Journal of Intelligent Manufacturing
https://doi.org/10.1007/s10845-025-02580-x

Exploring the synergy of human-robot teaming, digital twins, and machine learning in Industry 5.0: a step towards sustainable manufacturing

Even Falkenberg Langås[1,2] · Muhammad Hamza Zafar[1] · Filippo Sanfilippo[1,3]

Received: 2 August 2023 / Accepted: 5 February 2025

Abstract

Sustainable manufacturing remains a central objective of Industry 5.0. By successfully implementing harmonic human-robot teams in intelligent industrial systems, the efficiency and well-being of human workers can be increased. Achieving this requires a gradual approach from caged robots to advanced, seamless collaboration between humans and robots. Initially, that means transitioning to human-robot interaction (HRI) where there is an exchange of commands between the human and the robot. Further advancements within safety considerations, including collision avoidance through advanced machine vision, enable the exchange of workspace that defines human-robot collaboration (HRC). The next stage is physical HRC (pHRC) which requires safe and controlled exchange of forces through impedance and admittance control. Finally, this paper describes human-robot teaming (HRT), which is defined by the exchange of solutions as teammates. This is enabled by combining cutting-edge technologies such as digital twin (DT), advanced vision sensors, machine learning (ML) algorithms and mixed reality (MR) human–machine interfaces for operators. A key contribution of this work is reviewing the integration of HRT with DT and ML, highlighting how these technologies enable seamless perception, prediction, and decision-making in human-centric industrial systems. By reviewing these technologies, the paper highlights current challenges, limitations and research gaps within the field of HRT and suggests potential future possibilities for HRT, such as advanced disassembly of used goods for a more sustainable manufacturing industry.

Keywords Industry 5.0 · Human-robot teaming · Digital twin · Artificial intelligence · Machine learning

Introduction

Humans have throughout the evolution sought for ways to ease their tedious and hard work. This started with developing tools before animals became a central part of our lives. They were crucial for us to grow as species due to their contribution to agriculture. Horses were used for ploughing land and for transportation. Later on, wind mills were used to utilise wind energy for heavy tasks such as grinding grain, pumping water and sawing wood. The steam engine initiated the first industrial revolution, before the electric motor and the combustion engine, enabled mass production and assembly lines, hence the transition to Industry 2.0 (Mokyr & Strotz, 1998). During the 20th century there was a rapid growth of factories around the globe with large and powerful machinery. Enabling technologies of Industry 3.0 (information technology and electronics) meant that these machines could be automated, thereby increasing efficiency (Taalbi, 2019). In the 21st century, technological concepts such as the internet of things (IoT), big data, artificial intelligence (AI), and digital twin (DT) emerged, enabling the transition to Industry 4.0 (Xu et al., 2021). However, common for all industrial revolutions until now is the separation between

✉ Even Falkenberg Langås
even.falkenberg.langas@uia.no

Muhammad Hamza Zafar
muhammad.h.zafar@uia.no

Filippo Sanfilippo
filippo.sanfilippo@uia.no

1 Department of Engineering Sciences, University of Agder, 4879 Grimstad, Norway

2 Research and Development, Twilligent, 4846 Arendal, Norway

3 Department of Software Engineering, Kaunas University of Technology, 44029 Kaunas, Lithuania

human and machines due to the power, determination and lack of cognitive awareness present in most machines today. But just like we tamed animals in early human evolution, Industry 5.0 aims at bringing humans and machines closer together by building safer robots and intelligent sensory systems.

Furthermore, Industry 5.0 places a strong emphasis on sustainable manufacturing, aiming to minimise waste, conserve resources, and reduce the environmental footprint of production. This shift towards sustainability is not just an ethical imperative but also a strategic advantage for businesses, as it can lead to cost savings, enhanced brand reputation, and increased resilience in the face of resource scarcity and climate change.

The growing global demand for consumer goods is driving an increased need for production and recycling. It is forcing manufacturers to streamline their production through innovation. The use of robotic systems is a growing trend that can automate repetitive tasks such as pick-and-place and assembly. Furthermore, these robots and machines perform these tasks more efficiently and with higher loads than humans. Recycling on the other hand, can often include complex dismantling that requires dexterity, flexibility and cognitive decision-making, which is only feasible for human operators. Due to the big gap between human and machine, most of these complex dismantling processes are done by human operators, if done at all. To streamline these processes, it is crucial that we gradually transition from caged machines to the field of human-robot interaction (HRI), to human-robot collaboration (HRC), physical HRC (pHRC), and finally to human-robot teaming (HRT) to enable safe and harmonic collaboration for the future industry.

One could argue that new technologies like machine learning (ML), flexible robotics and advanced vision sensors should be able to perform tasks a human operator can do, and that semi-automatic processes are unnecessary on the way to a highly automated, circular society. But, despite rapid advancements, technology is not yet mature enough to replace human operators for many complex tasks that require cognition, intuition, and dexterity. To achieve a carbon neutral, sustainable consumption, there is a need for solutions for recycling materials. Human-robot interaction/collaboration/teaming (HRI/C/T) may be the most feasible solution to achieve EU's goal of becoming climate neutral before 2050.

Industrial environments are often populated by several hazardous machines. During the early stages of Industry 3.0, they used to be mostly caged, reducing the usable area on the shop floor. Technology closely related to HRI/C/T, such as human detection and human motion prediction, are gradually making it possible to remove the cages while increasing safety. By enabling simulations through a realistic DT with humans and machines, one can do advanced training with simulated sensor data. The learning potential for the simulated environment could greatly enhance control algorithms of complex systems compared to real-world testing alone.

The work in this study builds on Zafar et al. (2024) written by the same authors. That paper explains how collaborative robots (cobots) enable HRC and the importance of emerging technologies such as DT and AI. While including a comprehensive review of relevant hardware and software tools for DT-based HRC, it lacks in depth discussions on human centricity as well as specific implementations of AI. This paper aims to complement the previously published paper by providing: definitions of different stages of collaboration within HRI/C/T where the term HRT is defined (Sect. 3); new insights into the human-centric nature of Industry 5.0, including DT of robots and humans and mixed reality (MR) human–machine interfaces (HMI) (Sect. 4); an in depth review of AI strategies in HRI/C/T systems, including robotic perception systems for predicting human behaviour as well as robotic decision-making algorithms (Sect. 5); elaboration of DT-based HRI/C/T for disassembly tasks (Sect. 6). Finally, discussions and conclusions are given in Sect. 7 and 8. By elaborating these sections, the paper aims at addressing the following research questions:

- RQ1: What are the key characteristics that distinguish the different levels of HRI/C/T, and how can these be incorporated into a unified framework?
  - RQ1.1: What are the operational and safety requirements at each HRI/C/T level?
  - RQ1.2: How do technology enablers (e.g., ML, DTs) support transitions between HRI, HRC, and HRT?
- RQ2: How can we implement a human-centric approach in the design and deployment of HRT systems within the context of Industry 5.0?
  - RQ2.1: How can ethical considerations, such as privacy and autonomy, be addressed within HRT frameworks?
  - RQ2.2: What role can human-centric interfaces (e.g., MR-based interfaces) play in enhancing HRI/C/T?
- RQ3: How can recent advancements in AI be leveraged to enable effective and efficient HRT in various industrial and collaborative settings?
  - RQ3.1: What AI methods are most effective for real-time decision-making in collaborative HRT tasks?
  - RQ3.2: What are the challenges in deploying robust AI models for HRT, and how can they be mitigated through simulation or DTs?

Methodology

A comprehensive search strategy was employed to identify relevant studies. Further on, primary studies published between 2020 and 2024 were identified. This relatively short timespan was chosen due to the rapid advancements in AI and robotics in recent years, requiring up-to-date literature for this review.

The search and selection process for included studies is illustrated in Fig. 1. After defining search terms, see Table 1, results were filtered by publication date (2020–2024) and limited to the document types "Article" and "Review Article". The results from the initial search are presented in Fig. 2, showing a trend graph dating back to 2000. Further on, the results were filtered based on quality ranking, specifically Q1 or Q2 in Scientific Journal Ranking (SJR). Due to a high volume of studies, automated text filtering tools were employed to refine results based on specific keywords and relevance. Citation counts were also used to prioritise high-impact studies. Furthermore, the titles and abstracts were screened and filtered based on the following inclusion criteria: (1) focus on Industry 5.0 concepts and technologies, (2) exploration of HRI/C/T in industrial settings, (3) utilisation of DT technology and (4) application of ML algorithms. For a paper to be included, it had to fulfil (1) or (2) and (3) or (4). The full texts of the remaining papers were then screened. Further on, Connected Papers was used to find other relevant studies that might have been missed in the initial search through a visual graph. Reference lists of included articles were manually searched for other potential studies. Lastly, citations to our recent relevant works are included to highlight the process that guided us towards identifying the seminal contributions toward unifying the definitions of HRI/C/T, which we present in Sect. 3. In addition to search terms, Table 1 shows the papers that were considered primary studies within the different fields.

This review is limited by the scope of the databases searched and the specific keywords used. It is possible that relevant studies published in other sources or using different terminology might have been missed. The purpose of the Connected Papers analysis and manual reference screening, see Fig. 1, was to mitigate the risk of overlooking important publications. Additionally, the quality of the included studies varied, with some lacking detailed methodological descriptions or reporting biases. However, efforts were made to mitigate these limitations through a comprehensive search strategy and a critical appraisal of the included studies.

Human-robot interaction, collaboration, and teaming

In the literature, words like "interaction" and "collaboration" are used interchangeably. For instance, (Ghadirzadeh et al., 2016) talks about the concept of physical HRI where robots and humans exchange forces in a shared workspace. However, this misaligns with the International Organization for Standardization (ISO), who defines HRI as "information and action exchanges between human and robot to perform a task by means of a user interface" in ISO 8373:2021. Furthermore, ISO defines collaboration as an "operation by purposely designed robots and person working within the same space". On the other hand, (Ramasubramanian et al., 2022) defines collaboration as "working together to achieve a common goal".

Overall, this landscape proves to be challenging to navigate. The field of HRI/C/T is constantly evolving and definitions must adapt to the current state-of-the-art, which revolves around Industry 5.0, with a focus on the human-centric approach. Better sensors, better actuators (Hua et al., 2024), and better algorithms are driving progression. Due to the rapid advancements from recent years, this paper revise existing definitions in the literature to provide an up-to-date unified framework, marking a significant contribution.

