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Review

Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review

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ABSTRACT

Industry 5.0 aims at establishing an inclusive, smart and sustainable production process that encourages human creativity and expertise by leveraging enhanced automation and machine intelligence. Collaborative robotics, or "cobotics",is a major enabling technology of Industry 5.0, which aspires at improving human dexterity by elevating robots to extensions of human capabilities and, ultimately, even as team members. A pivotal element that has the potential to operate as an interface for the teaming aspiration of Industry 5.0 is the adoption of novel technologies such as virtual reality (VR), augmented reality (AR), mixed reality (MR) and haptics, together known as "augmentation". Industry 5.0 also benefit from Digital Twins (DTs), which are digital representations of a physical assets that serves as their counterpart — or twins. Another essential component of Industry 5.0 is artificial intelligence (AI), which has the potential to create a more intelligent and efficient manufacturing process. In this study, a systematic review of the state of the art is presented to explore the synergies between cobots, DTs, augmentation, and Industry 5.0 for smart manufacturing. To the best of the author's knowledge, this is the first attempt in the literature to provide a comprehensive review of the synergies between the various components of Industry 5.0. This work aims at increasing the global efforts to realize the large variety of application possibilities offered by Industry 5.0 and to provide an up-to-date reference as a stepping-stone for new research and development within this field.

1. Introduction

Robots have played an increasingly important role in industrial revolutions, from early automation in Industry 3.0 to the interconnected systems that enable collaborative human–robot teams in Industry 4.0. While Industry 4.0 introduced human–robot collaboration on production lines, Industry 5.0 aims to take this further by focusing on human-centric processes that promote resilience, sustainability, and closer symbiosis between human workers and robotic systems.

Whereas previous stages of industrial evolution focused heavily on using robots to maximize productivity and accuracy, Industry 5.0 has a dual emphasis on beneficial coexistence and shared prosperity. This involves not just enabling closer teamwork between humans and machines, but prioritizing worker safety, skills development, creative potential, and overall wellbeing alongside efficiency gains. Core goals of Industry 5.0 include seamless information sharing between humans and robots, adaptive production systems that can rapidly adjust to changes or faults, and leveraging AI and automation to augment human capabilities rather than replace jobs.

To achieve this, advanced sensor systems, internet-of-things connectivity, cloud analytics, and control mechanisms that allow for more flexible, resilient, and humans-in-the-loop decision making will be critical. By coupling these technologies with a focus on environmental and social responsibility, the promise of Industry 5.0 is production ecosystems where humans and intelligent machines can symbiotically enable one another to achieve shared goals around productivity, quality, and sustainability. The practical success of this next industrial evolution depends on carefully defining the roles, capabilities, and responsibilities of all players in these futuristic human–machine production teams.

In the following decades, the development of more advanced sensors and control systems enabled robots to interact with each other in a shared workspace. This led to the development of robot–robot sharing workspace [1,2], in which multiple robots work together to perform a task, coordinating their actions to achieve a common goal. For example, robots may work together to assemble a product, or to transport materials from one location to another.

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The next phase of evolution in robotics was the development of Human–robot interaction (HRI) [3]. This was made possible by advances in sensor/control system technologies [4]. This has led to the development of complex HRI in real time. However, even tough the level of interaction gradually reached higher and higher levels, relatively low levels of collaborative tasks were possible as limited forces were shared between robots and humans.

Advances in machine learning have recently empowered HRC. In HRC, a cognitive model is often constructed, which receives inputs from the environment and from the user, elaborates and converts these into information that the robots can utilize. Machine learning is a new way to developing cognitive models and behavioral blocks that has great potential in HRC [5,6]. Even tough HRC represents a step forward towards a shared collaboration between humans and robots, it is still limited in terms of solving new/unknown tasks that require a more efficient teamwork to be solved.

In the recent times, the convergence of new technologies, such as digital twins (DT), intrinsically safe robots (i.e., soft robots), and the concept of human augmentation have the potential to unleash the full potential of human–robot teaming (HRT).

Today, HRT is perceived as increasingly valuable across various industries, including manufacturing, healthcare, logistics, and more. This requires a major shift in the way that robots are integrated into human-centric environments, and has the potential to revolutionize the way that humans and robots interact and collaborate in the future. By combining the strengths of both humans and robots, this technology holds the promise to transform the way that work is performed and to create new opportunities for innovation and growth.

1.1. Review of existing work

In recent years, the confluence of technological innovation and industrial paradigm shifts, notably within the frameworks of Industry 4.0 and Industry 5.0, has spurred considerable interest in the field of human–machine collaboration. This literature review synthesizes insights from seven abstracts, each contributing to our understanding of various facets of this dynamic intersection. The work presented [7–9] revolves around the application of digital twin frameworks to enhance the design, construction, and control of human–machine cooperative systems. [7], specifically delve into the implementation of digital twins in the context of human–robot collaborative work environments, emphasizing their role in mirroring physical systems for continuous improvement and adaptability. [8] extends this exploration by investigating how digital twins address the complexities of collaborative production systems, offering a 'front-runner' for validation and control throughout the system's life cycle. These abstracts collectively highlight the evolving landscape of digital twin technologies and their potential impact on human–robot collaboration. Moving to a broader perspective, [10] focuses on Industry 4.0 as an enabler of smart factories, emphasizing the pivotal role of digital twins in supporting the entire product lifecycle. The abstract sheds light on the challenges associated with creating digital twins for human–robot collaboration, providing a comprehensive review of different approaches and discussing their functions and importance in collaborative scenarios. This adds depth to the evolving narrative surrounding the integration of digital twins in advanced manufacturing.

[11] introduces the paradigm shift to Industry 5.0, emphasizing its core principles of human-centricity, sustainability, and resiliency. This forward-looking perspective envisions a manufacturing era where the well-being of humans is central to industrial systems. The paper proposes a tri-dimensional system architecture for implementing Industry 5.0, offering insights into its technical, reality, and application dimensions. It also outlines key enablers, potential applications, and challenges in realizing realistic Industry 5.0 scenarios, contributing to the limited body of research on this emerging paradigm. The [12] investigates the evolving dynamics of human–robot interaction in the workplace, spurred by the advent of Industry 4.0 and Industry 5.0. The scoping review scrutinizes the effect of robot design features on human operators, revealing intricate many-to-many relationships. The findings underscore the critical role of effective communication between operators and robots, impacting teamwork and overall performance. The identified research gaps in this abstract emphasize the need for more comprehensive studies addressing human–robot interaction as a system.

Table 1
Comparison of existing surveys.

Ref	Year	Industry 5.0	Digital twins	HRC/HRT	AI/ML/DL
[7]	2018	×	✓	✓	×
[13]	2020	×	✓	✓	×
[8]	2021	×	✓	✓	✓
[9]	2021	×	✓	✓	✓
[10]	2022	×	✓	✓	×
[11]	2022	✓	✓	✓	×
[12]	2023	✓	×	✓	×
Our study	2023	✓	✓	✓	✓

Table 1 provides the comparison of different surveys presented in the literature in the context of different keywords i.e. Digital Twins, Industry 5.0, HRC/HRI, AI/ML/DL.

In the existing body of literature, several discernible gaps emerge with regard to the holistic understanding and application of Industry 5.0 components. Firstly, a comprehensive synthesis elucidating the synergies between collaborative robotics (cobots), Digital Twins (DTs), augmentation technologies, and artificial intelligence (AI) within the context of Industry 5.0 for smart manufacturing is notably absent. While previous works touch on individual aspects, there is a distinct lack of an overarching review that systematically explores how these components interplay to fulfill the objectives of Industry 5.0. Secondly, the exploration of Industry 5.0 dynamics has been somewhat fragmented in the current literature. While certain abstracts delve into specific elements such as human–robot collaboration or digital twin technologies, there is a noticeable dearth of studies providing an integrated examination of how cobots, DTs, augmentation technologies, and AI collectively contribute to the realization of Industry 5.0 objectives. The need for a more cohesive understanding of the interactions and dependencies among these components remains unaddressed. Moreover, the identification of application possibilities within the Industry 5.0 framework has been limited in existing research. Prior works discuss these technologies in isolation, but there is a distinct lack of exploration into the diverse application scenarios that arise from the synergistic interaction of cobotics, DTs, augmentation, and AI. This gap hampers the establishment of a comprehensive understanding of the practical implications and potential use cases of these technologies working in tandem.

Finally, the absence of a current and comprehensive reference for future research within the domain of Industry 5.0 is notable. While individual studies contribute insights into specific aspects, a comprehensive reference that researchers and practitioners can utilize as a foundational resource for new developments within the field is lacking. This gap emphasizes the need for an up-to-date and consolidated reference that encapsulates the latest knowledge on the subject.

