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Exploring multi-human multi-robot collaboration in assembly processes: Challenges and opportunities in quality and manufacturing

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Abstract. The recent evolution of robotic systems is pushing the manufacturing sector towards continuous adaptation, incorporating novel technologies. Industry 5.0 is shifting the attention from basic human-robot interactions, typically between a single human operator and a single robot, to more complex configurations of multi-human multi-robot (MH-MR) teams. These advanced systems, in which multiple human and robot agents collaborate on shared tasks, can offer significant advantages on flexibility, adaptability and productivity, while reducing operators' workload. However, integrating these systems introduces new challenges: such as governing interactions within the team, means of communication and human behavior. Traditional models may no longer be adequate to capture the complexity of MH-MR teams. This paper aims to investigate the challenges and the open questions surrounding the adoption of MH-MR teams in manufacturing. A real case study in assembly is presented as an illustrative example to explore some of the key issues. This serves as a starting point for a broader discussion on how to effectively implement MH-MR teams in industrial contexts.

Introduction

Driven by advances in robotics, digital technologies and automation, manufacturing is undergoing a significant transformation, evolving from Industry 4.0 to Industry 5.0. Industry 5.0 aims at creating a more flexible and adaptive manufacturing environment, emphasizing efficiency, human well-being, worker support and social sustainability. Collaborative robots, i.e., robots that can work closely with humans without safety barriers, are one of the crucial technologies for this paradigm shift. Collaborative robots enable the fusion of human skills with those of robots, leading to the concept of human-robot collaboration ("HRC"). This shift, known as "human-centered manufacturing", aims to develop sustainable, adaptable production systems that balance technological progress with human needs [1–3]. Traditional HRC models, typically involving a single human and a single robot working together towards common goals [3], are evolving into more complex configurations where multiple human operators work alongside multiple robots in shared workspaces. These Multi-Human Multi-Robot (MH-MR) teams enable more efficient task distribution, improved adaptability to dynamic environments and a redefinition of how humans and robots co-exist in industrial environments [4]. By leveraging the precision of robots and the adaptability of humans [5, 6], MH-MR teams can improve performance, employee well-being and operational support. However, their introduction brings new challenges that require a rethink of existing models of collaboration. As manufacturing moves towards MH-MR systems, critical questions arise: How can multiple agents interact effectively while minimizing inefficiencies? What team dynamics emerge when humans and robots work together in more complex work structures? How should tasks be allocated and how should systems react to unexpected disturbances? [4, 7]. Beyond the technical aspects, the integration of MH-MR teams also raises issues such as communication effectiveness, workload balance and trust building [8]. Neglecting these factors can lead to inefficiencies and to compromised product and process quality.

Despite their potential, MH-MR systems are still an emerging area in industrial applications and require further research. Given the increasing demand for flexible and scalable manufacturing systems, it is essential to address these research gaps [2]. In detail, this paper tries to answer the following research question: *What are the key challenges and opportunities associated with the introduction of MH-MR teams in assembly?* Specifically, through an exploratory case-study this paper tries to gain preliminary insight into the dynamics that emerge within teams, explore the benefits achieved and identify critical challenges. The article is organized as follows: Section 2 presents a literature review on MH-MR teams in manufacturing contexts; Section 3 briefly describes the exploratory case study; Section 4 reports the preliminary results and feedback from MH-MR and human teams; Section 5 discusses challenges and opportunities of MH-MR adoption, focusing also on insights and directions for future research.

Literature review

As human-robot collaboration evolves beyond simple dyads, multi-human multi-robot (MH-MR) teams have emerged as a new frontier of research. MH-MR refers to teams with at least two humans and two robots [9, 10], representing a more advanced subset of HRC that addresses the intricate dynamics of multi-agent collaboration. In manufacturing environments, introducing multiple humans and multiple robots (MH-MR) into a team can enhance system flexibility and throughput, but it also significantly increases complexity and uncertainty in several domains. For example:

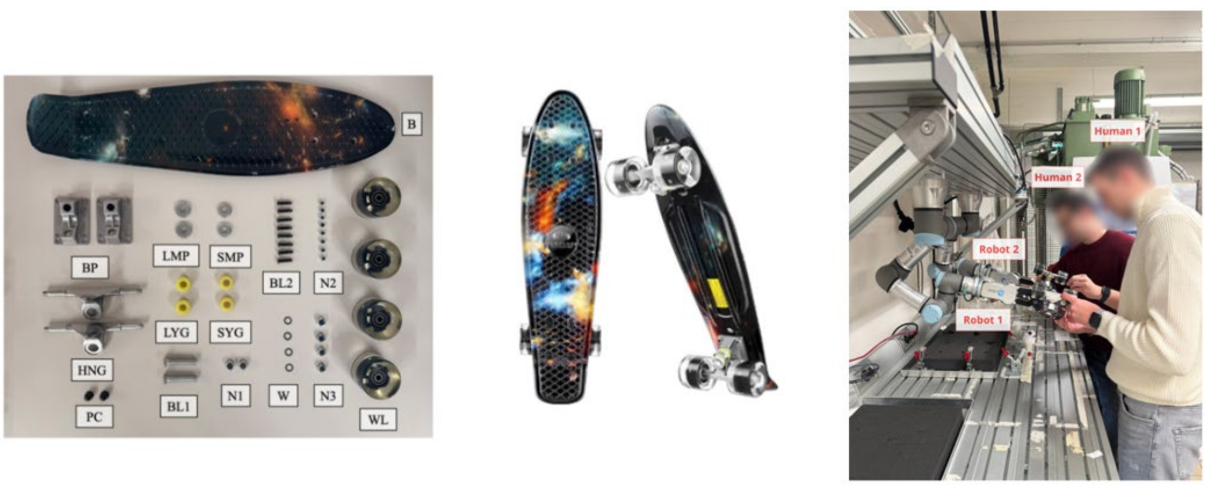
- task coordination becomes more intricate because responsibilities must be dynamically allocated among many agents [11];
- communication challenges grow as multiple humans and robots require seamless information exchange [12];
- safety risks rise due to unpredictable interactions among numerous moving agents [13];
- decision-making becomes more complicated as control and autonomy are distributed across different agents [12];
- system efficiency is more difficult to optimize with many interdependent components [7]
- performance measurement becomes complex due to the quantity of agents involved [7]

Therefore, managing MH-MR team performance, including workload distribution and role allocation, represents a critical challenge. Esterwood and Robert [13] highlighted the importance of team composition, believing that determining the optimal human-to-robot ratio and allocating roles effectively are essential for team cohesion and performance. Another critical aspect is building trust among team members, especially in dynamic environments. Trust directly influences interaction fluency, which significantly impacts overall team effectiveness [14, 15]. Similarly, cohesion in human-robot teams is crucial to reach an effective collaboration with robotic teammates [10]. Ma et al. [16] argued the impact of team members characteristics and of external factors, which can affect the outcome of teaming. Human factors such as cognitive workload, emotions, and performance are inherently variable and should be carefully managed to improve team performance [8]. Moreover, the effective design of human-robot teams requires an in-depth understanding of teamwork, supported by models and metrics that consider not only internal cognitive processes and observable behaviors, but also task characteristics, operational context and the collaborative dynamic between members [16]. In this regard, Riedelbauch et al. [7] provided a description of the relevant metrics for assessing human robot teaming in industrial scenarios considering the overall benchmarking process. Ma et al. [16] described the dimensions that should be investigated in MH-MR contexts to evaluate their effectiveness and present a case study application in spaceflight operations.

Despite these initial contributions, research into MH-MR collaboration is still at an early stage, particularly in manufacturing contexts. Existing studies tend to focus on isolated aspects, such as task allocation or interaction dynamics, without fully addressing the challenges of integrating these systems into real-world applications [4]. This paper aims to bridge these gaps by exploring the challenges and opportunities of MH-MR teams in manufacturing.

Case-study description

This paper explores a practical implementation of multi-human multi-robot (MH-MR) teams in a product assembly task through a case study. A comparison with fully manual teams serves only as a reference to highlight the key challenges, opportunities and implications of hybrid collaboration in light of the increasing integration of cobots in manufacturing. To achieve these objectives, experimental trials were conducted to preliminarily evaluate key performance metrics and gather qualitative feedback. The study involved six participants aged 24-25 years with no previous experience with collaborative robots. They were divided into three teams, each of which participated in the task of assembling a skateboard (see Fig. 1) in two configurations: parallel configuration (C1) and sequential configuration (C2). In parallel configuration tasks were performed simultaneously by humans or human-robot pairs in parallel, while in sequential one, tasks were divided and performed sequentially by all the agents. In addition, each configuration was performed in two modalities: manual and MHMR. In manual modality, two human agents collaborated to execute all steps of the assembly process independently, without any robotic intervention. In MHMR modality, human agents partnered with two robotic agents to complete the assembly process collaboratively.



(a) (b) (c)

Figure 1. *The components and the assembled skateboard used as case-study product (a,b) and the workstation with participants in MHMR modality during the assembly process (c).*

The experiments were held in the Mind4Lab of Politecnico di Torino (Italy) in controlled experimental conditions. During the experiment, participants operated at the workstation, consisting of a table and two collaborative robot Universal Robot UR3, as shown in Fig.1-c.

The assembly process involved 3 macro steps to be done twice per front and rear board to ensure the proper assembly of the skateboard: assembly of the truck, assembly of the truck on the board and assembly of the wheels on the truck. Steps to be followed for each assembly macro-phase and the related task allocation between humans and robots (for both modalities and configurations) are described in Table 1.