This section seeks to explain the different stages of collaboration to make it easier to compare and sort research in the following categories: HRI, HRC, pHRC, and HRT. Table 2 shows the gradual difference between these categories and Table 3 explains it in more detail. Further on, Fig. 3 visualises the content in the tables.

Human-robot interaction

HRI refers to the field of study that focuses on the design and use of robots, and how they interact with humans (Goodrich and Schultz, 2008). It involves understanding the ways in which humans perceive and respond to robots, as well as the ways in which robots can be designed to better fit into human environments and respond to human needs. The field of HRI draws on knowledge from a variety of disciplines, including computer science, psychology, sociology, and engineering. Researchers study the ways in which humans perceive and respond to different robot features, such as their appearance, behaviour, and movement. They also investigate how humans and robots can interact in ways that are safe, efficient, and comfortable. In practice, HRI can involve the development of user interfaces and control systems that allow humans to interact with robots in a natural and intuitive way (Thrun, 2004). For example, a robot may be designed to respond to human gestures or speech, or it may be equipped with sensors that allow it to perceive and respond to human emotions and intentions.

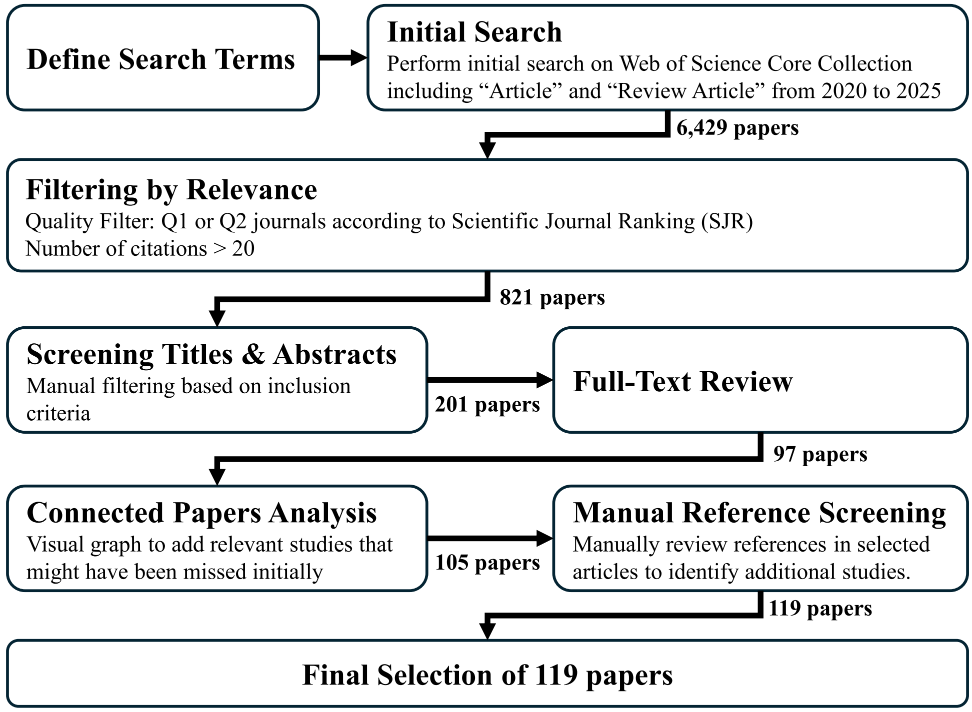

Fig. 1 Flow diagram illustrating the systematic process used to select papers, from defining search terms to final selection

Table 1 Search terms used for finding literature

	Search terms	Unfiltered hits on web of science	Primary studies
Term 1	"Industry 5.0" OR "Industry 5"	1696	Xu et al. (2021); Maddikunta et al. (2022)
Term 2	("Human-robot interaction" OR "HRI" OR "Human- robot collaboration" OR "HRC" OR "Human-robot teaming" OR "HRT") AND "Robot"	19,292	Simões et al. (2022); Natarajan et al. (2023)
Term 3	"Digital Twin" AND {Term 1}	155	Zafar et al. (2024)
Term 4	"Digital Twin" AND {Term 2}	180	Ramasubramanian et al. (2022)
Term 12	"Artificial intelligence" OR "Machine learning" OR "Deep Learning" AND {Term 1}	464	Akundi et al. (2022)
Term 13	"Artificial intelligence" OR "Machine learning" OR "Deep Learning" AND {Term 2}	1856	Mukherjee et al. (2022); Semeraro et al. (2023)

Table 2 The differences between human-robot interaction (HRI), human-robot collaboration (HRC), physical human-robot collaboration (pHRC), and human-robot teaming (HRT)

	Exchange commands	Share workspace	Exchange forces	Exchange solutions
Human-robot interaction (HRI)	X	–	–	–
Human-robot collaboration (HRC)	X	X	–	–
Physical human-robot collaboration (pHRC)	X	X	X	–
Human-robot teaming (HRT)	X	X	X	X

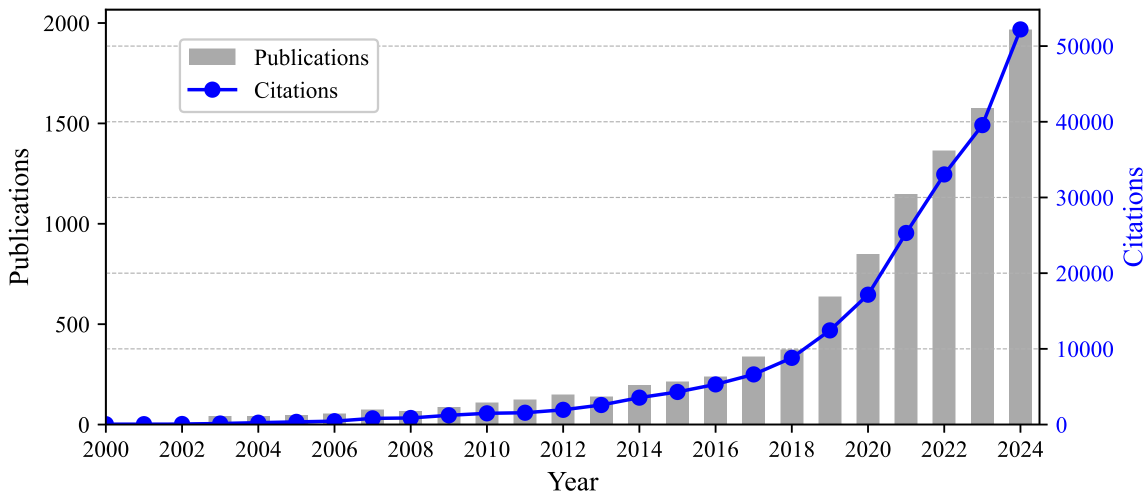

Fig. 2 Total number of publications and citations per year found in Web of Science Core Collection from all the defined search terms including document types "Article" and "Review Article". This data was extracted in December 2024. The numbers for 2024 are therefore expected to increase further

Table 3 Description and different case studies for human-robot interaction (HRI), human-robot collaboration (HRC), physical human-robot collaboration (pHRC), and human-robot teaming (HRT)

Type	Description	Case study	Case study description
HRI	Relies on exchanging commands. This can include traditional manual control of the robot, or more sophisticated commands like gestures or voice commands	Zafar et al. (2024)	Demonstrates intuitive control of a quadruped robot in search and rescue (SAR) operations using hand gestures. A bidirectional long short-term memory (BiLSTM) network interprets dynamic gestures, enabling real-time commands for locomotion and tasks
HRC	Also includes sharing workspace, which means that safety considerations are critical	Choi et al. (2022)	Implements a MR system for HRC, focusing on real-time safety through minimum safe distance monitoring. Using deep learning and DTs, the system tracks the human operator's movements and environment via red-green-blue-depth (RGB-D) sensors, providing safety guidance and task assistance through MR glasses to enhance HRC effectiveness
pHRC	In addition to sharing the workspace, pHRC includes the exchange of forces. In other words, it includes physical contact between the human and the robot	Cacace et al. (2023)	Demonstrates pHRC where a human guides a cobot to perform shared tasks. The robot interprets and adapts to human interventions in real time, adjusting tasks, motions, and compliance based on human intentions
HRT	HRT is defined by the exchange of solutions as well. This means that both the human and the robot can suggest solutions and contribute physically, as equal teammates	Lacking	

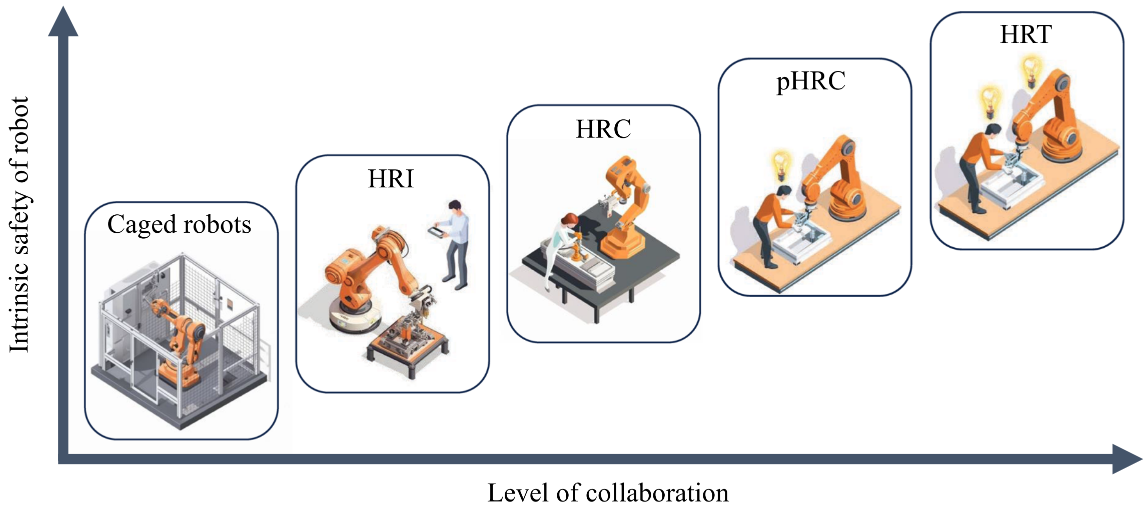

Fig. 3 Human-robot integration stages: Starting with caged robots, where humans and robots are isolated, progressing through human-robot interaction (HRI) with command exchange, human-robot collaboration (HRC) with shared workspaces, physical human-robot collaboration (pHRC) with force exchange, and culminating in human-robot teaming (HRT), where solutions are collaboratively exchanged. As the level of collaboration increases, so do the intrinsic safety requirements (Hua et al., 2023)

In this paper, HRI is only defined by the exchange of commands between the human and robot. However, the workspace of the robot is separated from the human, which implies that the robot does not need to be intrinsically safe. Workers can interact with this robot in numerous ways. Most industrial robots come with a controller, typically with a touch panel and a joystick, as visualised in Fig. 3 in the HRI box. Such a controller can be used to manually control the joints of the robot or the end-effector.