1.2. Contributions and paper organization

This work admirably fills critical gaps in the existing literature on Industry 5.0, presenting a pioneering contribution that systematically addresses the shortcomings identified in previous research. Firstly, it provides a comprehensive synthesis by being the first in the literature to explore and consolidate the synergies between collaborative robotics (cobots), Digital Twins (DTs), augmentation technologies, and artificial intelligence (AI) within the Industry 5.0 framework. This holistic examination offers a unified understanding of these components, rectifying the absence of a comprehensive review in the current literature. It bridges the gap in the holistic exploration of Industry 5.0 dynamics. While prior works touch on individual aspects, your paper offers a systematic review that considers the collective impact of cobots, DTs, augmentation technologies, and AI. This contribution provides a more cohesive understanding of the interactions and dependencies among these components, addressing the fragmented exploration in existing research.

Moreover, this work significantly contributes to the identification of application possibilities within the Industry 5.0 framework. By exploring the synergies between cobotics, DTs, augmentation technologies, and AI, your study goes beyond the isolated discussions of these technologies to identify specific applications and use cases. This fills a distinct gap in the literature, providing insights into the practical implications and potential scenarios arising from the collaborative interaction of these technologies. Also, this work acts as a current and comprehensive reference for future research within the domain of Industry 5.0. The absence of such a foundational resource in the existing literature is addressed by your work, providing valuable insights for both researchers and practitioners. As the first attempt to comprehensively review the synergies between various Industry 5.0 components, your paper serves as a timely and foundational resource, paving the way for further exploration and development within this dynamic field.

The rest of the review paper is organized as follows. Section 2 of the paper delves into the various types of HRC, collaborative robots, and the need for a digital twin to address the complexities of HRC. In Section 3, the concept of Industry 5.0 is introduced, and the applications and enabling technologies of this paradigm shift are discussed. The paper then moves onto Section 4, where digital twin-driven HRC systems are examined, and the fundamentals of digital twin with the HRC system are elaborated. In Section 5, the paper describes the state-of-the-art hardware requirements for HRC, while in Section 6, the use of artificial intelligence and machine learning in HRC systems is explored. Finally, Section 8 discusses the challenges of implementing HRC systems and concludes the paper.

2. Human Robot Collaboration (HRC)

2.1. Complexity in manufacturing system

A system is described as a grouping of several components working together to accomplish a single objective [14]. A system's components generate and store a considerable amount of data. Throughout the whole life cycle, the amount of this information grows, making it more challenging for the observer to forecast the system's future behavior. As a result, the complexity of a system is influenced by the amount of information and the predictability of interaction behavior. The industrial revolutions are described in Fig. 1. In this figure, three points are highlighted for each industrial revolution which includes, enabling technology, actors involved in the production process, and types of tasks that can b solved. It is quite evident that the involvement of humans with machines increases gradually, especially starting with HRI in the Industry 4.0, then evolving into HRC [15], and finally trending into HRT in the Industry 5.0:

1. The first industrial revolution, known as Industry 1.0, unfolded in the 1780s. This period marked a significant shift in manufacturing as mechanized production powered by steam and water became the norm. The behavior of the production system during this era was remarkably predictable, owing to the simplicity and transparency of its operations.
   - Enabling technologies: steam engine
   - Actors involved in the production process: single or multiple one-task machine
   - Types of tasks that can be solved: repetitive and specific tasks

   Industry 1.0 was characterized by the use of single or multiple machines, each designed for a particular, often repetitive, task. This revolution laid the foundation for modern industry by introducing the concept of mechanization and powered machinery.
2. Industry 2.0 emerged in the 1870s with the widespread use of electrical power, which fueled the advent of mass production via assembly lines. This revolution significantly boosted production rates, but it also introduced elements of chaos and increased complexity into the production systems.
   - Enabling technologies: electric power
   - Actors involved in the production process: assembly line
   - Types of tasks that can be solved: repetitive and specific tasks as mass production

   Industry 2.0 revolutionized manufacturing by optimizing efficiency through assembly line processes. However, this efficiency came at the cost of increased complexity and the need for more coordinated efforts.
3. The third industrial revolution, Industry 3.0, introduced complexity by integrating electronics and information technology into production processes. Caged robots, pre-programmed to perform specific tasks, became commonplace. The incorporation of computers facilitated better predictability of system behavior.
   - Enabling technologies: industrial robots
   - Actors involved in the production process: mostly single robots
   - Types of tasks that can be solved: pre-programmed/repetitive tasks

   Industry 3.0 ushered in an era of automation, where robots took on repetitive tasks previously done by humans. The integration of electronics and information technology made manufacturing more efficient but also more intricate.
4. Industry 4.0, the current industrial revolution, is marked by the complexity introduced by cyber–physical systems (CPS) communicating via the Internet of Things (IoT). Teams of sensorized robots perform flexible tasks, and processing vast amounts of sensor data is necessary to predict system behavior. This complexity introduces an element of surprise that can have critical implications.
   - Enabling technologies: IoT and complex control systems
   - Actors involved in the production process: teams of sensorized robots
   - Types of tasks that can be solved: flexible production

   Industry 4.0 brings about the interconnectedness of machines and systems, enabling dynamic and flexible production processes. However, the complexity and the element of surprise require advanced data processing and predictive capabilities to maintain system reliability.
5. Industry 5.0, the fifth industrial revolution, is still emerging as a human-centric model for technological progress. Sometimes called the "human-centered revolution", Industry 5.0 seeks to blend advanced technologies with human-centric design principles that focus on quality of life, sustainability, and societal well-being. The goal is to promote inclusive innovation where technology enhances humanity rather than replaces it. Humans are placed at the center of this new paradigm as active participants in technological advancement. Industry 5.0 emphasizes creating a new social contract that is fair and inclusive for all stakeholders in the production process. Key technologies like digital twins, augmentation, and soft robotics will enable safer

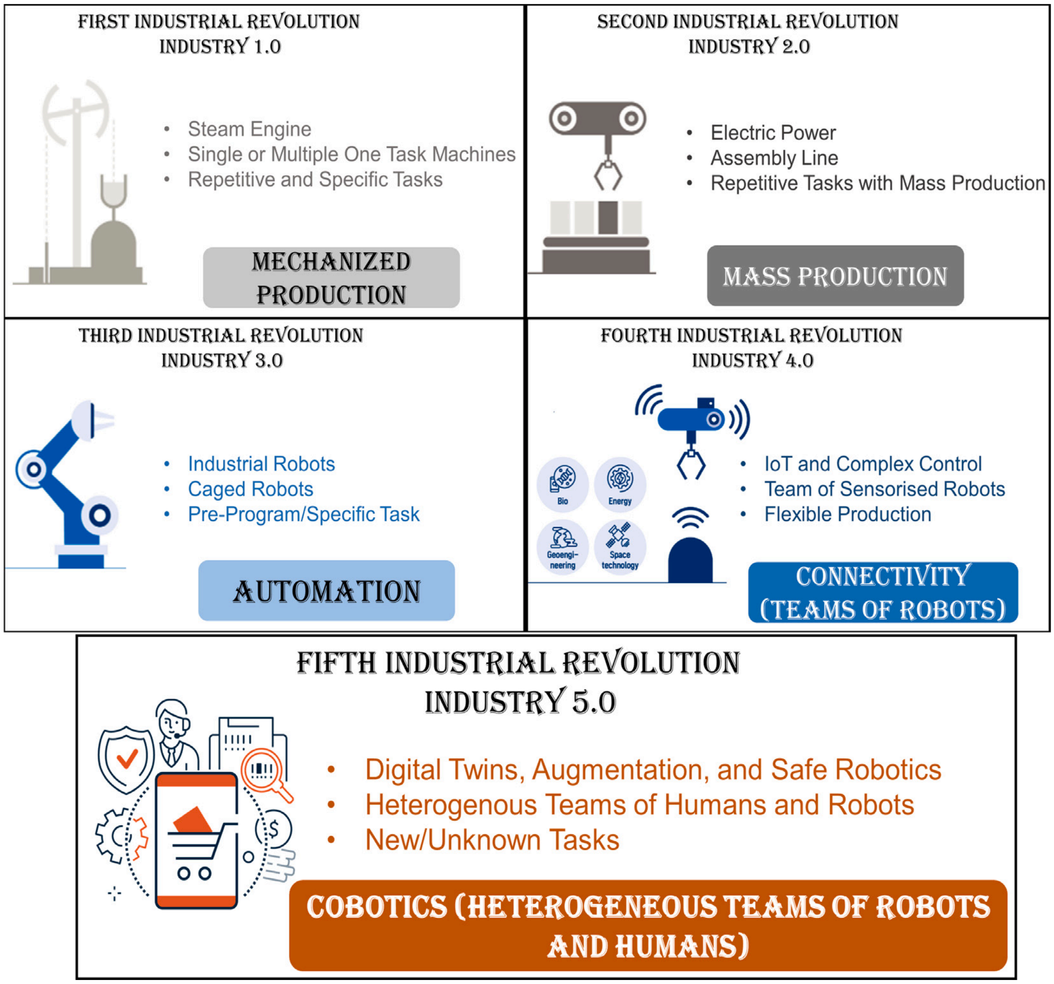

Fig. 1. Industrial revolution from Industry 1.0 to Industry 5.0.

and more collaborative human–robot interactions on production lines. Teams of humans and intelligent machines will be able to work together dynamically to perform novel or unfamiliar tasks safely and effectively. The fusion of human creativity and technological capabilities is positioned as a more resilient, ethical, and humanistic production model for the future.

