table 1 shows the allocation of these tasks between robot and humans and the respective times, for a total cycle time ("T_c") of 60 s.

The assembly process is graphically represented in Fig. 3.

With reference to the simple example of Table 1 and Fig. 3, there are 4 role switching between human and robot (i.e., $n_{rs} = 4$). The total number of elementary tasks is 7 (i.e., $N_t = 7$), hence $DoIR = \frac{n_{rs}}{N_t} = 0.57$.

Generally, a higher *DoIR* indicates a more complex system where the human operator is required to closely monitor and communicate with the robot, resulting in a higher cognitive effort on behalf of the human operator. Conversely, a lower *DoIR* may suggest that the robot is performing more autonomously, potentially reducing the cognitive load on the human operator, but also possibly decreasing the human's

Table 1
List of elementary tasks and the related allocations and assembly times.

ID	Elementary task	Allocation (H for human and R for robot)	Time [s]
A1	Pick and place C1	R	5
A2	Pick and place C2	H	3
A3	Screwing C1 and C2	H	15
A4	Pick and place C3	H	5
A5	Pick and place C4	R	10
A6	Screwing C4 on C1	H	15
A7	Pick and place the final product	R	10

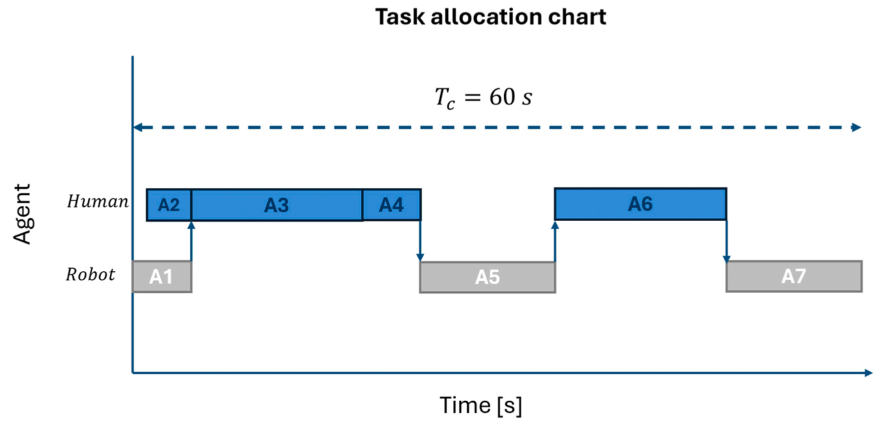

Fig. 3. Task allocation chart of the assembly process (cycle time $T_c = 60$ s).

situational awareness and engagement in the collaborative process. This may also designate situation in which there is no collaboration between human and robot. However, in collaborative processes, human-robot interactions are driven by shared goals, rather than merely for the sake of interaction. This perspective requires the introduction of a fourth layer, called "collaboration complexity".

3.4. Collaboration complexity

The collaboration complexity between human and robot goes beyond interaction complexity by introducing shared goals, spaces and times that require mutual adaptation and coordination. Collaboration requires working together towards a common goal, involving both parties to continuously adapt and coordinate their actions [4,24]. The resulting cognitive effort increases as the human operators need to understand not only their own role and tasks, but also how their actions influence the shared activity. In analysing collaborative work among humans, Patel et al. [82] identified the main factors, and contextual sub-factors, that influence a collaborative work environment, and some of them can be also adapted in human-robot collaboration. In detail they are:

- Communication represents the basis of how participants understand each other, involving verbal and non-verbal, formal and informal exchanges using a variety of methods [82]. In human-robot collaboration, this dimension not only includes verbal and gestural exchanges, but it embeds a comprehensive understanding and prediction of mutual intents and actions. This concept has already been addressed in Section 3.3 due to its closeness with interaction complexity.
- Coordination includes setting common goals, managing and integrating people and information, distributing tasks and providing feedback on performance [82]. In collaborative processes, coordination requires the precise allocation and synchronisation of tasks between humans and robots.
- Decision-making refers to cognitive processes that guide the selection of actions among alternatives, focusing on who makes decisions and how [82]. In the context of human-robot collaboration, decision-making is a complex process that requires robot's autonomy, whereby robots can make independent decisions within set parameters, and human oversight, to manage unexpected situations and ensure safety.
- Learning refers to opportunities for both formal and informal learning arising from collaboration that enable individuals to improve their skills and knowledge [82]. In human-robot collaboration, both humans and robots are learners who should mutually adapt to varying task demands and environmental conditions.

Furthermore, in collaborative processes, the closeness of the robot may increase the cognitive effort of the human operator, and thus the collaboration complexity. In the context of human-robot collaboration, an understanding of the proxemics of cobots, i.e., how physical space is shared and navigated, is of crucial importance. In this regard, the significant impact on human stress of the close presence of a cobot has been proved by several studies [86–88]. The premise is that the longer a robot works in close proximity to a human, the greater the potential stress on the human worker, requiring more complex coordination [88]. Indeed, the increased presence of the robot in the human's personal space could affect the psychological comfort and operational focus of the human worker. Studies on human proxemics were firstly performed by Hall [89] who identified four primary interpersonal distances commonly used to structure physical space in human interactions. These zones are designed to reflect different levels of intimacy and social interaction:

- Intimate distance: Ranging from direct contact to about 45 cm, this zone is reserved for those with whom one is very close, such as family members or close friends. Interactions within this zone typically involve personal or comforting gestures.
- Personal distance: Ranging from 0.5 to 1.2 m, personal distance allows for interactions that are more personal in nature but still maintain a boundary that provides a sense of space. It is the space used for conversations with friends and some group discussions.
- Social distance: Ranging from about 1.2 to 3.6 m, social distance is appropriate for interactions among acquaintances or within a professional setting. This space is used for interactions that require more formal boundaries and is typical of the workplace or social gatherings.
- Public Distance: Beyond 3.6 m, public distance is used for speeches, lectures and theatre; essentially any situation where one or a few people are addressing a larger group. This distance helps the speaker maintain a detached or more formal relationship with the audience.