Other ways of interacting with the robot is through wearable sensors. By equipping the human with inertial measurement units (IMU), one can detect different movements of made by the human, and use that as control inputs for the robot. Another method is to use surface electromyography (sEMG) sensors. sEMG sensors can detect electrical signals triggered by the activation of muscles. For example, different hand gestures can provide separable sEMG signals that could trigger different commands for the robot (Zafar et al., 2023).

Sometimes it can be inconvenient to use wearable sensors, as they require the worker to put on equipment that might be uncomfortable or not within the health, safety and environment (HSE) regulations of the company. In that case, external sensors might be the better option. Vision sensors such as traditional 2D cameras or state-of-the-art 3D sensors (i.e. 3D cameras or light detection and ranging (LiDAR) sensors) can be used to detect gestures made by the human. Further on, voice commands can be detected through the use of microphones. However, this might be disturbed by loud noises that are often present on factory floors in the manufacturing and process industry.

Contactless human-robot collaboration

HRC refers to the concept of humans and robots working together towards a common goal in a shared environment (Ajoudani et al., 2018). This type of interaction is different from HRI, which is more focused on how humans and robots interact with one another, whereas HRC focuses on their joint performance and cooperation (Galin & Meshcheryakov, 2020) in a shared workspace. One important aspect of HRC is ensuring that the robots are designed in a way that they can understand and respond to human cues and intentions. This requires the use of sensors and algorithms that can perceive human actions and emotions, as well as interfaces that allow humans to control the robots and receive feedback from them. Compared with HRI, HRC has a much higher safety demand due to the shared workspace. This requires an intrinsically safe robot to avoid dangerous contact between the robot and the human. Obstacle avoidance techniques are therefore implemented to tackle this challenge. This is enabled through the use of advanced vision sensors and path planning algorithms, which is further explained in Sect. 5.1.1.

Physical human-robot collaboration

pHRC differs from contactless HRC in that the human and robot exchange forces through physical contact. This implies that the robot needs to be safe, meaning that forces and torques need to be monitored and controlled. For example, by using a low-cost sensing approach, functions for torque sensing at the joint level, sensitive collision detection and joint compliant control need to be achieved (Sanfilippo et al., 2014, 2015). Even more intrinsically safe are soft/elastic robots (Hua et al., 2019; Sanfilippo et al., 2020; Tuan et al., 2022). Research on soft robotics is rapidly evolving to try and solve difficult tasks that require caution and precision, such as handling biological materials or fragile objects or collaborating with humans. Tuan et al. presented a soft robotic arm in Tuan et al. (2021) with elastic joints and rigid links. This makes the robot intrinsically safe, depending on the end effector. Simultaneously, it gains the strength benefits of the rigid links. However, the elastic joints limits the payload capacity, which is a challenge within soft robotics. Similarly to HRC, pHRC requires an intrinsically safe robot, but one should also consider the physical, cognitive, and emotional aspects of collaboration, and design safety mechanisms to prevent accidents and injuries in real-time.

pHRC introduces some challenges due to the variations in torque requirements caused by the unpredictable force contributions from the human. Traditional industrial robots are normally controlled by a position controller where a very high stiffness is applied to all joints to maximise the precision. For pHRC, these stiff joints are dangerous when the robot is moving as the robot will use all it's power to follow the desired path. But for pHRC, the robot needs to be intrinsically safe. It should give way when there is contact, just like a human colleague would. To achieve this, a special control technique is applied: impedance control. Impedance control is an approach to dynamic control relating force and position. It is based on the definition of mechanical impedance:

$$\frac{F(s)}{\dot{X}(s)} = Z_m(s), \tag{1}$$

where Z_m is the mechanical impedance, F is the applied force and $\dot{X}$ is the velocity (Zeng & Hemami, 1997). With this control strategy, the end-effector can be controlled to resemble a spring damper system. Further on, the spring stiffness and the damper coefficient can be tuned to fit a specific application. The drawback of impedance control is the reduced lifting capacity as the stiffness is reduced.

Admittance control is another technique that show promise in the context of pHRC. Mechanical admittance, A_m is defined as

$$A_m(s) = \frac{\dot{X}(s)}{F(s)}, \tag{2}$$

where A_m is equal to the inverse of mechanical impedance defined in Eq. (1) (Zeng & Hemami, 1997). While impedance control can be used to react to the environments forces, admittance control can be used to manipulate the environment. For instance, in healthcare, admittance control can be used to guide blind patients through the hospital with a constant force.

Human-robot teaming

HRT is the concept of collaborating with a robot as a teammate rather than the traditional use, which is robot as a "tool" (Mingyue Ma et al., 2018). This implies that humans and robots work together towards a shared goal with both parties able to make decisions to achieve this goal. AI enables this stage of collaboration. By utilising a combination of multiple ML algorithms, the robot can achieve situational awareness making it capable of planning cognitively, thereby enhancing the efficiency and reducing the mental load on the human worker. One of the most compelling challenges when implementing ML algorithms in HRT, which was pointed out in Mukherjee et al. (2022), is the lack of relevant datasets for training algorithms. The difficulty lies mainly within simulating dynamic environments with humans involved due to the unpredictable nature of humans. HRT also raises ethical and philosophical issues, such as how much freedom the robot should have in executing these spontaneous plans without the approval of a human. This should be carefully considered for each application. Enabling ML techniques for HRT will be explained in Sect. 5. Other enabling factors are represented by the increasing ubiquity of sensors, which are placed in the working environment, on board robots and on humans using wearable technology (wearables) (Sanfilippo & Pettersen, 2015).

HRT systems are complex systems that rely on advanced sensors, actuators, and algorithms, together with the coordination of human and robotic capabilities (Gao et al., 2020). Figure 4 highlights this complexity by illustrating the integration of numerous devices in the physical environment alongside the software and algorithms enabled by the digital twin. The following are some of the key complexities that need to be addressed in the design and implementation of HRT systems:

- Safety: ensuring the safety of the human operator is a critical consideration in HRT systems. This requires careful design of the physical components of the robot, as well as the development of algorithms that can detect and respond to potential hazards (Arents et al., 2021).
- Human factors: understanding and considering human capabilities, limitations, and preferences is crucial in HRT systems. This includes factors such as cognitive load, sensory and motor abilities, and emotional states (Hopko et al., 2022).
- Interaction design: designing the interaction between humans and robots is a complex task that requires understanding the ways in which humans perceive and respond to robotic systems, as well as the ways in which robots can be designed to better fit into human environments and respond to human needs (Vasic & Billard, 2013).

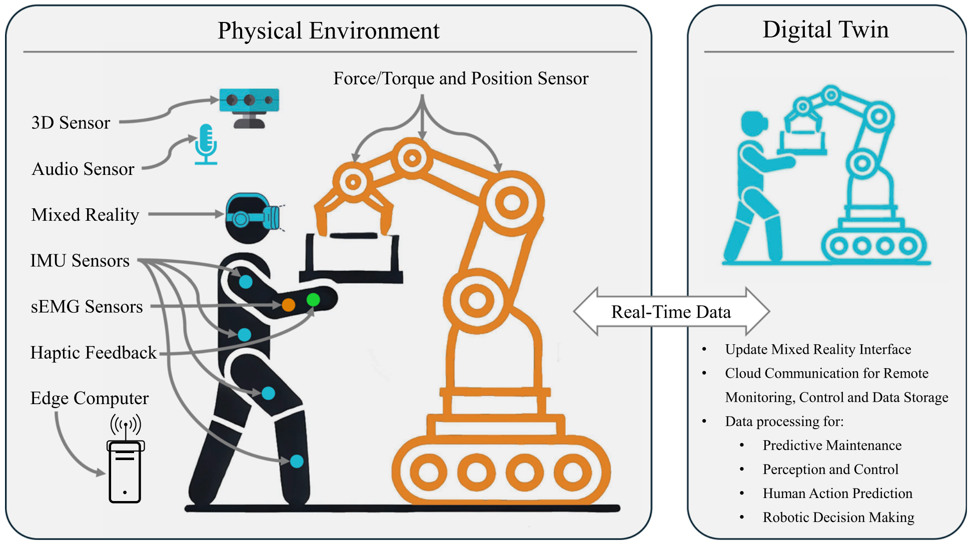

Fig. 4 Human-robot teaming (HRT) relies on a complex system of actuators, algorithms, and sensors (e.g. 3D sensors, audio sensors, inertial measurement units (IMU), and surface electromyography (sEMG) sensors). The physical environment (left) includes all the hardware and is where the physical tasks are performed. Real-time data acquisition enables the digital twin (right) to perceive the environment, predict human actions, assist robot decision-making, and provide feedback to the human via a mixed reality interface with goggles and haptic devices. The edge computer enables algorithms to run in real-time close to the data source

- Task allocation: determining the appropriate division of tasks and responsibilities between humans and robots is a complex problem, as it depends on the specific requirements of the task, the capabilities of the robots, and the limitations of the human operator (Malik & Bilberg, 2019).
- Adaptivity: HRT systems need to be able to adapt to changing conditions and respond to new information. This requires the development of algorithms that can modify the behaviour of the robots in real-time, based on the state of the environment and the human operator.

The research related to HRT is fragmented, and although there exists research on exchanging forces (Cacace et al., 2023) and exchanging solutions (You et al., 2023), there is a lack of complete implementations of HRT systems adhering to its definition from Table 2. However, the convergence of AI advancements in large language models (LLMs) (e.g., ChatGPT-4 for sequence planning (You et al., 2023)) and robot learning strategies (Mukherjee et al., 2022) points towards accelerated progress in HRT systems.