- Enabling technologies: digital twins, augmentation, artificial intelligence, internet of everything (IoE) and blockchain
- Actors involved in the production process: heterogeneous teams of humans and robots
- Types of tasks that can be solved: new/unknown tasks

As factories become more connected and reliant on data-driven decision-making, the amount and variety of data generated by manufacturing processes is growing at an unprecedented rate. This data must be processed, analyzed, and acted upon in real time to ensure efficient and effective production. This requires sophisticated algorithms and software systems that can handle the complexity of processing and analyzing large amounts of data in real time.

Additionally, the use of robotics and automation in Industry 5.0 factories is also increasing the complexity of manufacturing systems. These technologies are becoming more advanced and capable of performing a wider range of tasks [16], leading to the creation of complex, interconnected systems that must be monitored and managed in real time.

2.2. Collaborative robots (Cobots)

The transition of robots from caged robots to HRT has been a gradual process, driven by advancements in technology and changing attitudes towards robotics in the workplace, as seen in Fig. 2. Here is a brief overview of the key stages of this transition:

- Caged Robots: In the early stages of industrial automation, robots were confined within protective cages or enclosures. These physical barriers were designed to prevent any direct contact or interaction between robots and human workers. The primary objective of this approach was to ensure safety in the workplace, as the robots employed during this period were limited in their capabilities and lacked the advanced safety mechanisms necessary for safe coexistence with humans [17].
- Collision Avoidance: As technological advancements continued to unfold, robots began to be equipped with a range of sensors and cameras that enabled them to detect the presence of humans in their vicinity. These sensors allowed robots to identify the positions of nearby humans and respond appropriately to prevent potential collisions or accidents. This marked a significant step forward in enhancing safety in shared workspaces, as robots could now slow down or stop their movements when a human was nearby, reducing the risk of injuries and accidents [18].
- Human–Robot Interaction (HRI): Further progress in robotics brought about breakthroughs in natural language processing and speech recognition technologies. These developments enabled robots to understand and respond to verbal commands and cues

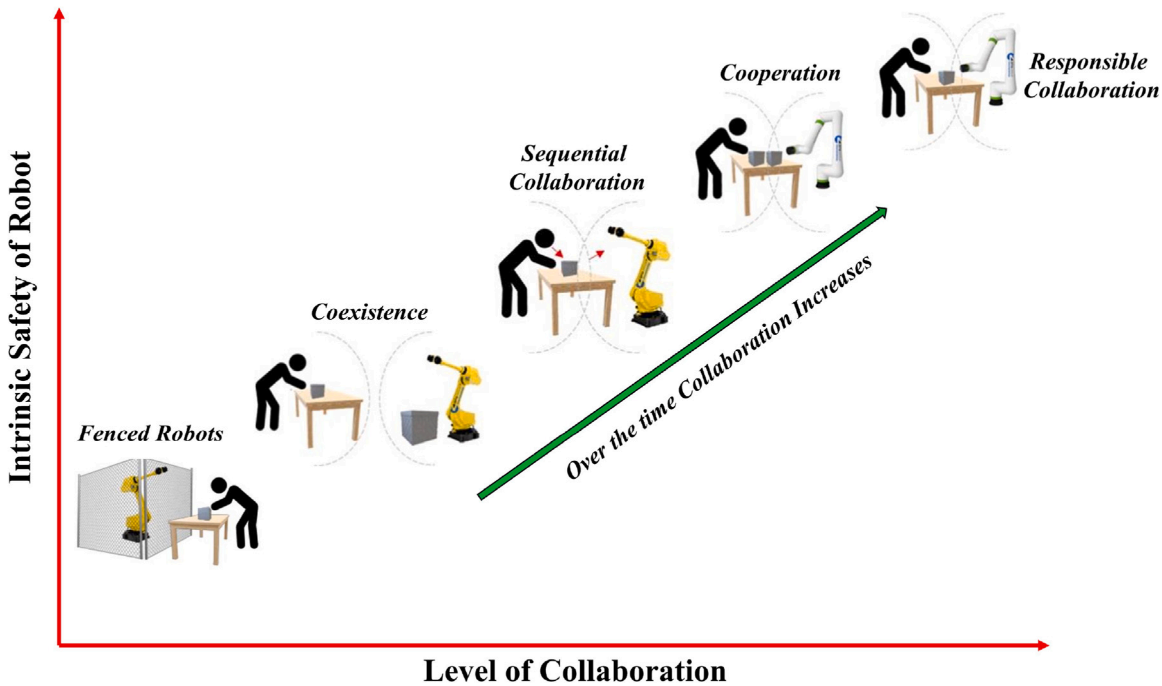

Fig. 2. Different types of shared workspace in HRC systems.

from humans. As a result, the communication gap between humans and robots began to narrow significantly. This phase ushered in a new era of more interactive and responsive robot behavior, making it easier for humans to work alongside and instruct robots effectively [19].

- Human–Robot Collaboration (HRC): Recent advancements have shifted the focus towards Human–Robot Collaboration (HRC). In this phase, robots and humans actively collaborate on tasks, often in close proximity. This collaborative approach necessitates robots' ability to interpret human intentions, cooperate effectively, and ensure safety throughout the collaborative process. HRC represents a profound shift from the earlier isolation of robot functions to a mode where humans and robots work together as complementary partners [20].
- Physical HRC (pHRC): The next stage in the evolution of robotics is Physical Human–Robot Collaboration (pHRC). At this level, robots are not only collaborating with humans but also physically interacting with them. This interaction may involve tasks such as sharing tools, passing objects, or jointly manipulating objects. Achieving successful pHRC requires the development of highly advanced sensing and control systems that ensure safe and efficient cooperation. This stage represents a deeper physical integration between humans and robots, where their actions are closely intertwined [21].
- Human–Robot Teaming (HRT): The pinnacle of robotics evolution is Human–Robot Teaming (HRT). In this advanced stage, robots are integrated into human teams as equal partners rather than mere tools. HRT demands sophisticated AI and machine learning algorithms that enable robots to adapt to human behaviors, preferences, and decision-making processes. These robots become active, adaptive team members that work alongside humans to achieve common goals. HRT marks a paradigm shift in the relationship between humans and robots, where robots are not just passive instruments but active contributors to collaborative endeavors. This level of integration and teamwork represents the cutting edge of robotics technology and opens up new horizons for a wide range of applications across various industries [22].

Cobots, commonly known as collaborative robots, are designed to work alongside human operators in shared workspaces. While they often exhibit advanced industrial features, it is important to note that the term 'cobot' encompasses a range of robotic systems with varying degrees of sophistication. Unlike traditional industrial robots, cobots are equipped with sophisticated sensors, software, and safety features that allow them to work safely and effectively alongside humans without the need for safety barriers or other protective measures [23]. A robot built for human collaboration does not necessarily need to be strictly different in design from typical industrial robots that adhere to safety standard ISO EN 10 218 [24]. Fig. 3 shows a collaborative robot sharing workspace with a human on the left and a conventional robot working separately without collaboration on the right side.

Collaborative robots and other auxiliary equipment enhancing the security of robotic workspaces are not intended to completely replace existing technology. The industry's range of robotic applications is widened by robotic assistants, who also bring a number of significant benefits [25]:

1. from a socioeconomic standpoint, the use of robots makes businesses more competitive relative to nations with extremely low labor costs;
2. repeatable positioning accuracy and continuous operation allow even small businesses to produce a product at a lower cost and focus on client requests;
3. robots can speed up some processes and adapt to unique circumstances, which can enhance output;
4. reducing the amount of unpleasant, boring, and tiresome labor relieves people of the burden that could otherwise lead to occupational sickness;
5. the ergonomics of operations and the workload on workers are related. A reduction in the number of occupational injuries may result from improving the workplace;
6. Unsafe situations typically occur when safety regulations are ignored, and procedures are oversimplified. The integration of collaborative robots and safety-focused technology goes beyond mere risk reduction; it establishes a robust framework for ensuring a secure working environment.

Fig. 3. HRC workspace sharing with human (on left) and conventional robot (on right).

Robot and laborer workspaces gradually become more integrated as their level of cooperation increases, as seen in Fig. 2 [26].