In collaborative assembly task robot often invades human's intimate area. Such invasion can cause discomfort, anxiety or stress. The intimate zone is typically reserved for close personal contact and when this space is invaded by an unfamiliar entity, such as a robot, it can trigger a defensive response, often referred to as a personal space invasion, reducing the effectiveness of the interaction and potentially the quality of process [86,90,91]. In light of this, as a first proxy to quantify collaboration complexity the authors propose an indicator, called Time of Collaboration Ratio, based on the time that humans and robots spend together in the same workspace. The idea behind this indicator is that the time humans and robots spend working together can be linked to the four factors of collaborative work identified by Patel et al. [82]. Increased collaboration time indeed necessitates greater mutual learning, as both humans and robots must adapt and optimize their behaviour based on shared actions. Additionally, longer collaboration duration may lead to more frequent decision-making instances, where decisions made by one agent directly impact the operations of the other. Finally, extended collaboration time requires enhanced coordination and communication to ensure the assembly process is completed efficiently. While it is acknowledged that using time as a proxy may oversimplify the concept of collaboration complexity, it serves as a preliminary attempt to provide a quantitative and practical indicator for such a broad concept.

3.4.1. Time of collaboration ratio

Time of Collaboration Ratio, henceforth referred as "*ToCR*", is an indicator introduced as first attempt to quantify collaboration complexity. This indicator is based on the idea that collaboration can be measured by the time humans and robots co-occupy the same work area. In line with the model proposed by Patel et al. [82], this metric reflects the need for continuous communication and adaptation as both parties work towards a common goal in a shared workspace, and also illustrates the link between shared physical presence and the contextual greater stress and cognitive effort induced by the presence of a robot in the human's intimate area. *ToCR* can be expressed as follows:

$$ToCR = \frac{T_{H+R}}{T_C} \tag{2}$$

where:

- T_{H+R} represents the time when the robot moves in the human worker's intimate area.
- T_C represents the total completion time of the collaborative assembly process.

The mathematical codomain of this indicator ranges from 0 to 1, where 0 represents a process where the human operator never shares the intimate space with the robot, and 1 represents a process in which all the robot's movements occur within the human's intimate space. Suppose to compute *ToCR* for the same example presented in Section 3.3.1 (see Table 1). Fig. 4 shows the same chart of the previous example (see Fig. 3), but with the additional information on the time robot operates in human's intimate area.

In this case, the sum of all the time intervals in which the robot moves within human worker's intimate area is $T_{H+R} = 2\,s + 4\,s + 7\,s = 13\,s$. Given that the total completion time (i.e., T_c) is 60 s, the time of collaboration ratio is $ToCR = \frac{T_{H+R}}{T_C} = 0.22$. A low "Time of Collaboration Ratio" could indicate a more isolated operation, where the robot and human work independently rather than interdependently. Conversely, a higher value of this metric indicates a greater presence of the robot in the human's intimate area during task performance. From an ergonomic and safety perspective, it potentially correlates with the psychological and physical stress levels experienced by the human worker. The closer and more frequent the robot's movements are to the human, the more likely it is to affect the worker's comfort and concentration, potentially increasing stress levels. However, at the same time this ratio could serve as a key indicator of the efficiency and quality of collaboration. A higher ratio indicates that the robot is very active in assisting tasks that require close cooperation, which could be seen as a positive attribute in scenarios where robot assistance is critical for task efficiency.

4. A proposal for a structured collaborative assembly complexity model

In this section, a preliminary quantitative methodology to assess collaborative assembly complexity will be presented. With reference to Fig. 2, the authors hypothesized that collaborative assembly complexity (i.e., C_{HRC}) can be obtained from four separate contributes: (i) product complexity; (ii) assembly complexity, (iii) interaction complexity and (iv) collaboration complexity. In this regard, it was decided to use the Samy and ElMaraghy's method [16] as a basis for the formulation of the C—HRC model. The model by Samy and ElMaraghy was originally formulated as follows to specifically assess product assembly complexity ($C_{product}$):

$$C_{product} = \left[\frac{n_p}{N_p} + CI_{product}\right] \log_2(N_p + 1) + \left[\frac{n_s}{N_s}\right] \log_2(N_s + 1) \tag{3}$$

where:

- $1 \le n_p \le N_p$, n_p is the number of unique parts and N_p is the total number of parts.
- $1 \le n_s \le N_s$, n_S is the number of unique fasteners and N_s is the total number of fasteners.
- $CI_{product} \in [0; 1]$ is a complexity index related to geometrical and dimensional features of components and thus it accounts for product complexity. The calculation of this index is based on the Design for Assembly tables (see Appendix A and B). These tables present different handling and joining difficulty factors depending on whether the assembly is carried out by a human or a robot [16].