Human centricity in Industry 5.0

Industry 4.0 refers to the integration of advanced digital technologies into industrial processes to create a highly interconnected and automated system (Lasi et al., 2014). It involves the utilisation of technologies such as IoT, AI, big data analytics, and robotics to improve efficiency, productivity, and flexibility in manufacturing. Industry 4.0 enables machines, products, and systems to communicate and cooperate with each other, leading to the emergence of smart factories and the optimisation of the entire value chain.

The transition from Industry 4.0 to Industry 5.0 represents a paradigm shift in the manufacturing landscape. While Industry 4.0 focuses on technology-driven advancements, Industry 5.0 emphasises the integration of humans and machines to work collaboratively. Industry 5.0 recognises the importance of human creativity, intuition, and social intelligence in the manufacturing process. It envisions a future where humans and robots work side by side, leveraging their respective strengths to create value (Xu et al., 2021). This transition signifies a move towards a more human-centric approach, where technology acts as an enabler rather than a replacement for human involvement (Demir et al., 2019).

In Industry 5.0, workers are empowered to actively participate in decision-making processes, leveraging their unique cognitive abilities to drive innovation and find solutions to complex challenges. This shift towards value-driven manufacturing not only aims to enhance productivity and efficiency but also to create a more sustainable, inclusive, and socially responsible industrial ecosystem (Aheleroff et al., 2022).

Digital twin of robots and humans

A DT is a virtual representation of physical objects, processes, or systems that mimic their real-world counterparts in a digital environment (Malik & Bilberg, 2018). DT plays a crucial role in enabling advanced manufacturing and production processes. By creating a digital replica of a physical asset, such as a machine, product, or entire production line, manufacturers can gain real-time insights into its performance, behaviour, and maintenance needs.

From Industry 4.0, we learned that a DT can serve as a powerful tool for various applications, such as predictive maintenance (Zonta et al., 2020), remote monitoring and control (Laaki et al., 2019) and simulation of complex systems (Boschert & Rosen, 2016). By leveraging these benefits of DTs, manufacturers can enhance efficiency, reduce costs, and improve overall productivity.

In the context of HRI/C/T, a DT can be used to address some of the complexities that arise in the design and implementation of these systems. The benefits of DT-based HRI/C/T include:

1. Safety: a DT can provide real-time understanding of robots and their environment, thereby improving decision-making and robotic collision avoidance, which is critical to ensure safety for human operators. Furthermore, a DT can predict safety incidents, simulate scenarios, and reduce the risk of harm (Choi et al., 2022).
2. Predictive maintenance: by analysing sensor data, a DT can detect patterns that indicate potential equipment failures, allowing for proactive maintenance scheduling. This minimises downtime, maximises equipment lifespan, and optimises overall performance (Aivaliotis et al., 2019; Ramasubramanian et al., 2022).
3. Remote monitoring and control: a DT provides a virtual representation of the physical environment and robots, enabling remote access for monitoring and control. This reduces the need for on-site visits, improves manufacturing efficiency, and allows for agile responses to changing needs (Pairet et al., 2019).
4. Virtual commissioning: DTs facilitate the simulation of new equipment before physical implementation, reducing downtime and streamlining the process. This aids in better purchasing decisions and lowers prototyping costs during equipment design.
5. Planning and operations: by gathering and analysing process-wide data, a DT can help identify bottlenecks and opportunities for optimisation. Simulations enable virtual testing of improvements and enhanced planning that considers the capabilities of both equipment and human workers.

Ethical and philosophical implications

Industry 5.0 nurtures simulating and monitoring human behaviour within DTs. Engineers can model and simulate the interaction between humans and robots in a virtual environment, allowing them to optimise efficiency and safety before deploying it to the real factory. However, the inclusion of people in DTs requires ethical and philosophical considerations, such as issues related to privacy, data security, and decision-making authority. The careful use of personal data has emerged as an essential step toward promoting workers' dignity, freedom, and mental health. Philosophically, we also have to consider the aspect of human autonomy: Who will make decisions in a human–machine relationship? And how will such a collaboration feel for a human operator? There is a lack of frameworks addressing these problems, which can improve the psychological and societal impact of Industry 5.0 (Hua et al., 2023; Zafar et al., 2023; Langas et al., 2023).

Human–machine interface

Humans and robots working together in harmony is impossible without a proper means of communication. Industrial robots and machines lack the emotional, spontaneous and cognitive ways of communication that humans have. The design of intuitive user interfaces can therefore be considered a critical component in seamless HRI/C/T.

So how can such an interface be built? Historically, user interfaces for human–machine interactions started with analogue instruments like gauges. Huge control rooms were built to gather information on numerous instruments. With electronic sensors, programmable logic controllers (PLC), and monitors, we could start building digital HMIs. However, only trained technicians and engineers can really understand these HMIs that are widely used in the industry today. In contrast, wearable technology, powered by DTs are enabling intuitive ways of visualising operations.

Mixed reality in human-robot interaction, collaboration, and teaming

The adoption of wearables enables the development of MR systems. With the advent of Industry 5.0, MR serves as a bridge between the physical and digital realms, allowing workers to interact with virtual elements in real-world settings (Rokhsaritalemi et al., 2020). By overlaying computer-generated graphics onto the physical environment, MR enhances the user's perception and understanding of the surrounding world, enabling more efficient and effective work processes (Alojaiman, 2023; Sanfilippo et al., 2022).

This immersive technology is enabled by 3D-based DTs. Sanfilippo et al. showed in Sanfilippo et al. (2023) an example of how a 3D-model-based DT with troubleshooting guidelines and real-time data can help operators maintain plants without extensive training and expertise.

A case study presented in Langås et al. (2024) demonstrates how virtual reality (VR) and cloud communication enable remote HRI, enhancing inclusivity by allowing individuals with disabilities to contribute to a robotic production line from any remote location.

An example including an augmented reality (AR) device is presented by Li et al. (2022). They showcase an AR-assisted interface for HRI using the Microsoft Hololens AR headset. It enables the operator to do real-time motion control, planned motion control, and robot monitoring in an AR workspace. However, any physical collaboration with the robot does not take place.

Some wearables can also give haptic feedback (Sanfilippo et al., 2013; Moosavi et al., 2022), which is the technology of creating an experience of touch, temperature, vibrations and motions. Pedersen et. al. shows how haptic fingertip devices can be used to give a virtual experience of playing instruments in Pedersen et al. (2022). This is done with the WeArt TouchDiver, which can provide force, temperature and vibrotactile feedback.

Overall, wearables show great promise in enhancing the user experience, improving efficiency and communication while increasing safety for HRI/C/T applications. In addition, it can reduce the cognitive load on the human operator leading to increased satisfaction and greater trust between humans and robots. Below is a summarised list of what a MR-based interface for HRI/C/T could include:

1. Visualisation of the computer vision data: detected obstacles or objects and whether or not it sees you. This would contribute to building trust.
2. Robot status and capabilities: the robot's current state, such as its current task or mode of operation, and any alerts or warnings. An example of an alert or a warning could be when it exceeds its torque limit and when it needs help from the human operator.
3. Robot's planned operations: visualise the path planning of the robot to help the operator anticipate and avoid potential safety hazards that might arise during the operation.
4. Data visualisation: data from the robot or the environment in a visual format, such as graphs or charts, which would help the human understand and analyse the data. These could be key performance indicators on the system performance. Getting feedback on productivity could bring motivation to the user, just like in a video game.
5. Haptic feedback for remote control: through the use of haptic devices, the human operator can remotely control a robotic manipulator by intuitively moving their hand and directing how the robot interacts with objects. This interaction provides the operator with the sensation of physically manipulating objects themselves.

Such an interface can provide a platform for humans to give commands, provide feedback and monitor the robot. In turn, the robot can respond appropriately to these inputs and adjust its behaviour accordingly. This two-way communication can help to improve the overall efficiency of the collaboration and can also reduce errors and misunderstandings.

Although MR offers great potential, it has some limitations. Today's wearable devices are bulky, heavy, and require significant processing power. Further on, current MR devices can cause motion sickness and discomfort when used for longer durations (Kim et al., 2018). Improving comfort and reducing weight while increasing computational power are ongoing priorities. Addressing these limitations will be crucial for wearables' widespread adoption in industrial settings.

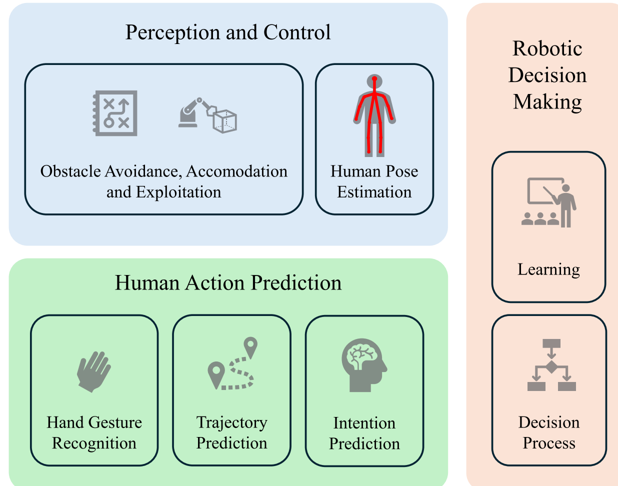

Fig. 5 Artificial intelligence (AI) for human-robot teaming (HRT): AI algorithms are used for perception and control (blue), human action prediction (green), and robotic decision-making (red).) (Color figure online).

Artificial intelligence in human-robot teaming

The emergence of AI in robotics has altered the decision-making processes in HRI/C/T systems (Semeraro et al., 2023). It eliminates the need for rigid instructions traditionally used in robotics. Instead, AI-powered robots can analyse data, weigh options, and even offer their own solutions and approaches in teamwork scenarios. The ability to participate in solving problems and making decisions marks a significant step towards HRT, where robots possess the autonomy and intelligence to become valuable teammates (Mukherjee et al., 2022). This section will present successful implementations of AI nurturing HRT as well as current limitations and challenges. Figure 5 highlights the topic of this section, including perception and control, human action prediction and robotic decision-making.