2.3. Barriers of HRC

HRC involves the interaction and cooperation between humans and robots to achieve a common goal. However, there are several barriers that hinder the seamless collaboration between humans and robots in terms of perception, actuation, and control. The main barriers are as follows:

- Perception: Perception can be a significant barrier in HRC, as robots and humans may perceive the environment differently. Humans use sensory cues such as vision, hearing, touch, and smell to understand their surroundings, while robots use sensors and cameras to perceive the environment. The difference in perception between robots and humans can lead to misinterpretation of the environment, making it challenging for humans and robots to collaborate effectively. For example, a robot may not be able to recognize subtle human gestures, facial expressions, or vocal tones, which can lead to miscommunication and misunderstandings.
  Moreover, humans can easily adapt to changes in the environment, while robots need to be programmed to recognize and respond to such changes. This can make it difficult for robots to keep up with the unpredictable nature of human behavior, which can further hinder effective collaboration. To overcome the perception barrier in HRC, robots must be equipped with advanced sensors and algorithms that enable them to perceive and interpret the environment accurately. Additionally, HRC should involve training humans on how to interact with robots, as well as training robots to recognize and respond to human behavior appropriately.
- Actuation: Actuation can also be a significant barrier in HRC, as robots and humans have different capabilities and limitations when it comes to physical actions. Robots may be designed to perform specific actions or movements, but they may not be able to perform them in the same way that humans do. For example, a robot may be able to lift heavy objects, but it may not be able to handle delicate items with the same level of care that a human can.
  Additionally, robots may have limitations when it comes to mobility, which can make it difficult for them to navigate complex environments or perform tasks that require fine motor skills. Robots may also be limited by their power source, as they may need to be recharged or have their batteries replaced frequently. On the other hand, humans may have physical limitations that can impact their ability to collaborate effectively with robots. For example, a human may not be able to lift heavy objects or perform physically demanding tasks, which can limit their ability to work alongside robots that are designed to perform such tasks.
  Soft-body robots, which are robots with flexible and deformable bodies, are being developed to overcome the actuation barrier in HRC [27]. These robots are designed to mimic the movement and flexibility of living organisms, enabling them to interact with humans more naturally and effectively. Soft-body robots are also equipped with sensors and algorithms that enable them to perceive and interpret the environment accurately, allowing them to navigate complex environments and perform tasks with greater precision [28]. Additionally, the soft and flexible nature of these robots makes them safer to work with, as they are less likely to cause harm or damage to their human collaborators. As soft-body robotics technology continues to advance, these robots have the potential to revolutionize HRC, enabling new applications in fields such as healthcare, manufacturing, and disaster response.
- Control: Control can be a significant barrier in HRC, as robots and humans have different methods of controlling their actions and movements. Robots are typically controlled through programming or remote control, which can make it difficult for them to respond quickly and adaptively to changes in the environment. On the other hand, humans have the ability to adjust their actions and movements in real-time based on their perception of the environment, enabling them to respond quickly and adaptively to changes.
  Moreover, humans may have different preferences or approaches when it comes to controlling robots, which can lead to miscommunication or misunderstanding. For example, a human may prefer to use a joystick to control a robot, while another human may prefer to use voice commands. To overcome the control barrier in HRC, robots must be designed to respond quickly and adaptively to changes in the environment. This may involve developing algorithms that enable robots to adjust their movements based on feedback from sensors or human collaborators.
  Additionally, HRC should involve providing humans with a range of control options, such as voice commands, gestures, or haptic interfaces, to enable them to control robots in a way that feels natural and intuitive. This can involve developing new technologies or interfaces that enable humans to communicate their intentions to robots more effectively, such as brain–computer interfaces or augmented reality displays. Overall, the key to overcoming the

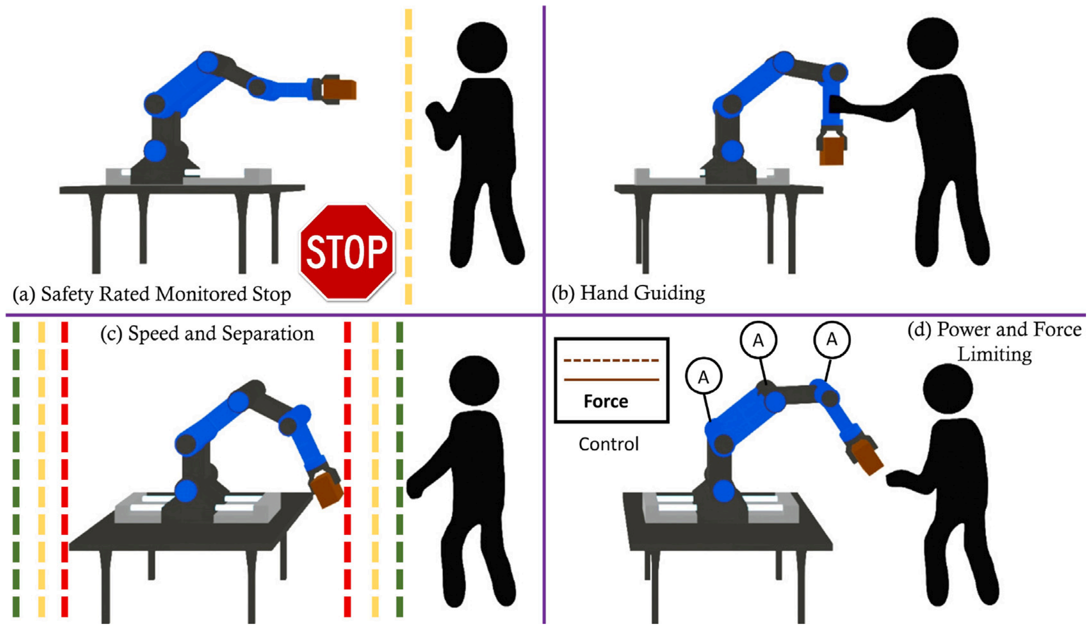

Fig. 4. Different types of HRC systems: (a) Safety Rated Monitored Stop; (b) Hand Guiding; (c) Speed and Separation; (d) Power and Force Limiting [30].

control barrier in HRC is to develop technologies and interfaces that enable robots and humans to work together seamlessly and effectively, with the ability to adapt to changes in the environment and respond to each other's actions and movements in real-time.

When the barriers are removed, it enables the utilization of machines in challenging tasks that require the presence of human operators, resulting in various advantages.

2.4. Types of HRC system

The safety requirements ISO EN 10 218 for robotics and robotic systems describe four basic types of HRC. It is required to use specialized cobots with integrated sensors for specific sorts of cooperation. With enhanced sensors and control, a typical robot can be used for other purposes. The four different types of HRC systems are shown in Fig. 4 and presented below [29]:

1. Safety-rated-Monitored-Stop-based HRI systems mainly focus on ensuring the safety of human operators. In these systems, safety components and software are used to monitor the safety of the HRI and to initiate a safe stop in the event of a safety concern.
2. Hand-guiding HRC refers to another mode of interaction in which the human operator physically guides the robot's movement through the workspace. This mode of interaction is used in various industrial and manufacturing applications to assist robots in performing complex tasks or to train robots to perform new tasks.
3. Speed and Separation-Monitoring HRC refer to the use of advanced monitoring systems to ensure safe interaction in industrial and manufacturing settings. These systems monitor the speed and separation between the human operator and the robot to prevent accidents and ensure the safety of the human operator. Speed and Separation Monitoring systems use various technologies, such as sensors and cameras, to detect the presence of a human operator in the workspace and to monitor the speed and separation between the human operator and the robot. The systems use algorithms to calculate the speed and separation between the human operator and the robot and to determine if a safety concern is present.
4. Power and Force Limiting HRC uses to limit the power and force generated by robots in order to prevent accidents and ensure the safety of human operators in industrial and manufacturing settings. Power and Force Limiting systems are designed to monitor the interaction between the human operator and the robot and to limit the power and force generated by the robot in real-time. This can be achieved through the use of sensors and other technologies that can detect the presence and position of the human operator, and through the use of algorithms that can adjust the power and force generated by the robot in response to these inputs.

2.5. Complexity in HRC system

HRC systems are complex systems that involve the integration of various technologies, such as robotics, artificial intelligence (AI), and human–computer interaction (HCI). These systems are designed to work alongside humans in shared workspaces, with the goal of increasing productivity and efficiency. However, the complexities arise from the need to ensure safety, to provide effective communication and collaboration between humans and robots, and to develop human-like capabilities in robots such as perception, reasoning, and decision-making. Ensuring safety in HRC systems is a major concern, as robots can be equipped with powerful and potentially dangerous tools or machinery. Therefore, it is necessary to develop effective safety measures to ensure that humans are not exposed to harm. The HRC workspace is shown in Fig. 5.