Specifically, according to Samy and ElMaraghy [16], $CI_{product}$ can be computed as follows:

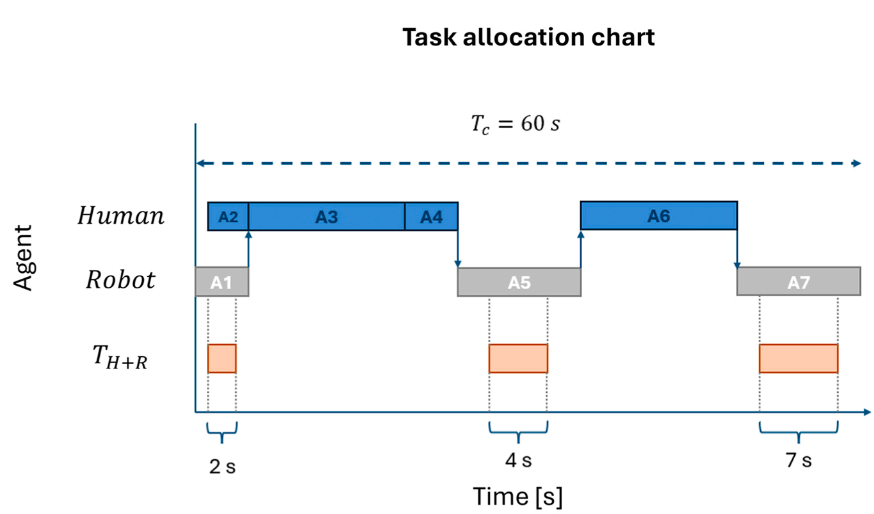

Fig. 4. Task allocation chart of the assembly process and the times humans and robot work in the human's intimate space (i.e., T_{H+R}).

- Calculation of average handling factor $C_h = \frac{\sum_1^J C_{h,f}}{J}$ and average insertion factor $C_i = \frac{\sum_1^K C_{i,f}}{K}$ for each part. The values proposed by Samy and ElMaraghy are provided in Appendix A and B. J and K represent respectively the number of handling and insertion features (to which specific difficulty factors correspond) that can be attributed to the part under assessment.
- Aggregation of handling and insertion factors through a weighted average:

$$C_{part} = \frac{C_h \sum_1^J C_{h,f} + C_i \sum_1^K C_{i,f}}{\sum_1^j C_{h,f} + \sum_1^K C_{i,f}} \tag{4}$$

- Computation of $CI_{product} = \sum_{p=1}^{n} x_p C_{part}$ where x_p is the percentage share of dissimilar parts.

Inspired by the model proposed by Samy and ElMaraghy, the authors decided to extend Eq. (3) with two novel contributions that account for interaction complexity and collaboration complexity, respectively. Thus, the C—HRC model can be expressed as follows:

$$C_{HRC} = \left[\frac{n_p}{N_p} + CI_{product}\right] \log_2(N_p + 1) + \left[\frac{n_s}{N_s}\right] \log_2(N_s + 1) + \left[\frac{n_{rs}}{N_t}\right] \log_2(N_t + 1) + \frac{T_{H+R}}{T_c} \log_2(N_c + 1) \tag{5}$$

Where the first two terms, $\left[\frac{n_p}{N_p} + CI_{product}\right] \log_2(N_p + 1) + \left[\frac{n_s}{N_s}\right] \log_2(N_s + 1)$, are the same defined in Eq. (3), and:

- $\frac{n_{rs}}{N_t}$ is the *DoIR* indicator presented in Section 3.3.1, with n_{rs} is the number of role switching between human and robot while N_t is the number of elementary tasks of the assembly process.
- $\frac{T_{H+R}}{T_c}$ is the *ToCR* indicator presented in Section 3.4.1, where T_{H+R} represents the time when the robot moves in the human worker's intimate area and T_C represents the total completion time of the collaborative assembly process.
- N_c is the number of robot's elementary tasks performed completely or partially in the human's work-area.

The original model, derived from the concept of information entropy [42], was based on the idea that greater variety in parts and fasteners increases the cognitive effort required by operators to successfully complete the assembly process. Consequently, higher variety may lead to greater difficulties and potential failures during the process. Similarly, the third term of Eq. (5) ($\left[\frac{n_{rs}}{N_t}\right] \log_2(N_t + 1)$), added to encompass the dynamics of human-robot interaction, was also inspired by entropic models. This term increases as the DoIR increases, reflecting the notion that more frequent role-switching between humans and robots leads to greater interaction complexity, and therefore, higher collaborative assembly complexity. High values of n_{rs} suggest more dynamic and potentially unpredictable interaction patterns, contributing to increased complexity.

In parallel, the fourth term of the equation increases as the *ToCR* increases. More time spent in close proximity requires greater effort from the human to coordinate and collaborate with the robot. Therefore, this model captures the concept that more frequent switching and prolonged time in the same workspace contribute to the overall complexity of the assembly process. Furthermore, this approach ensures that the new terms are mathematically consistent with the basic elements proposed by Samy and ElMaraghy, effectively extending the model to include interaction and collaboration complexity. The use of entropic models thus provides a quantitative value to express the increase in complexity due to variability and uncertainty in human-robot collaboration.

5. Model implementation: a small case study

In this section, the C—HRC model is applied to three different products: (i) a mechanical equipment, (ii) a skateboard and (iii) a diaphragm water pump. The aim of this case-study consists of providing a practical application of this model to real products (see Fig. 5). The list and quantities of parts and screws are detailed respectively in Table 2,3 and 4. The selection of these products is driven by their differences in geometrical characteristics, the number of components, and component variety, which result in varying levels of assembly complexity (Samy and ElMaraghy, 2010). Specifically, excluding fasteners, the mechanical equipment consists of only 4 components; the skateboard has 19 components, but only 9 different types; and the diaphragm water pump comprises 13 components, with 12 different types.

The assembly workstation is composed of a collaborative robot UR3 of the Mind4Lab Laboratory at Politecnico di Torino and a feeding tray used to place the parts of the products. The human operator works on the right-side of the table, i.e. "human's work area" (see Fig. 6). As previously mentioned, to compute the Time of Collaboration Ratio it is necessary to consider all the movements the robot makes within the human's intimate area, which can be schematized as a sphere with a radius of 45 cm. For practical purposes, it was hypothesized that the human's work area—measuring 50 cm by 60 cm, as illustrated in Fig. 6b—represents the "intimate area." In this space, humans and robots work closely together, necessitating coordination and adaptation, which increases the cognitive effort required from the operator. Consequently, all robot movements within this area were considered for the *ToCR* calculation.