Perception and control

Perception is a crucial part of enabling autonomous robotic systems. For computational systems, perception can be obtained through various sensors. Within the field of intelligent robotics, 3D sensors are becoming the preferred choice for most applications due to the rapid development of computer vision algorithms as the cost of computational power is reduced. Conventional 2D cameras are used frequently for object detection and automatic incident detection (Shehata et al., 2008). However, 2D cameras will in many applications fall behind because of the lack of depth information. Depth information can be estimated in 2D if the size of the perceived objects is known (Shahbazi et al., 2011). This is not always the case, and for collision avoidance applications with unknown obstacles, the raw depth information from the sensors can be crucial (Kaldestad et al., 2014). This is where the advantage of 3D sensors, such as LiDAR sensors and red-green-blue-depth (RGB-D) cameras, plays an important part.

Obstacle avoidance, accommodation and exploitation

Perception is the key to obstacle avoidance in dynamic environments. Mapping the entire work area of a robotic manipulator might be non-trivial and computationally expensive. Industrial robots on racks is a fitting example, where it can be demanding to sense all obstacles. A method of combining multiple 3D sensors with embedded filtering was proposed in Aalerud et al. (2018). They managed to map an area of $10 \times 15 \times 5\,\mathrm{m}$. This approach allows for modularity where edge computing enables the scalability of the system. Further on, one can use a DT to do path planning by feeding the 3D sensor data into a mapping framework such as the OctoMap (Hornung et al., 2013). This framework utilises octrees (Meagher, 1982), which means that the entire point cloud is divided into eight octants repeatedly until a given minimum resolution is reached. The algorithm will not divide volumes without any present data, resulting in a computationally efficient multi-resolution map of the environment.

The OctoMap can be used as input for motion planning libraries such as the Open Motion Planning Library (OMPL) (Sucan et al., 2012), Stochastic Trajectory Optimisation for Motion Planning (STOMP) (Kalakrishnan et al., 2011), Covariant Hamiltonian Optimisation for Motion Planning (CHOMP) (Ratliff et al., 2009), etc. However, for moving obstacles, these planning algorithms lack the computational efficiency desired for real-time replanning when using informationally rich 3D-maps like the OctoMap due to the obstacle-map's complexity. Thereby, the structuring of point cloud data and the motion planning can be potential bottlenecks when implementing such systems in an industrial setting. Bokneberg and Langås (2021) shows how the combination of vision sensors, OctoMap and path planning algorithms can be used to do autonomous pick-and-place with an industrial robot while avoiding obstacles.

For pHRC and HRT, it is desired to do obstacle accommodation (Shan & Koren, 1995). This means having controlled collisions, which can be used to establish safe physical contact or give haptic feedback. For example, in shared assembly tasks, a robot could lightly touch the human operator to signal a specific movement or guide them to a specific task. The perception and motion planning used in obstacle avoidance should be combined with an admittance control system (explained in Sect. 3.3) to achieve effective pHRC/HRT with safe physical contact (Keemink et al., 2018).

Obstacle accommodation enables obstacle exploitation, which means taking advantage of the environmental constraints of obstacles in the workspace. For example, when grasping strawberries from a shelf, a robot arm could first reach the shelf, touch the shelf with the end effector to take advantage of the environmental constraint, slide over the shelf and grasp the strawberries. Regarding other fields, e.g., snake robotics, obstacles can be exploited to achieve more efficient locomotion (Sanfilippo et al., 2016, 2017). Obstacle exploitation is something humans do every day, e.g. by grabbing railings when walking in stairs. Applying the concept to robotics would increase the versatility and efficiency of robotic applications within pHRC/HRT.

Human pose estimation

There are certain elements in the workspace that should not be treated as an obstacle. For example, objects you want to manipulate should be mapped in the scene with a precise pose. For objects with a variable pose, one can use 3D sensors to detect objects in point clouds and estimate a precise pose of the object. The same goes for humans in the scene. Traditionally, industrial robots and humans have not been a good match with terms of interactions in the work space. Many industrial robots have the strength and speed to seriously damage human workers, which is why they are caged in accordance with ISO 10218-1:2011 (ISO, 2011).

Precise human detection and 3D pose estimation has potential to remove the cages, reducing the required usable space for inserting a robot. Cobots, from vendors such as Universal Robot are approved as safe without cages. However, they lack the information on humans in the workspace. This implies that if you put a hazardous end-effector on a cobot, the human would not be able to safely collaborate without introducing perception sensors. By estimating the pose of the links and joints of the human body, one can include this information in motion path planning for collaboration or collision avoidance purposes.

With the setup from Aalerud et al. (2018), Aalerud and Hovland managed to perform human detection in Aalerud and Hovland (2020) with a relatively large detection area, using multiple RGB-D cameras to capture point cloud data from multiple angles. Although, their detection algorithm was limited to outputting velocity and x- and y-coordinates, it enhances safety in collaborative environments consisting of humans and robots. The detection was performed using YOLOv3 (Redmon & Farhadi, 2018), a real-time object detection system built with convolutional neural networks (CNN).

CNN is a kind of artificial neural network (ANN), that is inspired by the biological visual cortex and use convolutional layers to extract features from image data (Chua & Roska, 1993). CNNs are designed to handle image data with varying scales, rotations, and translations, making them well-suited for computer vision tasks such as object detection, segmentation, and classification (Zhang et al., 2017). CNNs can also be used to process 3D point clouds. Vasileiadis et al. showed in Vasileiadis et al. (2019) how a 3D-CNN can be used for multi person 3D pose estimation, see Fig. 6. By processing data from an RGB-D camera, they are able to extract the joints and links of a person. Although 3D sensors are getting cheaper along with computational cost, there is still a challenge to achieve highly accurate, real-time estimation of human pose in 3D using point cloud data, due to the size and complexity of point cloud data.

On the other hand, there are methods to estimate 3D human pose using 2D cameras, thereby offering a cheaper alternative with regards to the sensor and computational cost. This is demonstrated in Zheng et al. (2021), where a spatial and a temporal transformer Vaswani et al. (2017) algorithm are used to estimate the pose of links and joints of a human body in traditional 2D video. Transformers represent a significant departure from traditional recurrent neural networks (RNNs) and CNNs when it comes to language modelling, translation, and text summarisation. In addition to becoming the go-to method for natural language processing, transformer algorithms have proven themselves capable of solving various computer vision problems such as human pose estimation, gesture recognition, and visual object tracking (Zheng et al., 2023).

Human action predictions

When people interact, they make predictions about each other continuously to enable seamless interactions. Traditionally, this has not been the case with robots. Even with computer vision and detection algorithms, robots have been controlled with a reactive approach. The advent of advanced ML algorithms together with reduced computational cost enables the development and deployment of real-time prediction algorithms, paving the way for creating proactive decision-making algorithms for robotic systems.

Trajectory prediction

An initial step to understanding human behaviour in industrial settings includes predicting and tracking their trajectories on the shop floor. In this way, autonomous mobile robots can proactively navigate while taking into account the predicted path of a human operator. The same predictions can be used to slow down hazardous machines or boot collaborative systems before the human operator arrives, thereby decreasing downtime and increasing safety and efficiency.

Martinez et al. (2017) shows how deep RNNs can be used to predict the 3D pose of a human a few seconds in advance. This enables cobots to do path planning based on future poses. However, in a typical factory floor, you might also want to predict long term trajectories of human workers to proactively plan operations of multiple workstations. Langås et al. (2024) proposes a method of predicting long term trajectories using a stacked long short-term memory (LSTM) network in a typical factory floor. LSTM networks are a specific category of RNNs that contain non-linear elements in their structure, making them capable of capturing long-term dependencies Lu et al. (2020). Similarly, Petković et al. (2019) demonstrates a method to predict goal locations of human operators walking through a warehouse, but using a hidden Markov model (HMM) (Rabiner & Juang, 1986).

Hand gesture recognition

Hand gestures represent another aspect of human behaviour that is important to consider in HRI/C/T scenarios. It leverages a communication method that is deeply ingrained in human nature. With real-time hand gesture recognition, human workers can seamlessly communicate with robotic teammates through simple hand movements. This approach can reduce training requirements and improve the overall efficiency in HRI/C/T.

Hand gesture recognition can be done using similar sensors and techniques as for human pose estimation (Liu & Wang, 2018). However, capturing the pose of links and joints of fingers requires high fidelity and is prone to occlusion in the vision data. Another method, using wearable sensors was presented in Zafar et al. (2023). The proposed method uses sEMG sensors on the wrist of a human operator to predict hand gestures in real-time using a Henry Gas solubility-based stacked CNN (HGS-SCNN). Although the method requires operators to wear additional sensors, it eliminates the need to be within the enclosed field of view of a camera.

Intention prediction

Understanding the human's goals and planned actions would enable the robot to proactively adapt and assist. This could involve recognising subtle cues like gaze direction, body posture, or initial movements to anticipate the next steps in a task.

To predict intentions, it is important to first detect them. Human pose estimation or hand gesture recognition are examples of intention detection covered above. Chen et al. (2020) shows how a CNN can be used to detect wrist config-

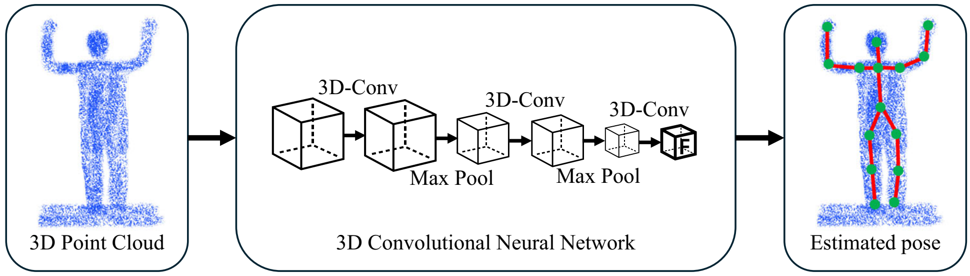

Fig. 6 3D pose estimation. The algorithm receives as input a 3D point cloud and extracts the coordinates in 3D space of the skeletal joints, for all the people present in the scene through a convolutional neural network (Vasileiadis et al., 2019)

uration, using sEMG data, to help control the robot reactively based on the human intention.