Another challenge of HRC is the need to provide effective communication and collaboration between humans and robots. This involves developing effective human–robot interfaces, such as natural language processing and gesture recognition, to enable seamless communication. Additionally, it is important to develop robots that are able to perceive and respond to human gestures, and to understand the context in which they are operating. This requires the development of cognitive and decision-making capabilities in robots so that they can effectively

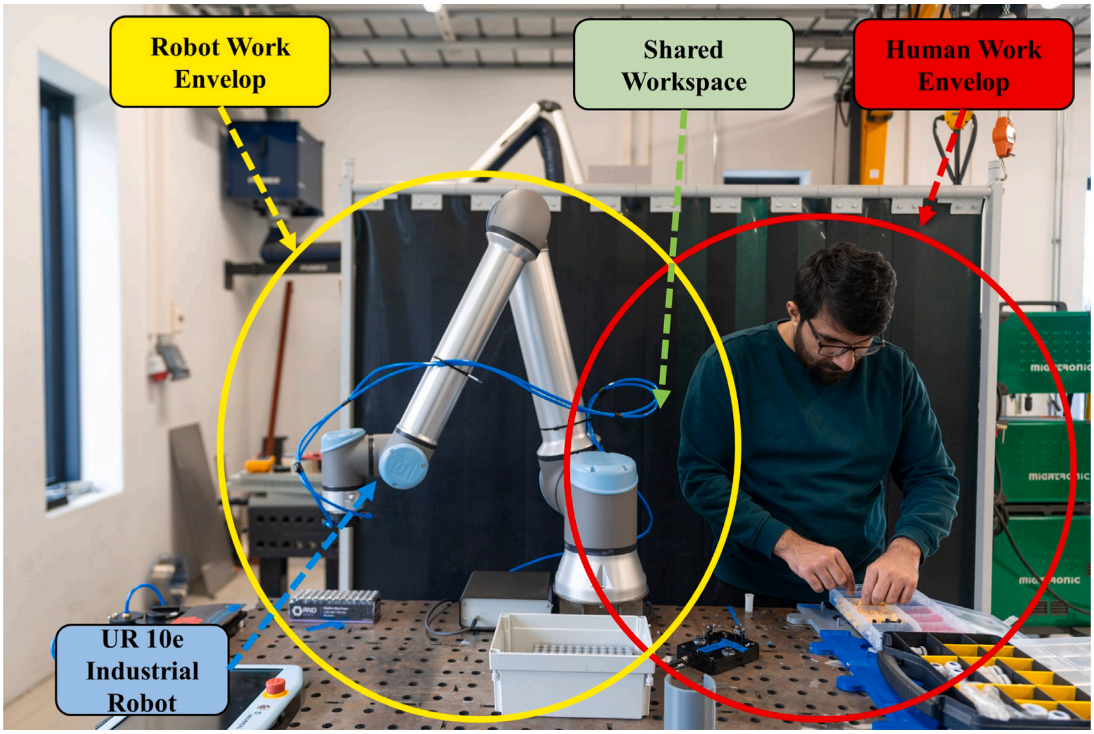

Fig. 5. Human–robot collaborative workstation.

interact with humans in real-world environments. These complexities require interdisciplinary approaches, and ongoing research and development to overcome, to achieve truly effective HRC [31].

2.6. Applications of HRC system

HRC can greatly benefit workers in industry by increasing efficiency and productivity while reducing the risk of workplace injuries. By partnering with robots, workers can delegate repetitive or dangerous tasks to the robots, allowing them to focus on higher-value tasks that require human skills and expertise [30]. For example, robots can be used for tasks such as material handling, assembly, and quality control, freeing up human workers to focus on more complex tasks such as troubleshooting, problem-solving, and decision-making.

In addition to increasing efficiency, HRC can also improve the overall work environment by reducing the risk of workplace injuries [32]. Robots can perform tasks that are too dangerous or physically demanding for human workers, such as working in hazardous environments or handling heavy loads. This not only protects human workers, but also helps to reduce workplace accidents and injuries, which can be costly in terms of both human and financial resources [33].

Moreover, HRC can lead to the development of new and innovative products and processes, as human workers and robots can share their unique strengths and capabilities to solve problems and achieve common goals. By working together, human workers and robots can accomplish tasks that would be difficult or impossible to achieve independently, leading to greater innovation and competitiveness in industry. Human Collaborative Robots can have different applications and some of them are discussed below:

HRC has a wide range of applications in the automobile industry, from assembly and manufacturing to quality control and inspection [34]. The use of HRC in this industry can increase efficiency, reduce the risk of workplace injuries, and lead to the development of new and innovative products.

One example of an HRC system currently deployed in the automobile industry is the collaborative robot, or ‘‘cobot’’. Cobots are designed to work alongside human workers in shared workspaces, performing tasks such as material handling, assembly, and quality control [35,36]. They are equipped with sensors and safety features, such as force control, to ensure that they can work safely in close proximity to human workers.

Another example of an HRC system in the automobile industry is the use of robots for painting and finishing operations. These robots are equipped with advanced sensors and control systems that allow them to work in close collaboration with human workers, applying paint and other finishes to vehicles with precise control and high accuracy [37].

HRC systems are also used in the automobile industry for assembly operations, where robots are used to perform repetitive and physically demanding tasks, such as the assembly of car parts and components. This not only increases efficiency and reduces the risk of workplace injuries, but it also allows human workers to focus on higher-value tasks, such as quality control and inspection. Overall, the use of HRC in the automobile industry has the potential to revolutionize the way that work is performed, by increasing efficiency, reducing the risk of workplace injuries, and fostering innovation and competitiveness.

HRC in assembly line is a rapidly growing field in the manufacturing industry, where robots and human workers are integrated to increase efficiency and productivity. In assembly line operations, robots can perform repetitive and physically demanding tasks, while human workers can handle tasks that require dexterity and problem-solving skills [38–40]. The integration of human workers and robots [41] in the assembly line allows for more efficient and effective use of resources, leading to higher overall productivity.

Some examples of currently deployed HRC systems in assembly line include KUKA’s HRC system, Universal Robots’ UR+ Platform, and ABB’s YuMi. KUKA’s HRC system uses advanced sensor technology to allow robots and human workers to work safely in close proximity. Universal Robots’ UR+ Platform enables the integration of third-party tools and accessories with its collaborative robots, allowing human

Table 2
Overview of the literature for the industrial applications of HRC.