The detailed list of all the elementary tasks to assemble the three reference products and the related task allocation and assembly times are presented in Appendix C.

The calculation of C_{HRC} includes the following steps:

- Calculation of $CI_{product}$: in computing $CI_{product}$, both manual and automatic assembly difficulty factors were used, depending on the agent handling or joining the specific part (see task allocation of appendix C - Tables 8,9,10). This approach is different from the one originally proposed, but it is essential as in a collaborative scenario some parts are handled/joined by human and others by the robot. For those part handled/joined by the human operator, difficulty factors for manual assembly were considered (see Appendix A) while for those handled/joined by the robot, difficulty factors for automatic assembly were used (see Appendix B). Hence, using Eq. (4) and the difficulty factors derived from Design for Assembly of Appendix A and B [16], the respective values for the three products can be obtained:

$$CI_{product,\ mechanical\ equipment} = 0.697 \tag{6}$$

$$CI_{product,\ skateboard} = 0.709 \tag{7}$$

$$CI_{product,\ pump} = 0.713 \tag{8}$$

- Calculation of *DoIR*: Using Eq. (1), the value of *DoIR* is:

$$DoIR_{mechanical\ equipment} = \frac{n_{rs}}{N_t} = \frac{6}{8} = 0.75 \tag{9}$$

$$DoIR_{skateboard} = \frac{n_{rs}}{N_t} = \frac{15}{46} = 0.326 \tag{10}$$

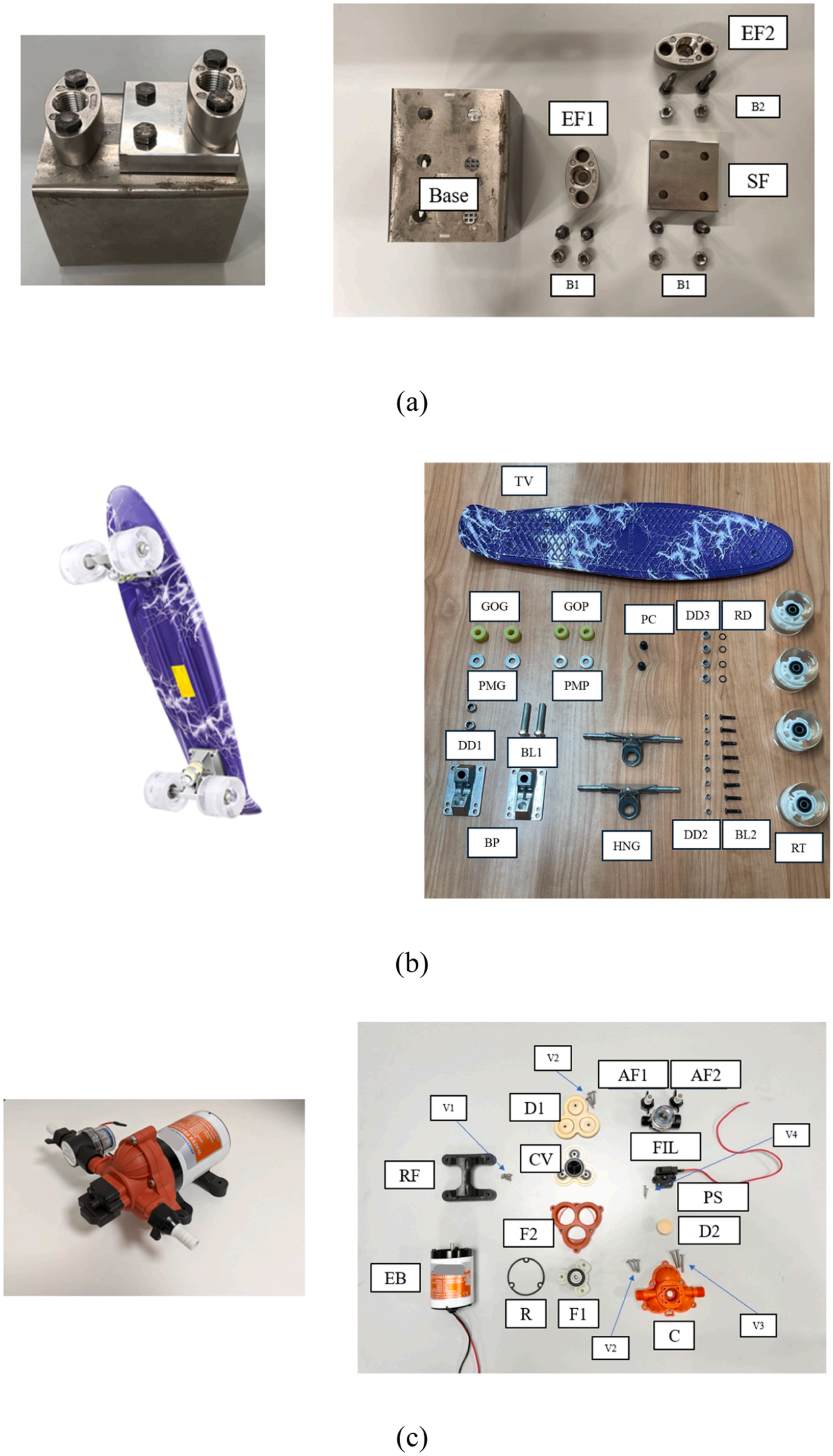

Fig. 5. (a) mechanical equipment, (b) skateboard and (c) diaphragm water pump. The final assembled products are on the left side and the related parts and screws on the right side.

Table 2
List of parts and quantities of the mechanical equipment (see Fig. 5-a).

Part name	Part code	Quantity
Base	Base	1
Elliptical flange	EF1/EF2	2
Square flange	SF	1
Bolt type 1	B1	4
Bolt type 2	B2	2
Total (parts + fasteners)		10

Table 3
List of parts and quantities of the skateboard (see Fig. 5-b).