Materials Research Proceedings 57 (2025) 410-417 https://doi.org/10.21741/9781644903735-48

Table 1. *Skateboard assembly instructions and the related task allocation between humans (H1, H2) ad robots (R1, R2)*

Assembly macro-phase	Detailed steps	Manual Modality C1	Manual Modality C2	MHMR Modality C1	MHMR Modality C2
A) Assembly of the truck (x2)	1. Take the baseplate (BP) and put it in the correct orientation.	H1/H2	H1	R1/R2	R1
	2. Insert the bolt (BL1) into the baseplate (BP)	H1/H2	H1	H1/H2	H1
	3. Mount the larger metal protector (LMP) on the larger yellow grommet (LYG).	H1/H2	H2	H1/H2	H2
	4. Insert them onto the bolt (BL1) with the larger metal protector (LMP) at the bottom.	H1/H2	H1	H1/H2	H1
	5. Put the black pin cup (PC) on the hanger (HNG).	H1/H2	H2	H1/H2	H2
	6. Mount it on the baseplate (BP).	H1/H2	H1	H1/H2	H1
	7. Mount the smallest metal protector (SMP) on the smallest yellow grommet (SYG).	H1/H2	H2	H1/H2	H2
	8. Insert them onto the bolt (BL1) with the smallest metal protector (SMP) at the top.	H1/H2	H1	H1/H2	H1
	9. Screw the nut (N1) onto the bolt	H1/H2	H1	H1/H2	H1
B) Assembly of the truck on the board (x2)	1. Take the board (B) in the correct orientation.	H1	H1	R1/R2	R1
	2. Put and align the truck on the board.	H1/H2	H1	H1/H2	H1
	3. Insert the bolts (BL2) into the four holes, tighten them with the nuts (N2) to join the truck and the board.	H1/H2	H1	H1/H2	H1
C) Assembly of the wheels on the board (x2)	1. Take the first wheel (WL).	H1/H2	H2	R1/H2	R2
	2. Mount the wheel on the hanger, insert the washer (W) and tighten with a nut (N3).	H1/H2	H2	H1/H2	H2
	3. Take the second wheel (WL).	H1/H2	H2	R1/R2	R2
	4. Mount the wheel on the hanger, insert the washer (W) and tighten with a nut (N3).	H1/H2	H2	H1/H2	H2

Each team underwent two training trials followed by two "official" trials for each of the four scenarios (two configurations in two modalities). The data collected were the following:

- Questionnaires: participants completed the NASA Task Load Index (NASA-TLX) questionnaire to assess perceived workload, providing detailed insights into the human operators' experience [17]. This tool is based on the evaluation on a scale from 0 to 100 of six dimensions affecting perceived workload: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, Frustration. The total perceived workload value is obtained through a weighted average of the scores of each dimension. A low NASA-TLX score suggests that the task was perceived as relatively easy and not demanding, while a high score implies that the user experienced significant workload during task execution.
- Unstructured feedback: open-ended questionnaires were used to gather qualitative feedback about the overall experience.

Preliminary results

The preliminary findings of the proposed case study serve as a starting point to better understand the implications of incorporating MH-MR teams in manufacturing assembly. Table 2 shows the results of NASA-TLX (mean perceived workload by configuration) while Table 3 shows an overview of the unstructured feedback collected.

Table 2. *NASA-TLX preliminary results (where lower values are preferable, indicating lower perceived workload)*

	NASA-TLX [0-100]		
Configuration	Mean	Max	Min
C1-M	25.3	38	11.7
C1-MHMR	25.8	52.7	9
C2-M	38.5	52.7	23.7
C2-MHMR	18.8	44.7	9.7

Table 3. *Overview of the preliminary unstructured feedback (voice of participants) collected, grouped by macro-categories for the two modalities (manual and MHMR)*

Voice of participants		
Macro category	**Manual modality**	**MHMR Modality**
Operational efficiency	• Higher execution speed • Higher flexibility in adapting to change	• Stable execution • High dependency on cobots' pace with potential slowdowns due to technical limitations
Workload	• Higher physical effort due to the absence of cobots' support • Higher mental effort required to coordinate work	• Reduced physical strain due to cobot support • Effort to adapt to cobot interactions
Task Structure and Coordination	• Dynamic roles with higher individual responsibility • Need for continuous adjustment	• More predefined and rigid roles • Cobots assist rather than actively collaborating
Control and Autonomy	• Full control over work pace and task management	• Dependency on cobots' timing • Limited ability to intervene freely in the process
Team Dynamics	• Strong cohesion and greater sense of belonging within the team • Natural communication	• Lower interpersonal engagement • Cobots are perceived as tools rather than collaborative partners