Further on, LSTM networks show promise in predicting human intentions, as demonstrated in Lu et al. (2020) and Yan et al. (2019). By using an LSTM network, Ya et al. presents in Yan et al. (2019) a method of using human skeleton information of human motion to predict which assembly part a human picks up. In this way, a robot predicts what tool the human operator needs for that specific part, and provides the tool accordingly. This is a great example of HRC with efficient collaboration between a human and a robot in a shared workspace.

Unsupervised action recognition

Algorithms to recognise human actions can be trained using supervised learning techniques, thus using labelled datasets. However, the amount of possible actions a human can take are endless, making it difficult to obtain labelled datasets for all possible actions. Fortunately, there are methods to handle unlabelled data. Unsupervised learning is a type of ML in which an algorithm is trained on a dataset without explicit guidance or labels (Barlow, 1989). Unlike supervised learning, the algorithms learn to identify patterns or structure in unlabelled data on their own. Clustering and dimensionality reduction are two popular techniques used in unsupervised learning.

Clustering algorithms group together similar data points into clusters based on their distance from one another in some feature space. The most common clustering algorithm is K-means (Likas et al., 2003), which partitions data points into K clusters based on minimising the sum of squared distances between the points and the cluster centroids. Dimensionality reduction algorithms are used to transform high-dimensional data into lower-dimensional space while preserving the most important information. Principal component analysis (PCA) (Maćkiewicz & Ratajczak, 1993) is a popular technique for dimensionality reduction that identifies the principal components in the data that account for the most variance.

Another popular algorithm within the field of unsupervised learning is the Gaussian mixture model (GMM), which is a probabilistic model that represents a collection of Gaussian distributions, where each distribution represents a cluster in the data (Reynolds, 2009). It is a type of clustering algorithm that seeks to identify underlying patterns in data by partitioning the data into groups or clusters based on their statistical properties. The GMM assumes that the data is generated from a mixture of several Gaussian distributions, each with its own mean and covariance matrix.

Huang et al. (2018) presents a task-parameterised GMM (TP-GMM), which is used to train a robot from human demonstrations. TP-GMM learns how external factors (task parameters) influence the parameters of multiple Gaussian distributions, making it particularly useful for modelling systems where behaviour changes depending on specific conditions or goals. Thus, their method is especially useful in the context of HRC/T where humans and robots share workspace, as the robot can learn from the human operator during task execution.

HMM is another ML model trained with unsupervised learning algorithms, which is particularly useful in time-dependent scenarios. In HMM, random variables are assumed to depend on their previous timestamp values, taking into account the time dependence. These variables are observed only through indirect observations, connected to the related timestamp node. Rozo et al. (2016) used HMMs to perform a pouring task while the human held a cup, while Vogt et al. (2016) utilised HMMs to handle collaborative assembly between humans and robots. The structure of HMMs allows for the consideration of time dependence during the learning phase, making it crucial for HRI/C/T scenarios.

To summarise, unsupervised learning models are trained to learn from a set of unlabelled data and can be used for various applications such as object detection, speech recognition and gesture recognition. This approach is especially beneficial in HRI/C/T scenarios, where it is often impractical to anticipate and label all possible interactions and environmental conditions in advance.

Robotic decision-making

Traditionally, autonomous robotic systems have worked in fixed sequences doing repetitive tasks in controlled environments. This is not the case for HRC/T where humans share workspace with robots. The combination of intelligent perception and control with predictions of human action, such as trajectories, hand gestures and intentions, enables the development of advanced decision-making algorithms. Furthermore, the unpredictable nature of organic beings, together with the complexity of the shared tasks at hand, requires robots to perform real-time adaptation and learning.

Reinforcement learning (RL) is emerging as a powerful method to control robots in dynamically changing environments. RL is a subfield of ML that deals with the problem of decision-making in an interactive environment (Dayan & Niv, 2008). In RL, an agent learns to take actions that maximise a cumulative reward signal, which is often defined by a scalar value that represents the quality of the agent's behaviour over time. At its most basic, the agent makes an action based on a current state of the perceived environment and receives a reward based on the results of that action. The agent's objective is to learn a policy that maximises the expected cumulative reward when it maps states to actions.

The mathematical framework behind many RL algorithms is based on the Markov decision process (MDP). MDP provides a framework for modelling decision-making in environments where the outcome is partly random and partly decided by an agent. This type of model is relevant to HRI/C/T applications, where the robot represents the agent and the collaborative scenario the environment. The observability might vary, meaning the amount of information the agent has of the environment. MDPs can be fully (Ghadirzadeh et al., 2016), partially (Ghadirzadeh et al., 2020) or mixed observable (Roveda et al., 2019) depending on what sensors are used. The MDP model has given rise to many RL algorithms whose goal is to maximise the value function, which represents the cumulative reward over time.

There are several RL algorithms that have been developed over the years to solve problems in robotics. Some of the most popular RL algorithms include:

- Q-learning: Q-learning is a model-free RL algorithm that learns the optimal action-value function using the Bellman equation. It is an off-policy algorithm that is guaranteed to converge to the optimal policy under certain conditions (Jang et al., 2019).
- State-action-reward-state-action (SARSA): SARSA is a model-free RL algorithm that learns the optimal policy by estimating the action-value function using the on-policy temporal-difference(0) (TD(0)) algorithm. It is an on-policy algorithm that is guaranteed to converge to a locally optimal policy (Jiang et al., 2019).
- Deep Q-Networks (DQN): DQN is a deep RL system that uses deep neural networks and Q-learning to learn a policy from unprocessed sensory data. To stabilise learning, it makes use of target networks and experience replay (Wang et al., 2018).
- Policy gradient methods: a family of RL algorithms known as "policy gradient methods" compute predicted cumulative reward gradients with respect to the policy parameters in order to directly optimise the policy. They are widely employed in high-dimensional continuous action spaces as model-free algorithms (Wu et al., 2022).
- Actor-critic methods: actor-Critic Methods are a class of RL algorithms that combine the benefits of value-based and policy-based methods. They learn both a policy and a value function by using separate function approximators for the actor and the critic (Grondman et al., 2012).

Different works have achieved good results in RL through various methods. Model-free algorithms are commonly used since they don't require a pre-designed model of environment transition. Q-learning is the most popular algorithm of this type, updating the Q-value function with a percentage of the current reward and the highest value based on the action and future states (Wu et al., 2020). Although most works stick to the traditional Q-learning formulation, some have tried variations of it, such as using eligibility traces and fuzzy logic. For instance, Lu et al. (2020) used Q-learning with such techniques for their object handling task.

Apart from Q-learning, there are other model-free RL algorithms, including inverse RL (IRL). IRL aims to solve the opposite problem of Q-learning, where the training phase doesn't rely on a pre-defined reward function. Instead, it uses a history of past actions and observations to come up with a reward function that motivates those actions. This approach is useful in HRI/C/T problems, where the complexity of the problem makes it difficult to start training with a reward function (Wang et al., 2018).

While model-free algorithms are more commonly used, there are some works that employ model-based RL algorithms. For example, Roveda et al. (2020) utilised a model-based RL algorithm by building a neural network model of the human-robot dynamics. Another study used a path integral stochastic optimal control (PI2) algorithm (Chebotar et al., 2017), which explores noisy variations of the robotic manipulator trajectories to search for an optimal policy. The task parameters are updated on the basis of the cumulative value of a cost function, which can be seen as the opposite of a reward function.

Overall, RL shows promise in robotics but faces challenges in dynamic HRC and HRT scenarios, particularly regarding the lack of training data that reflects the variability of human operators. Advances in generative AI have the potential to address this by automating training environment generation with diverse 3D scenarios and reward functions (Katara et al., 2024). However, these methods often omit the complexity of human behaviours, highlighting a critical research challenge. Bridging this gap could significantly enhance RL's adaptability and accelerate the development of HRC and HRT systems.

Integration with digital twins

Digital models provides a great platform to fully utilise the potential of learning strategies, such as RL. Having a realistic, 3D virtual environment enables simulations of different scenarios. A robot can learn safely in the virtual space, and the performance can be evaluated by specialists before deploying algorithms to real-world applications. Thousands, if not millions of simulations can be done to optimise the robots policy.

The same digital model can be used to create a connected DT of the environment. Further on, the integration of DTs in the decision-making process enables simulating the outcome of a decision before it is taken. In this way, potential risks and benefits of the decision can be identified. Furthermore, this can be used to alter the decision-making process in real-time.

Finally, the decisions made by the robot can be communicated to the human operator through a HMIs that is connected to the DT. Overall, the integration with DTs offers significant enhancements for HRI/C/T systems with regards to robotic decision-making.

Digital twin-based human-robot teaming for disassembly

Complex or hazardous dismantling tasks may be challenging or risky for either humans or robots to perform individually (Lee et al., 2020). Humans possess domain knowledge and decision-making abilities that can contribute to identifying valuable components or materials for reuse or recycling. Combined with robotic precision and efficiency, the disassembly process can maximise the recovery of valuable resources and minimise waste (Lee et al., 2022; Liu et al., 2019).

Applications of DT-based HRT in disassembly

In the context of HRT in disassembly, there are various scenarios where the combination of human and robot capabilities can be effectively utilised. Here are a few examples:

- Battery pack disassembly: with the growing demand for electric vehicles and energy storage systems, battery pack disassembly plays a vital role in recycling and repurposing battery cells. Humans possess knowledge in handling different battery chemistries, identifying safety protocols, and recognising potential hazards. Robots, equipped with precision tools, perception capabilities (Qu et al., 2023), and safety features, can assist in the physical disassembly process, separating battery modules and disconnecting electrical connections. The collaboration enhances worker safety and enables the recovery of reusable battery cells for secondary applications (Zhang et al., 2023). Potential safety hazards like thermal runaway or chemical leaks can be detected by sensors and processed in a DT to alert operators and emergency services if accidents occur. Table 4 shows more implementations of HRI/C/T for battery disassembly.
- Electronics waste recycling: in the automation industry, the recycling and disposal of electronic components are crucial. HRI/C/T can be employed in disassembling electronic devices, such as circuit boards or control panels. Humans can provide expertise in identifying valuable components and hazardous materials, while robots can perform tasks such as component removal, cutting wires, or dismantling circuitry. This collaboration ensures efficient and precise disassembly, allowing for optimal resource recovery and environmentally responsible recycling practices (Chen et al., 2022). DT technology enable virtual disassembly planning by utilising 3D information from computer aided design (CAD) models or 3D scanning. More examples of HRI/C/T-based electronics waste recovery is shown in Table 5.
- Automated material recovery from end-of-life machinery: in the automation industry, there is a need to recover valuable materials from end-of-life machinery or industrial equipment. Humans can analyse the composition of the machinery, identify recyclable materials, and determine the optimal disassembly sequence. Robots can perform tasks such as removing fasteners, cutting metal components, or handling heavy machinery parts. The collaboration between humans and robots streamlines the disassembly process, maximising material recovery and minimising waste in an efficient and cost-effective manner (Duddek et al., 2023). A DT can simulate the wear and tear of robotic tools used in disassembly. This allows for predictive maintenance, scheduling tool replacements or repairs before they cause downtime in the recycling process.