Part name	Part code	Quantity
Base	TV	1
Big rubber ring	GOG	2
Small rubber ring	GOP	2
Big metallic ring	PMG	2
Small metallic ring	PMP	2
Bolt type 1 (screw + nut)	BL1+DD1	2
Base plate	BP	2
Pivot cup	PC	2
Hanger	HNG	2
Bolt type 2 (screw + nut)	BL2+DD2	8
Bolt type 3 (nut + washer)	DD3+RD	4
Wheel	RT	4
Total (parts + fasteners)		33

Table 4
List of parts and quantities of the diaphragm water pump (see Fig. 5-c).

Part name	Part code	Quantity
Engine block	EB	1
Rubber feet	RF	1
Ring	R	1
Flange 1	F1	1
Flange 2	F2	1
Diaphragm	D1	1
Cover with valves	CV	1
Cover	C	1
Pressure switch	PS	1
Pressure switch diaphragm	D2	1
Filter	FIL	1
Flow adapter	AF1/AF2	2
Screws type 1	V1	2
Screws type 2	V2	6
Screws type 3	V3	3
Screws type 4	V4	2
Total (parts + fasteners)		26

$$DoIR_{pump} = \frac{n_{rs}}{N_t} = \frac{7}{19} = 0.368 \tag{11}$$

- Calculation of *ToCR*: Using Eq. (2), the three values of *ToCR* (and related N_c) are:

$$ToCR_{mechanical\ equipment} = \frac{T_{H+R}}{T_c} = \frac{34}{125} = 0.272\ (N_c = 5) \tag{12}$$

$$ToCR_{skateboard} = \frac{T_{H+R}}{T_c} = \frac{103}{622} = 0.166\ (N_c = 11) \tag{13}$$

$$ToCR_{pump} = \frac{T_{H+R}}{T_c} = \frac{27}{376} = 0.0718\ (N_c = 5) \tag{14}$$

- Calculation of C_{HRC}: Considering the respective values of n_p, N_p, n_s, N_s and $CI_{product}$ (see Table 5) the resulting value of C_{HRC} of the three reference products are:

$$\begin{aligned} C_{HRC_{mechanical\ equipment}} &= \left(\frac{3}{4} + 0.697\right)\log_2(4+1) + \frac{2}{6}\log_2(6+1) \\ &\quad + \frac{6}{8}\log_2(8+1) + \frac{34}{125}\log_2(5+1) \\ &= 7.38 \end{aligned} \tag{15}$$

$$\begin{aligned} C_{HRC_{skateboard}} &= \left(\frac{9}{19} + 0.709\right)\log_2(19+1) + \frac{3}{14}\log_2(14+1) \\ &\quad + \frac{15}{46}\log_2(46+1) + \frac{103}{622}\log_2(11+1) \\ &= 8.35 \end{aligned} \tag{16}$$

$$\begin{aligned} C_{HRC_{pump}} &= \left(\frac{12}{13} + 0.713\right)\log_2(13+1) + \frac{4}{13}\log_2(13+1) \\ &\quad + \frac{7}{19}\log_2(19+1) + \frac{27}{376}\log_2(5+1) \\ &= 9.18 \end{aligned} \tag{17}$$

With reference to Fig. 7, it is important to note that the first two terms provide a baseline value for product assembly complexity, to which the contributions of interaction complexity and collaboration complexity are added. These increases are attributed to the additional cognitive effort required from the human operator to effectively communicate, coordinate, and work closely with the robot. Interaction complexity indicates that integrating robot collaboration into the assembly process introduces a layer of complexity that demands greater cognitive involvement from the human operator. As the number of role-

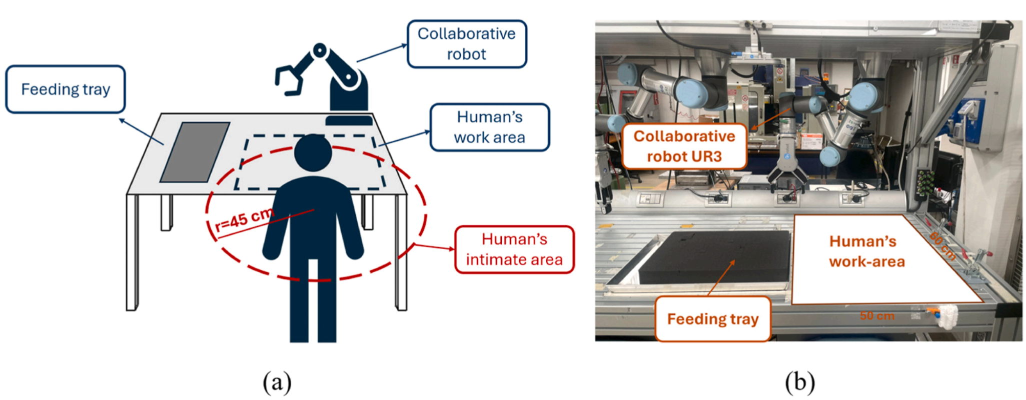

Fig. 6. Assembly work-station layout (a) and the real workstation at the Mind4Lab laboratory at Politecnico di Torino (b).

Table 5
Overview of all the model parameters for each reference product.