Application	Ref.	Summary
Disassembly	[42]	This paper addresses sustainable manufacturing, a crucial aspect of sustainable development, by focusing on human–robot collaborative disassembly (HRCD) and its contributions to economic, environmental, and social sustainability. The work presents a detailed and systematic approach to implementing HRCD, integrating advanced technologies such as cyber–physical production systems (CPPS) and artificial intelligence (AI). The approach encompasses five key aspects: perception, cognition, decision, execution, and evolution, targeting the dynamics, uncertainties, and complexities in disassembly processes.
	[43]	This paper explores the role of robotics in the disassembly process, a critical first step in the remanufacturing, repair, and recycling of products at the end of their life cycle. The complexities associated with the variety and condition of End-of-Life (EoL) products necessitate a balance between productivity and flexibility in robotic disassembly. To address this, the paper proposes a semi-automated approach using human–robot collaboration, which can adapt to the uncertainties in frequency, quantity, and quality of EoL products.
	[44]	This paper introduces a comprehensive disassembly sequence planning (DSP) algorithm tailored for human–robot collaboration (HRC) in disassembly processes, taking into account several critical factors such as limited resources and the safety of human workers. The main objective of the algorithm is to optimize the distribution of disassembly tasks between human operators, robots, and their collaborative efforts to minimize total disassembly time while adhering to resource and safety constraints.
	[45]	This paper addresses the growing importance of recycling end-of-life power batteries, driven by both performance benefits and increased environmental awareness among consumers. It emphasizes that disassembly is a critical step in the recycling and remanufacturing process of these batteries. To enhance the efficiency of this process, the paper introduces a human–robot collaboration model designed to minimize completion time. The paper compares the performance of HPSO-QL with other well-known metaheuristic algorithms across different scenarios. The results demonstrate the effectiveness and robustness of HPSO-QL, establishing its superiority over existing algorithms in solving the HRCD-PBs problem. This advancement represents a significant step forward in optimizing the disassembly process for end-of-life power batteries, contributing to more efficient and sustainable recycling and remanufacturing practices.
Automotive	[46]	Emerging automotive assembly technologies and methods used in manufacturing facilities are discussed in this study. In response to this acknowledged impossibility for mass customization, concepts incorporating various new technologies into supporting both automated and human-based assembly procedures are given and addressed. Future assembly lines must routinely use flexibility in both system design and operation. A close loop method is discussed for this reason.
	[47]	The design of a robotic platform for sophisticated human–robot cooperation assembly is covered in this article, along with all the technical methods that have been employed to make it easier for human operators to participate and be supported. Manual guidance methods and innovative wearable gadgets that support multi-modal engagement as well as robot safety control features are examples of enabling technology. Under a service-oriented architecture, wearable gadgets like smartwatches and augmented reality glasses are employed to close the communication gap between operators and robots.
	[48]	Various layout configurations are described and assessed with an eye towards industrial application in a series of strategies for designing hybrid workstations that concentrate on secure yet effective HRC. Two diverse automotive use cases are given as examples to show the unique characteristics of lightweight and high-payload robots, as well as small and big size product assembly.
Food Industry	[49]	The focus of the paper is on the impact of integrating collaborative robots into the food catering industry, showcased through a case study on the end-of-line operations of a catering production system. It proposes a generalizable methodology to assess the technical and economic feasibility of implementing such technology. This methodology is designed to aid food industry managers in analyzing constraints that limit process automation and in evaluating the expected system performance in terms of throughput, ergonomics, and economic benefits. The paper emphasizes the potential for collaborative robots to revolutionize automation in the food industry, particularly in catering.
	[50]	This article delves into the transformation of the agri-food sector through the adoption of modern machinery, tools, and information and communication technologies (ICTs), particularly focusing on Internet of Things (IoT) capabilities. This advancement has ushered in the 'Agri-Food 4.0' era, characterized by automation, connectivity, digitalization, the use of renewable energies, and efficient resource utilization.
Smart Manufacturing	[51]	The work focuses on enhancing human–robot collaboration (HRC) in smart manufacturing by integrating sensing, cognition, and prediction into robot controllers for real-time interaction in mixed environments. The goal is to develop Proactive Adaptive Collaboration Intelligence (PACI) and switching logic for robots, enabling them to adapt their actions based on predefined plans and knowledge. This involves improving robots' decision-making for better situational awareness and smart reactions during varying human–robot interactions, while ensuring safety and efficiency. The effectiveness of this approach, including its modularity and flexibility, was demonstrated through simulations and tests with the e.DO robot in a controlled setting.
	[52]	This work delves into human–robot collaboration (HRC) in smart manufacturing, emphasizing the need for robots to use commonsense knowledge (CSK) for effective support in dynamic environments. CSK allows robots to make more intuitive decisions, aiding humans in complex tasks like paint spraying and assembly, thus enhancing safety and efficiency. The paper presents a novel approach linking HRC with CSK, specifically focusing on improving human–robot co-assembly tasks. Evaluations using online simulations and real-world experiments showed that CSK-based robot priorities improve HRC compared to simpler approaches.
	[53]	This paper addresses the need for new safety strategies in Human–Robot Collaboration (HRC) within the evolving manufacturing industry, which aims to combine human flexibility and intelligence with robotic accuracy and strength. A key issue identified is the lack of a clear safety strategy in existing HRC systems. To address this, the paper first establishes an extensive taxonomy of human–robot relations, offering a clear classification for various robotic scenarios. Following this, it develops a comprehensive action strategy tailored to different scenarios and roles of human stakeholders. A novel aspect of the approach is a dynamic HRC layout, which considers the actual speed and distance between humans and robots.

workers and robots to work together on the assembly line. ABB's YuMi is a dual-arm collaborative robot designed for use in assembly line operations, featuring built-in safety features to allow it to work safely alongside human workers. These systems and others like them demonstrate the growing trend of HRC in the assembly line and the benefits it can bring to manufacturing operations.

Table 2 reports a synthetic overview of the relevant literature for the industrial applications of HRC discussed hereafter.

2.7. Digital twin to address the complexity

To cope with the increasing complexity related to the gradual transition from Industry 4.0 to Industry 5.0, digital twin (DT) technology may offer a solution by creating a virtual representation of a physical system, such as a robot or the entire production line, in real-time [54]. DTs differ from static, three-dimensional models in that they are continuously updated with data from numerous sources [55]. The digital twin allows for simulation and testing of different scenarios, including HRI, without risking harm to the physical system or to the human collaborators [13].

One of the primary benefits of using a digital twin in HRC is the ability to test and optimize performance. The digital twin can be used to evaluate different control algorithms and interaction strategies to determine the best approach for HRC. This can help to improve the efficiency and effectiveness of the collaboration and reduce the risk of accidents or incidents. Another advantage of using digital twins in HRC is the ability to anticipate and mitigate potential safety concerns. For example, the digital twin can be used to simulate the behavior of a robot in hazardous environments and to assess the potential impact of that behavior on human collaborators. This can help to identify potential hazards and develop strategies to minimize risks. The use of digital twins also facilitates communication and coordination between human and robot collaborators. The digital twin can provide a shared visual representation of the physical system, which can help to improve the understanding of the system and its behavior. This can improve the accuracy of decision-making and reduce the likelihood of misunderstandings or miscommunications between human and robot collaborators.

Therefore, the use of digital twins in HRC offers several benefits that can address the complexities of this type of collaboration. The technology can be used to optimize performance, anticipate and mitigate safety concerns, and facilitate communication and coordination. By leveraging the capabilities of digital twins, organizations can improve the efficiency and effectiveness of HRC while reducing the risk of incidents or accidents.

3. Industry 5.0

Industry 5.0 is a term used to describe the fifth industrial revolution, which is expected to build upon the current trend of Industry 4.0. The previous industrial revolutions brought about the use of steam, electricity, computers and automation in manufacturing, and Industry 4.0 introduced digital technologies and the Internet of Things (IoT) to the production process. Industry 5.0 is anticipated to combine advanced technologies such as robotics, artificial intelligence (AI), and the IoT with human-centric design principles to create more efficient, flexible, and sustainable production systems [56]. Industry 5.0 is an integration of resilient, sustainable, and human-centric technologies, organizational concepts, and management principles for designing and managing cost-efficient, responsive, resilient, sustainable, and human-centric value-adding systems at the levels of ecosystems, supply chains, and manufacturing and logistics facilities, data-driven and dynamically and structurally adaptable to changes in the demand and supply environment to secure the provision of society with products and services in a sustainable and human-centric way through the rapid rearrangement and reallocation of its components and capabilities [57]. One of the main drivers of Industry 5.0 is the need for greater collaboration between humans and machines. As machines become more advanced and can perform more tasks, they will need to be designed to work seamlessly with human operators. In this way, machines can assist workers in tasks that require precision, strength, or speed, while humans can provide creativity, decision-making, and problem-solving skills [58]. Industry 5.0 also has the potential to greatly reduce waste and environmental impact in the manufacturing process. Smart factories can use data analytics to optimize production processes and reduce material waste, while also implementing more sustainable energy sources and reducing greenhouse gas emissions [56].

3.1. Applications in industry 5.0

The possibilities of Industry 5.0 are vast and diverse, as the integration of advanced technologies with human-centric design principles can transform the manufacturing industry in a myriad of ways. In this section, we will explore some of the key applications of Industry 5.0, including the use of smart factories [11], collaborative robots [59], healthcare [60], cloud manufacturing, sustainable manufacturing [11], predictive maintenance systems, and advanced data analytics. We will discuss how these technologies can improve efficiency, safety, and sustainability in manufacturing processes, and explore their potential to drive innovation and growth in various industries (see Fig. 6).

3.1.1. Smart healthcare

The integration of Industry 5.0 in the healthcare sector can revolutionize the way medical care is provided, making it more efficient, accessible, and personalized. With advancements in robotics, artificial intelligence (AI), and the Internet of Things (IoT), Industry 5.0 has the potential to transform healthcare in several ways, such as reducing medical errors, improving patient outcomes, and optimizing healthcare delivery [61].

One of the primary applications of Industry 5.0 in healthcare is the use of robotic assistants. Robots can assist healthcare providers in tasks that require precision, such as surgical procedures or medication delivery [62]. They can also take over routine tasks, such as monitoring vital signs or cleaning, freeing up healthcare workers to focus on more complex tasks that require human intervention. Robots can also be used to provide care in remote or underserved areas, expanding access to healthcare services.

Another application of Industry 5.0 in healthcare is the use of AI-powered diagnostics and treatment. AI can analyze vast amounts of medical data to identify patterns and predict outcomes, helping to diagnose and treat patients more accurately and efficiently [63]. For example, AI algorithms can analyze medical images such as X-rays, CT scans, and Magnetic resonance imaging (MRI), to detect diseases or abnormalities that may be missed by human observers [64]. AI-powered chatbots and virtual assistants can also provide patients with real-time advice and support, making healthcare services more accessible.

The IoT can also play a significant role in healthcare, enabling the collection of real-time patient data and facilitating remote monitoring [65]. Wearable devices and smart sensors can track vital signs, such as heart rate and blood pressure, and provide this information to healthcare providers in real-time. This can improve the accuracy of diagnoses and help detect health issues before they become serious, allowing for more proactive and personalized treatment [66].

Another critical aspect of Industry 5.0 in healthcare is the application of data analytics. With the vast amounts of data generated in the healthcare sector, advanced data analytics can be used to identify trends, patterns, and outcomes, leading to better decision-making and improved patient care. Predictive analytics can help healthcare providers anticipate and prevent medical errors or complications, while prescriptive analytics can suggest the best course of treatment for a particular patient based on their medical history and other data points.