Benefits of DT-based HRT for disassembly

DT-based HRT offers significant benefits for disassembly tasks. It provides a range of advantages that enhance efficiency, safety, and effectiveness. Here are some detailed benefits:

- Enhanced planning and simulation: DTs enable detailed planning and simulation of disassembly operations before they are executed in the physical environment. By creating a virtual representation of the disassembly task, engineers and operators can assess the feasibility, sequence, and potential challenges of the operation. This allows for the identification of potential risks and the optimisation of the disassembly process, including the selection of

Table 4 Literature of human-robot interaction/collaboration/teaming (HRI/C/T)-based battery disassembly

References	Summary	Outcome
Zhang et al. (2023)	This paper presents a knowledge-driven flexible human-robot hybrid disassembly line for waste electric vehicle batteries (EVBs). The disassembly line splits EVB disassembling tasks into primitive-level subtasks and generates optimal disassembling sequences based on knowledge. Key technologies include high-accuracy screw disassembly using visual and force perception, and a disassembly planning system based on NeuroSymbolic, effectively solving complex disassembly scenarios	The implementation of high-accuracy screw disassembly and the disassembly planning system based on NeuroSymbolic demonstrates the system's ability to effectively solve complex disassembly tasks
Engelen et al. (2023)	The paper emphasises the economic and environmental advantages of demanufacturing over complete product shredding in the transition to a circular economy. Automated disassembly is crucial for cost-effectiveness and safety, particularly for products like battery-containing ones. An intuitive interface using a low-cost SpaceMouse®sensor is developed to guide a Staubli robot, resulting in faster teaching with minimal decrease in position accuracy compared to traditional methods	The developed intuitive teaching method using a low-cost sensor significantly reduces the time by 57% required for teaching robotic motions in automated demanufacturing processes
Yin et al. (2022)	This paper focuses on addressing the uncertain disassembly challenges in recycling electric vehicle (EV) batteries. It proposes a novel human-robot collaborative flexible remanufacturing system to handle the disassembly and remanufacturing process. The system incorporates kinematics analysis, trajectory planning using the rapidly exploring random tree (RRT) algorithm, and a depth vision-based system with the YOLOv7 algorithm to improve recognition and motion accuracy	By incorporating kinematics analysis, trajectory planning, and a depth vision-based system, the system improves recognition and motion accuracy, enabling sustainable and efficient disassembly and remanufacturing processes

appropriate tools, robotic actions, and human interventions. As a result, the collaboration between humans and robots can be carefully planned and executed, minimising errors and improving overall efficiency.

- Real-time monitoring and feedback: during the actual disassembly operation, DTs provide real-time monitoring and feedback, facilitating effective HRT. By integrating sensors and data acquisition systems, the DT can capture information about the physical environment, robot movements, and human actions. This data can be analysed to provide insights, alerts, and feedback to both humans and robots. For example, if a robot is exerting excessive force or a human is approaching a hazardous area, the DT can issue warnings or adapt the task execution in real-time. This enhances safety, prevents accidents, and improves the overall quality of the disassembly process.
- Remote collaboration and expert guidance: DTs enable remote collaboration and expert guidance during disassembly tasks. Through the DT interface, experts located remotely can access real-time information about the disassembly operation and provide guidance to human operators and robots. This is particularly valuable in situations where specialised knowledge or skills are required. Remote collaboration reduces the need for experts to be physically present on-site, leading to cost savings, increased flexibility, and the ability to leverage expertise from anywhere in the world. DTs also facilitate knowledge transfer and skill development by capturing and documenting successful disassembly procedures for future reference.
- Training and skill development: DTs can be used as training tools to develop the skills and proficiency of human operators and robot programmers. By simulating realistic disassembly scenarios, trainees can practise and refine their techniques in a safe and controlled environment. DTs provide a platform for learning, allowing trainees to understand the interactions between humans and robots, explore different disassembly strategies, and gain experience in handling complex objects or structures.

Table 5 Literature of human-robot interaction/collaboration/teaming (HRI/C/T)-based electronic waste recycling

References	Summary	Outcome
Lee et al. (2022)	The paper introduces a comprehensive disassembly sequence planning (DSP) algorithm for HRC that considers limited resources and human worker safety. The algorithm plans and distributes disassembly tasks among the human operator, robot, and HRC to minimise total disassembly time while adhering to resource and safety constraints. The study includes numerical and experimental studies on disassembling a used hard disk drive (HDD) to validate the effectiveness of the proposed algorithm in real-world scenarios	The proposed disassembly sequence planning algorithm successfully minimises total disassembly time while considering limited resources and human worker safety in the HRC setting
Alvarez-de-los-Mozos and Renteria (2017)	The paper addresses the challenges faced by manufacturing companies in reducing the environmental impact of their operations, specifically in classifying and dismantling e-waste. It proposes a solution that combines human operators and robots to optimise the recycling process of electronic equipment, considering technical and economic criteria. The research takes into account the latest developments in cobots to achieve efficient and cost-effective e-waste recycling	Combining human operators and robots to optimise the recycling process of electronic equipment, considering technical and economic criteria
Chen et al. (2022)	This study focuses on the use of cobots in e-waste disassembly processes to reduce labour costs and improve working efficiency. Through a human subject experiment, it was found that using a cobot significantly reduced the human workload and improved ergonomics, as indicated by decreased National Aeronautics and Space Administration Task Load Index (NASA-TLX) scores and improved body posture. However, the disassembly task took longer to complete with the cobot, highlighting a trade-off between efficiency and deployment of cobots in e-waste disassembly. These findings contribute to advancing knowledge on HRC in e-waste disassembly tasks	The disassembly task took longer to complete with the cobot, highlighting a trade-off between efficiency and cobot deployment in e-waste disassembly. These outcomes contribute to understanding HRC in e-waste disassembly and inform the design of better human-robot collaborative systems for this context

This reduces the learning curve, improves performance, and ensures that operators and programmers are well-prepared for real-world disassembly tasks.

- Data-driven optimisation and continuous improvement: DTs generate a wealth of data during the disassembly process, which can be used to optimise and continuously improve future operations. By analysing data from previous disassembly tasks, patterns, inefficiencies, or bottlenecks can be identified and addressed. The insights gained from the DT analytics can inform process improvements, automation enhancements, or adjustments to HRT strategies. This data-driven approach promotes continuous learning, efficiency gains, and the evolution of best practices in disassembly operations.

Discussion and limitations

The transition to Industry 5.0 is highly dependent on the synergy of HRT, DTs and ML. To enable this harmonic synergy, one must be able to combine multiple fields of engineering, such as information and communications technology (ICT), mechanical and electrical engineering as well as technical experience with the industrial process in focus. The field of mechatronics engineering combines these fields to gain a high-level system knowledge of these fields, enabling the ability to design and plan Industry 5.0 systems.

A key aspect of this transition is understanding the different levels of collaboration between humans and robots, which forms the basis of RQ1. This paper defines a set of characteristics distinguishing HRI, HRC, pHRC, and HRT based on a set of criteria: (1) exchanging solutions, (2) sharing workspace, (3) exchanging forces and (4) exchanging solutions. These criteria make up a framework for characterising work within the field, marking an important contribution of this paper.

Furthermore, for the industry to succeed in this transition, it is crucial that they move towards human-centric design methods. If the goal of Industry 5.0 is to increase the prosperity of the human species for generations to come, it is important that humans are happy in robot-inhabited environments. This aligns with RQ2, which focuses on implementing a human-centric approach in the design and deployment of HRT systems. A comprehensive philosophical and ethical discussion should be engaged to foster this development in a healthy way. Human factors research and interdisciplinary collaboration between robotics, psychology, and social sciences can provide valuable insights into understanding and enhancing the human experience in HRI/C/T systems. Furthermore, the implementation of HRI/C/T systems raises ethical dilemmas, such as issues related to privacy, data security, and decision-making authority Hua et al. (2023); Zafar et al. (2023); Langas et al. (2023). It is essential to establish ethical frameworks and guidelines to guide the development and deployment of HRI/C/T systems, promoting responsible and ethical use of Industry 5.0 technologies.

Based on the literature reviewed in this paper, there are some technical challenges that still need to be overcome. Firstly, from an industrial point of view, the payload capacity and speed of cobots is still lower compared to the traditional rigid industrial robots (Tuan et al., 2021). However the gap has been decreasing in recent years.

In addition, the environmental awareness of robots is still a challenge that researchers try to solve. As of today, the informationally rich 3D-sensor-based obstacle maps can cause a delay in the robotic system due to the complexity of motion planning that can be a potential bottleneck in an industrial setting. In addition, when introducing humans into the system, the lack of simulation data for HRI/C/T, makes it non-trivial to collect large amounts of data for training (Mukherjee et al., 2022). With the rapidly evolving development within computing power and point cloud processing, the problem might be negligible in a few years.

ML algorithms have gained significant attention in the development of HRI/C/T systems. Supervised learning techniques, such as ANNs, CNNs, and LSTM networks, have been successfully employed in various HRI/C/T applications. These algorithms enable robots to learn from labelled data, making accurate predictions and decisions based on the learned patterns. For instance, CNNs have demonstrated excellent performance in perception tasks, such as hand gesture recognition, object recognition and object tracking, enhancing the robots' ability to understand the surrounding environment. Furthermore, LSTM networks have proven effective in capturing and modelling temporal dependencies, enabling robots to comprehend and respond appropriately to dynamic human behaviours.