Product	$CI_{product}$	n_p	N_p	n_s	N_s	n_{rs}	N_t	T_{H+R} [s]	T_c [s]	N_c	C_{HRC}
Mechanical equipment	0.697	3	4	2	6	6	8	34	125	5	7.38
Skateboard	0.709	9	19	3	14	15	46	103	622	11	8.35
Diaphragm water pump	0.713	12	13	4	13	7	19	27	376	5	9.18

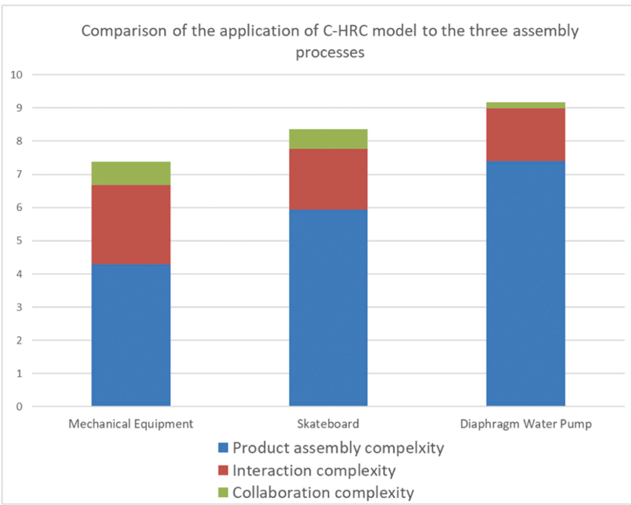

Fig. 7. Comparison of the C—HRC results for the three products.

switching instances increases, so does the interaction complexity. It is interesting that in this example the greatest share of interaction complexity occurs with the simplest assembly process, i.e., the mechanical equipment. Indeed, neglecting the contribution of interaction and collaboration complexity, the assembly complexity of the three products, computed using Eq. (3), would be: $C_{mechanical\ equipment} = 4.3$, $C_{skateboard} = 5.95$ and $C_{pump} = 7.4$. In the assembly process of the mechanical equipment, in fact, although there are only a few tasks to be performed, the interactions between human and robot are very frequent ($DoIR = 0.75$) and the human will therefore have to communicate more often with the robot to complete the assembly, increasing the cognitive effort required. Moreover, the share of collaboration complexity is also higher in this case, given that for 34 s out of a total completion time of 125 s human and robot work in close contact. This result is also reasonable, as there are frequent interactions and the human will have to co-ordinate more often with the robot and thus work more closely together. As far as the skateboard is concerned, interactions between humans and robots are less frequent $DoIR = 0.326$, thus leading to a decrease in the complexity of interaction and even collaboration, given the less time spent in close contact. Finally, for the diaphragm water pump, it is worth noting the low value of the collaboration complexity ($ToCR = 0.0718$). This is mainly due to both the fact that human and robot work in considerable autonomy, thus reducing the time both are together in the human's work area, and from the fact that the longest assembly tasks are carried out exclusively by the human operator. This reduces the share of T_{H+R} in relation to T_c. In all three cases, however, it can be seen that the largest share remains that of product assembly complexity to which the two new contributions are added.

Obviously, this case study serves only as an initial demonstration of the model's applicability in real collaborative assembly processes. For a more structured validation, future steps will involve conducting additional experiments across a broader range of scenarios and settings to rigorously test and refine the model's effectiveness and reliability.

5.1. Preliminary sensitivity analysis of the C–HRC model

In this section, a preliminary sensitivity analysis of the proposed C—HRC model is conducted, using the mechanical equipment as a reference. Modifications were made to the task allocation and associated collaboration times to observe their impact on the overall C—HRC values. This analysis is crucial for understanding the model's responsiveness to changes in operational parameters. For example, consider that the elementary tasks outlined in Appendix C are rearranged as shown in Table 6.

In this case, the number of role switching is reduced ($n_{rs} = 2$), given that the pick and place activities are performed by the robot at the beginning of the process. Once all the parts have been placed, the operator performs all the screwing activities and, once finished, interacts by sending a command to the robot to pick up the final product. Therefore, the value of the interaction complexity is lowered considerably as $DoIR = \frac{2}{8} = 0.25$ leading to a lower $C^{*}_{HRC_{mechanical\ equipment}} = 5.79$. On the other hand, $ToCR$ remains constant since the robot's movements take place in the human's work area anyway, which could generate discomfort situations for the operator.

Now, suppose the original task allocation is maintained, but with the new times shown in Table 7.

In this situation the robot performs all the pick and place activities out of the human's work-area, except for the picking up of the final product. In this case the share of collaboration complexity is almost negligible, since $ToCR = 0.048$, while the interaction complexity remains constant as $DoIR = 0.75$ leading to $C^{'}_{HRC_{mechanical\ equipment}} = 6.8$. This case refers to processes where, although human and robot often interact, they work most of the time in sufficiently separated spaces not to induce discomfort or stress in the human operator. The sensitivity analysis showed that the C—HRC model is highly sensitive on how tasks are allocated within the assembly process between human and robot. Especially, these findings can be used by process designers to iteratively change task allocation to optimise complexity and promote efficient human-robot collaboration in collaborative assembly processes.

6. Conclusions

This paper presents a novel contribution to the field of collaborative robotics in assembly processes by introducing a comprehensive conceptual framework for assessing collaborative assembly complexity. Traditional assembly complexity assessment methods are not suitable

Table 6
New task allocation for the mechanical equipment.

ID	Elementary task	Allocation (H for human and R for robot)	Time [s]	T_{H+R} [s]
A1	Pick and place BASE	R	8	4
A2	Pick and place EF1	R	10	8
A4	Pick and place SF	R	12	11
A6	Pick and place EF2	R	8	5
A3	Screwing EF1 with Base	H	22	
A5	Screwing SF with Base	H	25	
A7	Screwing EF2 with Base	H	30	
A8	Pick the final product and place out of the assembly area	R	10	6

Table 7
Modified task allocation and the new collaboration times of the mechanical equipment.