3.1.2. Cloud manufacturing

Cloud manufacturing is a term used to describe the use of cloud computing technologies in the manufacturing process [67]. In Industry 5.0, cloud manufacturing has the potential to transform the manufacturing industry by enabling more efficient collaboration and resource-sharing among businesses and manufacturers. Cloud manufacturing can help to optimize production processes, reduce costs, and improve the quality of products.

One of the key advantages of cloud manufacturing is that it allows businesses to share resources and collaborate with one another more efficiently. This can be particularly useful for small and medium-sized businesses that may not have the resources to develop their own manufacturing capabilities [68]. By leveraging cloud manufacturing, these businesses can access a wider range of resources, including production equipment, expertise, and logistics, allowing them to compete more effectively in the market.

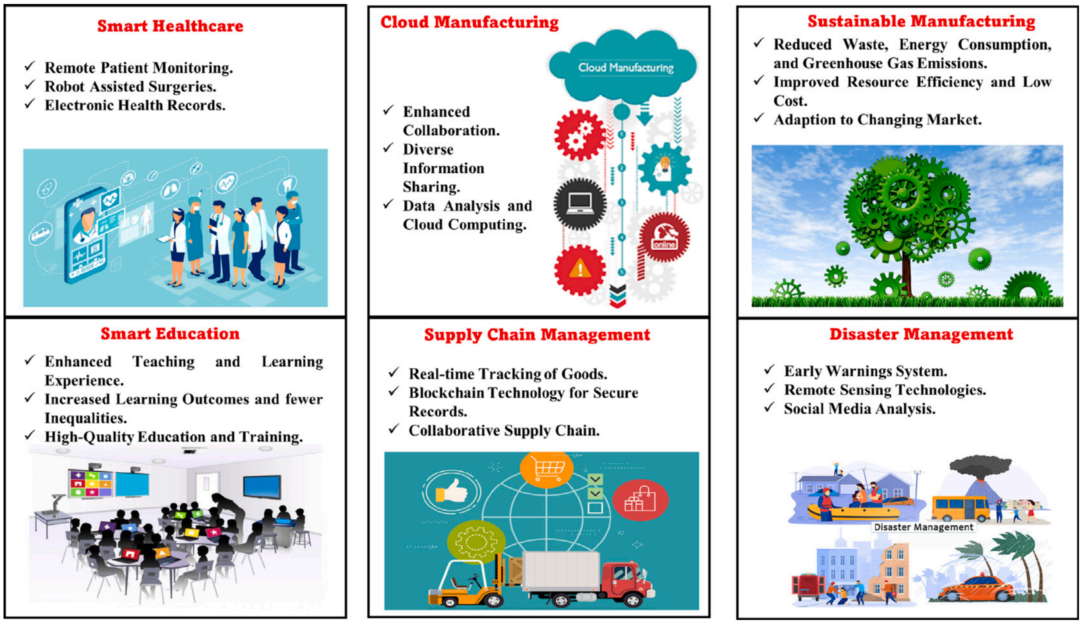

Fig. 6. Applications in Industry 5.0.

Cloud manufacturing can also enable manufacturers to optimize their production processes by providing real-time access to data and analytics. Cloud-based platforms can collect and analyze data from different stages of the manufacturing process, such as production, supply chain, and logistics, to identify areas of improvement and optimize processes. This can lead to more efficient use of resources, reduced waste, and higher quality products [69]. Another advantage of cloud manufacturing is the ability to customize and personalize products at scale. Cloud-based platforms can enable manufacturers to collect and analyze customer data, allowing them to develop personalized products and services that meet the specific needs of their customers. This can be particularly useful in industries such as fashion or furniture, where customers may want unique products that reflect their personal style or preferences.

Cloud manufacturing can also improve supply chain management by enabling real-time communication and collaboration among manufacturers, suppliers, and distributors. By sharing data and resources on a cloud-based platform, businesses can improve their coordination and reduce lead times, resulting in faster delivery and lower costs.

3.1.3. Sustainable manufacturing

Sustainable manufacturing is a key application of Industry 5.0, as it focuses on integrating advanced technologies with sustainable principles and practices. Sustainable manufacturing aims to minimize the negative environmental impacts of manufacturing processes, while also improving efficiency and reducing costs [70]. By leveraging advanced technologies, such as AI, IoT, and data analytics, sustainable manufacturing can enable manufacturers to achieve their sustainability goals while also enhancing their competitive advantage.

One of the primary applications of sustainable manufacturing in Industry 5.0 is the use of predictive maintenance systems. Predictive maintenance uses data analytics and machine learning to monitor equipment and identify potential issues before they occur, allowing for proactive maintenance and reducing the likelihood of unexpected downtime. This can not only improve efficiency and productivity but also reduce waste and emissions by minimizing the need for reactive maintenance. Another application of sustainable manufacturing is the use of advanced analytics to optimize energy and resource use. By analyzing data from sensors and other sources, manufacturers can identify areas of inefficiency and waste and develop strategies to improve energy and resource efficiency. This can lead to reduced costs and emissions while also improving the overall sustainability of manufacturing processes [71].

The Internet of Things (IoT) can also play a significant role in sustainable manufacturing. By connecting sensors and devices across the manufacturing process, manufacturers can collect real-time data on energy use, water consumption, and other sustainability metrics [72]. This can enable them to identify areas of waste and inefficiency and make data-driven decisions to optimize resource use.

Two important applications are predictive maintenance systems and remanufacturing processes. Predictive maintenance uses data analytics and machine learning to monitor equipment and identify maintenance needs before issues occur, enabling proactivity and waste reduction [73]. Remanufacturing involves taking products at the end of their lifecycle and restoring them to like-new condition through replacement of worn parts and rigorous cleaning. This extends product value and saves costs over new materials and production.

3.1.4. Human cyber–physical systems

Industry 5.0 emphasizes Human Cyber–Physical Systems (HCPS), integrating the sophisticated capabilities of cyber–physical systems (CPS) with design principles centered around human experiences [74]. HCPS aims to enable humans and machines to work together more seamlessly and efficiently, improving the overall performance of manufacturing processes.

The integration of humans into the manufacturing process is a crucial component of Industry 5.0, as it allows for greater flexibility and adaptability in the face of changing customer needs and market demands. HCPS enables humans to work alongside robots and other machines, taking advantage of their respective strengths and capabilities to optimize the manufacturing process [75].

One key application of HCPS is the use of augmented reality (AR) and virtual reality (VR) technologies to enable more immersive and interactive human–machine interfaces. This can enhance the ability of humans to work effectively with machines, allowing them to better understand and control the manufacturing process. For example, workers can use AR to visualize the internal workings of machines, identify potential issues and make adjustments in real-time [76].

HCPS can also enable more efficient collaboration and communication among workers and machines. For example, workers can use natural language processing (NLP) and voice recognition technologies

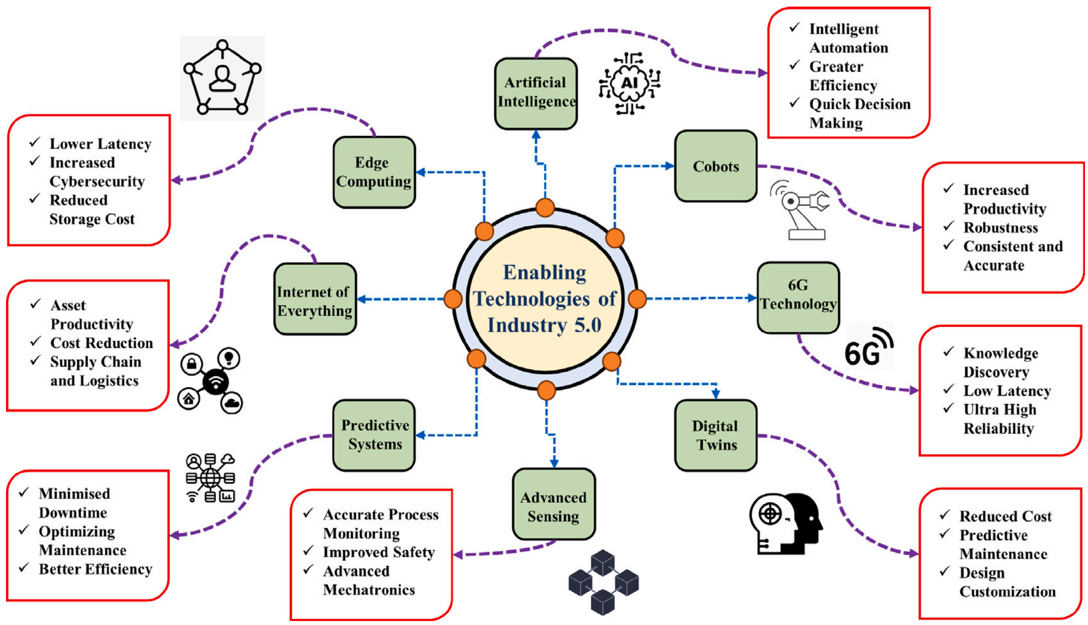

Fig. 7. Enabling technologies in Industry 5.0.

to communicate with machines, making it easier to control and adjust manufacturing processes. This can improve the efficiency of the manufacturing process, reducing the time and resources required to achieve optimal performance.