Unsupervised learning techniques, particularly GMMs, have shown promise in HRI/C/T systems. Unsupervised learning allows robots to analyse unlabelled data and discover hidden patterns and structures. By clustering similar data points, GMMs enable robots to differentiate between different objects, environments, or human behaviours without explicit labelling. This capability is particularly useful in scenarios where the robot needs to adapt to new or evolving environments, as it can autonomously identify and categorise sensory information, facilitating efficient and adaptive HRI/C/T.

RL is another powerful technique that has found applications in HRI/C/T systems. Algorithms like Q-learning and Deep Q-Learning enable robots to learn optimal decision-making policies through trial and error and interactions with the environment. RL allows robots to adapt and improve their behaviours based on feedback from the environment and human interaction. This capability is particularly valuable in dynamic and complex collaborative tasks, where robots need to learn how to interact and cooperate effectively with humans in real-time. By applying RL, robots can learn to make informed decisions and actions, optimising the overall performance and efficiency of HRI/C/T.

However, a limitation arises from the computational complexity of training and deploying ML algorithms on resource-constrained robots. Efficient implementation techniques and optimisation strategies, such as model compression, lightweight network architectures, and distributed computing, are necessary to overcome these constraints and enable the effective utilisation of ML in HRI/C/T systems.

Despite the advancements in Industry 5.0 and HRI/C/T systems, there is still a lack of standardised protocols and interfaces for seamless integration and interoperability between different robots, devices, and systems. Establishing common frameworks and protocols would facilitate smoother interactions and collaboration between humans and robots in diverse industrial settings.

Answers to research questions

This section addresses the research questions outlined in this paper, which focus on the distinct characteristics of HRI/C/T, the integration of a human-centric approach within Industry 5.0, and the application of recent advancements in AI to enable effective HRT.

RQ1: What are the key characteristics that distinguish the different levels of HRI/C/T, and how can these be incorporated into a unified framework?

The distinct levels in HRI/C/T each focus on the complexity of interactions, from basic command exchange in HRI to shared workspace in HRC, progressing to physical interactions in pHRC and solution-oriented exchanges in HRT (Sects. 3.1–3.4). These levels create a hierarchy that prioritises safety, operational efficiency, and adaptability across applications (Hua et al., 2023; Maddikunta et al., 2022; Goodrich and Schultz, 2008).

RQ1.1: What are the operational and safety requirements at each HRI/C/T level?

Each level necessitates unique safety protocols. HRI uses segregated spaces, minimising risk to humans. HRC requires enhanced vision and sensors to prevent collision (Zafar et al., 2023), while pHRC, involving physical contact, relies on impedance/admittance control to manage interaction forces (Zeng & Hemami, 1997; Keemink et al., 2018) (Sects. 3.1–3.4). In HRT, AI algorithms support cognitive interactions, enabling equal decision-making and situational awareness to facilitate safe teamwork (Sect. 5.3).

RQ1.2: How do technology enablers (e.g., ML, DTs) support transitions between HRI, HRC, and HRT?

ML and DTs are essential in enabling these transitions by fostering intelligent automation and predictive interaction capabilities (Ramasubramanian et al., 2022) (Sect. 5.2). ML algorithms enhance sensory capabilities and decision-making, while DTs simulate interactions and optimise task allocation across levels, offering safety and operational continuity (Pairet et al., 2019; Mukherjee et al., 2022).

RQ2: How can we implement a human-centric approach in the design and deployment of HRT systems within the context of Industry 5.0?

A human-centric approach requires designing systems that prioritise cognitive ergonomics, intuitive interactions, and well-being. By implementing MR interfaces, Industry 5.0 can bridge the gap between humans and robots, creating an environment that is both productive and supportive (Demir et al., 2019; Langas et al., 2023) (Sect. 4).

RQ2.1: How can ethical considerations, such as privacy and autonomy, be addressed within HRT frameworks?

Ethical considerations are essential in balancing autonomy and human oversight. Privacy, autonomy, and the psychological impact of robots in shared spaces are addressed through transparent AI and adaptive controls, promoting trust and inclusivity (Hua et al., 2023; Zafar et al., 2023) (Sect. 4.1.1). These measures are integral to human-centric designs in Industry 5.0 applications.

RQ2.2: What role can human-centric interfaces (e.g., MR-based interfaces) play in enhancing HRI/C/T?

MR-based interfaces facilitate seamless communication between humans and robots by overlaying information, providing real-time data, and offering operational guidance (Langås et al., 2024). This reduces cognitive load and fosters trust, allowing humans to intuitively interact and control robots, which is critical in HRT for effective collaboration (Li et al., 2022) (Sect. 4.2.1).

RQ3: How can recent advancements in AI be leveraged to enable effective and efficient HRT in various industrial and collaborative settings?

AI advances drive HRT by enabling real-time adaptation, human intention prediction, and proactive decision-making. RL and predictive modelling algorithms facilitate seamless transitions between HRI, HRC, and HRT, improving safety and interaction quality (Mukherjee et al., 2022; Dayan & Niv, 2008) (Sect. 5).

RQ3.1: What AI methods are most effective for real-time decision-making in collaborative HRT tasks?

Real-time decision-making in HRT is enhanced by using RL and supervised learning algorithms, which are adept at predicting human actions and adapting robot responses (Dayan & Niv, 2008; Ghadirzadeh et al., 2016; Lu et al., 2020). These methods enable proactive path planning, obstacle avoidance, and real-time interaction adjustments, critical for dynamic environments (Sect. 5).

RQ3.2: What are the challenges in deploying robust AI models for HRT, and how can they be mitigated through simulation or DTs?

A significant challenge lies in developing adaptable AI for unstructured, dynamic environments, partly due to the lack of relevant datasets that includes the human aspect (Mukherjee et al., 2022). Recent works on generative AI show promise in accelerating dataset generation by automating 3D asset generation and reward functions for RL (Katara et al., 2024). However, for HRC and HRT to flourish, it is critical to advance this research by also generating models with variable human behaviour. This represents an exciting and important research direction for future work. Further on, with the existence of relevant models and datasets, DTs can enable safe, iterative training of AI algorithms, enabling simulation-based optimisation before deployment (Pairet et al., 2019) (Sect. 5.3.1). DT integration reduces deployment risks by identifying potential hazards and utilising ML algorithms in real time (Aalerud et al., 2018; Ramasubramanian et al., 2022).

Conclusion

This review paper highlights the state-of-the-art within the fields of digital twins (DTs), human-robot interaction/collaboration/teaming (HRI/C/T), and artificial intelligence (AI) in the context of Industry 5.0. The integration of these technologies is crucial to safely and efficiently achieve the goals set for Industry 5.0, providing new solutions for complex problems.

Firstly, definitions for human-robot interaction (HRI), human-robot collaboration (HRC), physical HRC (pHRC), and human-robot teaming (HRT) are given together with their current challenges and state-of-the-art. A simple framework is presented making it easy to categorise work within HRI/C/T based on 4 different criteria: exchange commands, share workspace, exchange forces and exchange solutions. The paper reveals a critical research gap in the implementation of complete HRT systems. This gap presents a compelling opportunity for future research to develop and test holistic approaches that fully integrate HRT across various industrial applications. Although current real-world HRT is extremely limited, this paper outlines key challenges that, if addressed, could pave the way for fluent collaboration between humans and robots.

Furthermore, the paper's emphasis on the human-centric approach of Industry 5.0 provides a comprehensive overview of the benefits, challenges, and limitations of developing DTs of both humans and robots. The discussion on state-of-the-art human–machine interfaces (HMI) and mixed reality (MR) technologies underscores the importance of creating intuitive and effective interfaces between humans and machines. In addition, this paper uniquely reviews the integration of HRT with DT and ML, focusing on human-centric design to enable seamless perception, prediction, and decision-making in collaborative industrial systems.

The paper dives into techniques like artificial neural networks (ANN) and reinforcement learning (RL), that forms essential stepping stones for the successful implementation of HRT systems. Finally, the paper sheds light on the practical applications of integrating DTs in HRI/C/T, demonstrating the potential for improved efficiency and safety in disassembly tasks.

In conclusion, this comprehensive review illuminates the current landscape and future trajectory of integrating DTs, HRI/C/T, and AI in the context of Industry 5.0. Their potential in disassembly tasks, marks crucial steps towards sustainable manufacturing. The paper not only serves as a valuable resource for researchers and practitioners but also provides a road map for future research and development to achieve the goals set for sustainability and human-centric design in Industry 5.0.

Future work

The findings of this study suggest several potential directions for future research. Future work could include a comprehensive literature survey mapping the amount of research within these different levels of collaboration, from interaction to collaboration and teaming.

The limited implementation of comprehensive HRT systems highlights a promising research direction. Focusing on integrating decision-making algorithms, automated solutions, intelligent motion planning, and human behaviour prediction could address this gap and advance the development of fully functional HRT implementations.

Acknowledgements This research is supported by Twilligent, Norway, and by the Artificial Intelligence, Biomechatronics, and Collaborative Robotics research group at the Top Research Center Mechatronics (TRCM), University of Agder (UiA), Norway.

Author Contributions Conceptualisation, M.H.Z., F.S.; methodology, E.F.L., M.H.Z., F.S.; software, E.F.L., M.H.Z.; validation, E.F.L., M.H.Z. and F.S.; formal analysis, E.F.L., M.H.Z.; investigation, E.F.L., M.H.Z. and F.S.; resources, E.F.L., M.H.Z. and F.S.; data curation, E.F.L., M.H.Z. and F.S.; writing—original draft preparation, M.H.Z.; writing—review and editing, E.F.L., M.H.Z. and F.S.; visualisation, E.F.L.; supervision, F.S.; project administration, F.S.; funding acquisition, E.F.L., M.H.Z. and F.S. All authors have read and agreed to the published version of the manuscript.

Funding Open access funding provided by University of Agder This research is funded by Twilligent and the Research Council of Norway through the Industrial PhD Scheme, project number 337501. It is supported by the Artificial Intelligence, Biomechatronics and Collaborative Robotics research group at the Top Research Center Mechatronics (TRCM), University of Agder (UiA), Norway.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare no Conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication All co-authors have been duly acknowledged, and their consent for submission has been obtained.

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