ID	Elementary task	Allocation (H for human and R for robot)	Time [s]	T_{H+R} [s]
1	Pick and place BASE	R	8	
2	Pick and place EF1	R	10	
3	Screwing EF1 with Base	H	22	
4	Pick and place SF	R	12	
5	Screwing SF with Base	H	25	
6	Pick and place EF2	R	8	
7	Screwing EF2 with Base	H	30	
8	Pick the final product and place out of the assembly area	R	10	6

for collaborative assembly processes, since they fail to take into account the interaction dynamics among different agents, which in this case are humans and robots. This framework not only formalizes the parameters that influence collaborative assemblies but also integrates them into a cohesive structure, incorporating two novel proxies: "interaction complexity" and "collaboration complexity." This framework is essential for understanding how various elements of assembly tasks impact overall system performance. The quantitative formulation of the C—HRC model is inspired by the assembly complexity model proposed by Samy and El-Maraghy [16], which has proven highly effective across a wide range of manufacturing applications. The results obtained with C—HRC model align with expectations, as they show that the complexity of collaboration and interaction adds additional layers to the product assembly complexity. This finding is consistent with observations collected in previous experimental campaigns where, while workers often recognise the assistance provided by collaborative robots, they also experienced increased cognitive effort due to the need to co-exist and coordinate with robots. Therefore, the C—HRC model offers a practical tool for process designers involved in the ex-ante design of workstations. By employing this approach, designers can proactively identify areas where higher cognitive efforts may be required, thus leading to greater occurrence of errors. In this way, designers can enhance the quality of manufacturing processes through more effective task allocation and optimized layout designs. This proactive approach in workstation design can lead to significant improvements in the ergonomic and operational aspects of manufacturing systems, facilitating more integrated and effective human-robot collaborations.

7. Future work

While the contributions of the C—HRC model are novel and promising, they also underscore some limitations of the current approach. First, experimental validation across different products and large operator samples is essential to ensure the model's generalizability and accuracy. The case study presented serves only as an initial test of the model's applicability in real-world contexts; however, a broader range of products and related experiments are necessary for thorough validation. Indeed, larger studies could provide additional insights into the scalability and adaptability of the model. Furthermore, a major limitation is the static nature of the model, as it does not take into account the influence of time and learning on collaborative assembly complexity. Over time, operators may adapt to the presence of collaborative robots, improving coordination and reducing the perceived effort required to interact with them.

Secondly, it is important to note that this model integrates four distinct terms, each contributing to the overall complexity value. However, this summation can lead to compensation issues, where higher values in one term may offset lower values in others, potentially resulting in equivalent complexity values in scenarios that are significantly different [45,92]. In addition, future work could focus on developing new metrics to complement or extend the existing framework to ensure that it remains relevant and comprehensive in addressing the HRC assembly complexity. As a future development, it is possible to automate the calculation of the C—HRC model value, thereby streamlining the process. This could potentially be integrated into task allocation algorithms aimed at reducing the complexity of HRC assembly.

Third, while the results obtained are consistent with expectations based on previous observations, their generalisability remains limited. The lack of comparative studies or parallel research using alternative models limits the ability to compare the findings. Future work should explore how differences in product complexity might vary if other models or frameworks were used. Moreover, the choice of the layers included in the model, although based on previous research and empirical evidence, may not fully capture the nature of collaborative assembly complexity. In this regard, future research should also focus on investigating additional factors that could further refine the accuracy of the model.

Finally, future research will also focus on a detailed analysis of how well the C—HRC model correlates with process failures and perceived workload. Since both of these factors are recognized as effects of assembly complexity, establishing a relationship with them will enhance the robustness of the C—HRC model. Additionally, investigating the relationship between the C—HRC model and perceived complexity will provide valuable insights into how these aspects are interconnected. Concurrently, future studies may also involve the development of a scale of collaborative assembly complexity based on the proposed model. This scale could be instrumental in identifying and prioritizing processes where failures are more likely to occur, ultimately leading to improvements in collaborative assembly.

CRediT authorship contribution statement

Matteo Capponi: Writing – original draft, Methodology, Data curation, Conceptualization. **Riccardo Gervasi:** Writing – original draft, Formal analysis, Data curation. **Luca Mastrogiacomo:** Methodology, Funding acquisition, Conceptualization. **Fiorenzo Franceschini:** Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Luca Mastrogiacomo reports financial support was provided by Ministry of University and Research Italy. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Assembly attributes and difficulty factors for manual assembly [16]

Group	Attribute	Description	Average difficulty factor, C_f
Handling attributes	Symmetry ($\alpha + \beta$)	$\alpha + \beta < 360$	0.70
		$360 \leq \alpha + \beta < 540$	0.84
		$540 \leq \alpha + \beta < 720$	0.94
		$\alpha + \beta = 720$	1.00
	Size	> 15 mm	0.74
		6 mm $\leq$ size $\leq$ 15 mm	0.81
		< 6 mm	1
	Thickness	> 2 mm	0.27
		0.25 mm $<$ size $\leq$ 2 mm	0.5
		≤ 0.25 mm	1
	Weight	< 10 lb (light)	0.5
		> 10 lb	1
	Grasping and manipulation	Easy to grasp and manipulate	0.91
		Not easy to grasp and manipulate	1
	Assistance	Using one hand	0.34
		Using one hand with grasping aids	1
		Using two hands	0.75
		Using two hands with assistance	0.57
	Nesting and tangling	Parts do not severely nest or tangle and are not flexible	0.58
		Parts severely nest or tangle or are flexible	1
	Optical magnification	Not necessary	0.8
		Necessary	1
Insertion attributes	Holding down	Not required	0.54
		Required	1
	Alignment	Easy to align or position	0.86
		Not easy to align or position	1
	Insertion resistance	No resistance	0.87
		Resistance to insertion	1
	Accessibility and vision	No restrictions	0.57
		Obstructed access or restricted vision	0.81
		Obstructed access and restricted vision	1
	Mechanical fastening processes	Bending	0.34
		Riveting	0.58
		Screw tightening	0.42
		Bulk plastic deformation	1
	Non-mechanical fastening processes	No additional material required	0.58
		Soldering processes	0.67
		Chemical processes	1
	Non-fastening processes	Manipulation of parts or sub-assemblies (fitting or adjusting of parts, …)	0.75
		Other processes (liquid insertion, …)	1