The lowest mean workload was observed in C2-MHMR (18.8), suggesting that according to participants the support of cobots reduced the perceived workload. Conversely, C2-M reported a much higher workload (38.5), potentially reflecting the cognitive and emotional challenges of high-interaction in human teams. Given the exploratory nature of this study, feedback from participants were analyzed and reorganized in macro-categories, as shown in Table 3. MH-MR teams have the potential to improve ergonomic comfort and streamline workflows with cobot support. Furthermore, the unstructured feedback suggests that MH-MR teams, while requiring some adaptation, can lead to increased efficiency and reduced physical and cognitive effort in repetitive tasks, making them a sustainable and feasible solution for future manufacturing contexts.

Discussion and conclusions

The introduction of multi-human multi-robot (MH-MR) teams in manufacturing represents a paradigm shift with the potential to redefine industrial workflows. As highlighted by participant feedback and supported by the literature, MH-MR systems offer a promising pathway to increased worker well-being. However, their integration also presents significant challenges that need to be addressed in order to fully realize their benefits. MH-MR teams unlock several opportunities that can drive the transformation of manufacturing environments:

- *Improved worker support and dynamic task allocation*: Robots relieve workers of repetitive and physically demanding tasks, allowing them to focus on high-value cognitive activities. This redistribution of workload aligns with the broader goal of improving workers' condition within Industry 5.0. The presence of multiple robots and multiple human workers enables dynamic collaboration, allowing tasks to be shared in a way that can improve efficiency without overburdening any single team member [7].
- *Flexibility and agile adaptation*: In MH-MR environments, the combination of human adaptability and robotic precision enhances workflow agility, as different team members step in to compensate for delays, reassign tasks and optimize output together [18].
- *Improved workplace ergonomics and job satisfaction*: Reduced physical strain, as reported by participants, contributes to improved ergonomics and job quality. In MH-MR environments, workers can collaborate with multiple robots simultaneously, minimizing the risk of fatigue and allowing for a more balanced distribution of physical and cognitive workload [19].
- *Trust and transparency in human-robot interaction*: Predictability and transparency in robot behavior have been identified as key enablers for seamless collaboration. In MH-MR teams, trust dynamics become more complex due to the increased number of interacting agents. Hence, effective communication strategies and trust-building mechanisms becomes mandatory to ensure productive and coordinated teamwork [20].

Alongside the opportunities, there are also challenges to be faced in efficiently and effectively integrating MH-MR teams in manufacturing:

- Unlike simpler human-robot collaborations, MH-MR teams require sophisticated coordination of tasks between multiple agents, thus adding an additional layer of complexity. Therefore, coordination strategies need to address emergent team dynamics, where workflow adjustments are required as human and robot agents interact in real time [12].
- In MH-MR teams, human operators must simultaneously manage interactions with multiple robots and coordinate with other human teammates. Unlike single human-robot collaboration, MH-MR environments require a higher level of shared situational awareness, necessitating advanced decision support systems that reduce cognitive overload while maintaining efficient collaboration among all agents [19].
- The effectiveness of MH-MR teams cannot be measured by traditional productivity metrics alone. Unlike traditional human-robot environments, MH-MR teams exhibit complex interdependencies where performance is influenced not only by the efficiency of individual agents, but also by the overall harmony of the team. Evaluating performance requires a shift towards multi-dimensional metrics that capture also inter-agent coordination, the quality of human-robot communication and role balance.

Overall, this paper contributes to an early understanding of MH-MR teamwork by outlining key challenges, considerations and potential benefits for manufacturing contexts. However, given the small sample size findings are not generalizable, but only serve as early insights into the dynamics

Materials Research Proceedings 57 (2025) 410-417 https://doi.org/10.21741/9781644903735-48

of these teams in manufacturing. To advance research and practice, future research should focus on:

- Long-term effects analysis of how learning curves, trust development and worker adaptation evolve over time in MH-MR settings involving larger samples of participants. The long-term sustainability of these teams depends on their ability to integrate effectively into existing workflows and to evolve with technological advances.
- Defining a multidimensional evaluation framework. It is necessary to establish standardized methodologies to assess MH-MR performance beyond efficiency, including factors such as cognitive workload, quality of collaboration, inter-agent synchronization and well-being at work.
- Developing of adaptive coordination models. Intelligent synchronization strategies that dynamically adjust robot behavior in response to human actions are needed. Future efforts should focus on using AI and machine learning to create more responsive and context-aware MH-MR systems that optimize both productivity and human experience.

The integration of MH-MR teams represents both a challenge and an opportunity for the future of industrial manufacturing. By proactively addressing these challenges, the manufacturing industry can exploit the benefits of MH-MR systems to drive productivity, innovation and sustainable working environment.

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