Appendix B. - Assembly attributes and difficulty factors for automatic assembly [16]

Group	Feature	Feature description	Average Difficulty factor, C_f
Handling attributes	Symmetry	*Rotational part*	
		α symmetric and β symmetric	0.45
		β symmetric only	0.66
		α symmetric only	0.77
		No symmetry	1
		Non-rotational part	
		180° symmetry about three axes	0.6
		180° symmetry about one axis only	0.77
		No symmetry	1
	Flexibility	Non-flexible	0.67
		Flexible	1
	Delicateness	Non-delicate	0.8
		Delicate	1
	Stickiness	Not sticky	0.8
		Sticky	1
	Tangling/nesting	Not tangle/nest	0.8
		Tangle/nest	1
Insertion attributes	Holding down after insertion	Not required	0.75
		Required	1
	Insertion resistance	Does not exist	0.67
		Exists	1
	Alignment and positioning	Easy	0.67
		Not easy	1
	Mechanical fastening methods	Screwing or other processes	0.5
		Riveting or similar processes	0.56
		Bending or similar processes	1
	Non-mechanical fastening methods	Chemical processes	0.67

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(*continued*)

Group	Feature	Feature description	Average Difficulty factor, C_f
		Additional material required	0.92
		No addition of material (friction, …)	1
	Insertion direction	Straight line from above	0.5
		Straight line not from above	0.54
		Not straight line insertion	1

Appendix C. List and times of the elementary task of the collaborative assembly processes

Table 8
List of elementary tasks and the related allocations and times for the mechanical equipment (see Fig. 4a).

ID	Elementary task	Allocation (H for human and R for robot)	Time [s]	T_{H+R} [s]
1	Pick and place BASE	R	8	4
2	Pick and place EF1	R	10	8
3	Screwing EF1 with Base	H	22	
4	Pick and place SF	R	12	11
5	Screwing SF with Base	H	25	
6	Pick and place EF2	R	8	5
7	Screwing EF2 with Base	H	30	
8	Pick the final product and place out of the assembly area	R	10	6

Table 9
List of elementary tasks and the related allocations and times for the skateboard (see Fig. 4b).

ID	Elementary task	Allocation (H for human and R for robot)	Time [s]	T_{H+R} [s]
1	Pick and place BP	R	10	8
2	Pick and place BL1 in BP	H	6	
3	pick PMG and GOG	H	5	
4	Insert PMG, GOG on BL1	H	13	
5	Assembly PC and HNG	H	4	
6	Insert HNG on BP	H	6	
7	Pick and place PMP and GOP	H	14	
8	Pick and place DD1	H	3	
9	screwing DD1 on BL1	H	6	
10	Pick and place semi-assembly out of the work area	R	9	7
11	Pick and place BP	R	10	8
12	Pick and place BL1 in BP	H	6	
13	pick PMG and GOG	H	5	
14	Insert PMG, GOG on BL1	H	13	
15	Assembly PC and HNG	H	4	
16	Insert HNG on BP	H	6	
17	Pick and place PMP and GOP	H	14	
18	Pick and place DD1	H	3	
19	screwing DD1 on BL1	H	6	
20	Pick and place semi-assembly out of the work area	R	9	7
21	Pick TV	R	18	14
22	Place truck on TV	H	6	
23	Pick and place bl2	H	36	
24	Screwing DD2 on BL2	H	84	
25	Rotate TV	R	11	8
26	Place truck on TV	H	6	
27	Pick and place bl2	H	36	
28	Screwing DD2 on BL2	H	84	
29	Pick and place assembly supports	H	10	
30	Pick TV on bases	R	11	11
31	pick RT	R	14	10
32	Insert RT on axis	H	8	
33	Pick and place DD3 and RD	h	3	
34	screwing DD3 on axis	H	17	
35	pick RT	R	14	10
36	Insert RT on axis	H	8	
37	Insert RD	H	3	
38	screwing DD3 on axis	H	17	
39	pick RT	R	14	10
40	Insert RT on axis	H	8	

(*continued on next page*)

Table 9 (*continued*)

ID	Elementary task	Allocation (H for human and R for robot)	Time [s]	T_{H+R} [s]
41	Insert RD	H	3	
42	screwing DD3 on axis	H	17	
43	pick RT	R	14	10
44	Insert RT on axis	H	8	
45	Insert RD	H	3	
46	screwing DD3 on axis	H	17	

Table 10
List of elementary tasks and the related allocations and times for the diaphragm water pump (see Fig. 4c).

ID	Elementary task	Allocation (H for human and R for robot)	Time [s]	T_{H+R} [s]
A1	Pick and place RF	H	3	
A2	Pick and place EB	R	10	8
A3	Screwing EB with RF	H	46	
A4	Pick and place F1	R	5	4
A5	Pick and place F2	R	5	4
A6	Insert F1 in F2	H	6	
A7	Pick and place D1 on sub-assembly F1+F2	H	4	
A8	Screwing D1, F1 and insert CV on D1	H	67	
A9	Pick and place C	R	5	4
A10	Screwing C and F2	H	43	
A11	Insert R on EB	H	9	
A12	Insert and screwing sub-assembly pump head on EB (joining F1-EB)	H	60	
A13	Pick and place D2 and PS on C	H	19	
A14	Screwing PS and C	H	48	
A15	Pick and place FIL	H	4	
A16	Screwing FIL	H	6	
A17	Pick and place AF1 and AF2	H	8	
A18	Screwing AF1 and AF2	H	18	
A19	Pick the final product and place out of the assembly area	R	10	7

Data availability

No data was used for the research described in the article.

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