3.2. Enabling technologies

One of the key aspects of Industry 5.0 is the use of enabling technologies, which play a critical role in enhancing human–machine collaboration and improving overall productivity. Enabling technologies are those technologies that facilitate the implementation of Industry 5.0. From artificial intelligence and robotics to the Internet of Things and 5G connectivity, a range of cutting-edge technologies are driving the evolution of Industry 5.0. In this section, we will explore some of the key enabling technologies that underpin Industry 5.0 and the ways in which they are transforming the manufacturing landscape. Fig. 7 shows the enabling technologies of industry 5.0.

3.2.1. Edge computing

Edge computing is a technology that has gained significant attention in recent years, and its impact is expected to be felt across a wide range of industries, including Industry 5.0. Industry 5.0 refers to the fifth industrial revolution, which is focused on the integration of humans and machines in the workplace.

Edge computing is a distributed computing model that involves processing and analyzing data closer to the source, rather than relying solely on centralized cloud servers [77]. This approach reduces latency, bandwidth requirements, and security risks, and enables real-time decision-making. In Industry 5.0, edge computing technology can be used to improve the efficiency, productivity, and safety of manufacturing processes. For example, edge computing can be used to collect and process data from sensors and other devices on the factory floor, and then use that data to optimize production, reduce downtime, and improve product quality. In addition, edge computing can be used to improve worker safety by enabling real-time monitoring of workers and equipment [78]. For example, sensors can be used to monitor the location, movement, and vital signs of workers, and to detect potentially hazardous situations such as the presence of hazardous gases or the overheating of machinery.

Edge computing can also be used to improve product quality by enabling real-time monitoring of product performance and detecting issues early in the production process. This can help to reduce the cost of quality control and increase customer satisfaction. One of the key benefits of edge computing technology in Industry 5.0 is its ability to enable more efficient and autonomous decision-making [79]. By processing data closer to the source, edge computing can enable real-time analysis and decision-making, which can improve the speed and accuracy of production processes. For example, edge computing can be used to enable predictive maintenance, where equipment is serviced before it fails, reducing downtime and improving efficiency.

Another benefit of edge computing technology in Industry 5.0 is its ability to enable more personalized and customized products. By analyzing data from sensors and other devices, edge computing can enable more precise control over the production process, which can be used to produce products that better meet the needs of individual customers.

3.2.2. Digital twins

Digital twins are virtual representations of physical assets or systems that are created using real-time data, machine learning algorithms, and advanced analytics [7]. These digital replicas enable engineers and operators to monitor, control, and optimize physical systems in real time. The concept of digital twins has been around for a while, but with the advent of Industry 4.0 and 5.0, their importance has increased significantly.

Industry 5.0 is the next phase of the industrial revolution that is focused on HRC and teaming especially in manufacturing systems [56]. In this era, digital twins play a critical role in enabling seamless collaboration between humans and robots. By creating a virtual replica of a physical system or process, engineers and operators can test and optimize the system before it is implemented in the real world. This reduces the risk of errors and helps to identify potential issues before they become a problem.

One of the key benefits of digital twins in Industry 5.0 is their ability to facilitate HRC/T. With a digital twin, engineers can model and simulate the interaction between humans and robots in a virtual environment, allowing them to optimize the system for maximum efficiency and safety. For example, engineers can use digital twins to design and test collaborative robots that can work alongside human workers in a factory without posing a risk to their safety.

Digital twins also enable better teaming between humans and robots. By creating a digital twin of a physical system or process, engineers can provide real-time data and insights to both humans and robots, allowing them to work together more effectively. This can lead to improved productivity, reduced downtime, and increased safety.

In addition to enabling HRC and teaming, digital twins have several other benefits in Industry 5.0. For example, they can help to reduce maintenance costs by identifying potential issues before they become a problem, and they can improve overall system efficiency by optimizing the system in real time. They can also provide valuable insights into the performance of a system, enabling engineers and operators to make data-driven decisions.

3.2.3. Internet of everything

The Internet of Everything (IoE) technology is a powerful concept that is expected to revolutionize various aspects of our lives, including the way we work, communicate, and interact with the world around us. IoE is an evolution of the Internet of Things (IoT), which refers to the connectivity of devices and objects to the internet. However, IoE expands the concept to include people, processes, and data, creating a network that connects everything and everyone [80].

Industry 5.0, also known as the "Human-Centered Industry", is the next step in the evolution of manufacturing and industry. It involves combining the strengths of humans and machines to create a more productive, efficient, and sustainable manufacturing environment. IoE is expected to play a crucial role in enabling Industry 5.0 by providing a seamless and interconnected platform for various devices, machines, and humans to collaborate and communicate.

IoE technology is expected to transform various industries in Industry 5.0, including manufacturing, logistics, and supply chain management. For example, in manufacturing, IoE technology can be used to optimize the production process, reduce downtime, and improve quality control. By connecting various sensors and machines, IoE technology can provide real-time data on the performance of each machine, allowing operators to identify and fix any issues quickly. IoE can also be used to improve worker safety by monitoring the conditions of the work environment and alerting workers in case of any potential hazards.

In logistics and supply chain management, IoE technology can be used to optimize the movement of goods, reduce delivery times, and improve supply chain visibility. By connecting various sensors, RFID tags, and other devices, IoE technology can provide real-time data on the location, status, and condition of goods. This data can be used to identify and address any potential issues, such as delays or damage to goods, before they become major problems.

Another key aspect of IoE technology is its ability to enable intelligent decision-making. By connecting various data sources, IoEtechnology can provide a holistic view of the manufacturing process or the supply chain. This data can be used to identify patterns and trends, which can be used to make informed decisions that improve efficiency, reduce costs, and enhance the overall customer experience.

However, the widespread adoption of IoE technology in Industry 5.0 is not without its challenges. One of the biggest challenges is data security and privacy. With so much data being generated and shared between various devices and machines, there is a risk of sensitive information being compromised. Therefore, robust data security and privacy measures must be put in place to protect against cyber-attacks and data breaches.

Another challenge is the need for interoperability between various devices and systems. IoE technology involves connecting a wide range of devices and machines, many of which may have been developed by different manufacturers using different standards and protocols. Therefore, there is a need for standardization and interoperability to ensure that devices can communicate and work seamlessly together.

4. Digital twin driven HRC system

Digital twin technology is a key component of Industry 5.0, which involves the creation of virtual replicas of physical objects and processes. One application of digital twin technology in Industry 5.0 is in the context of HRC, where virtual representations of robots and their environments can be used to optimize and enhance the interaction between humans and robots. In this section, we will explore the concept of digital twin-driven HRC and the ways in which it is transforming the manufacturing landscape.

4.1. Digital twin/digital thread/digital shadow

"Digital Twin", "Digital Thread", and "Digital Shadow", are terms used in the field of digitalization and Industry 5.0. These terms describe the use of digital technologies to capture, store, and analyze data related to physical objects and processes. The differences between the three terms are explained in the following:

- Digital Thread: A digital thread is a continuous, secure chain of data that follows a product or component throughout its life cycle, from design to end of life. It provides a complete view of all the data related to a product and its interactions with other products and systems [81].
- Digital Shadow: A digital shadow refers to a real-time, digital representation of a physical object that updates as the object changes. It is a real-time digital replica of a physical asset, allowing the tracking of its location, status, and other attributes in real time [82].
- Digital Twin: A digital twin is a virtual representation of a physical asset that can be used to simulate, analyze, and optimize its performance, behavior, and interactions with its environment [83].

It is a digital replica of a physical object that is used for monitoring, control, and optimization purposes. In summary, a digital thread provides a complete history of an object, a digital shadow tracks the real-time status of an object, and a digital twin provides a virtual representation of an object for simulation and analysis purposes.

4.2. Potential of DT and HRC

Digital twin-based HRC (DT-HRC) is a cutting-edge technology that leverages the principles of digital twins to enable effective collaboration between humans and robots. In DT-HRC, digital twins are used to modeling and simulate HRI's, allowing engineers and researchers to analyze, optimize, and improve the performance and safety of HRC systems [84]. Fig. 8 depicts an abstract illustration of a robot's digital twin model. In the scenario shown, sensors are used to collect the state of the physical system (robot) and transfer it to the digital model (a virtual copy of the robot).

By using sensors to read motor speed, angle, orientation, ON/OFF state, and compute the optimal parameters with an efficient control scheme and fault assessment for the real system, a digital twin or virtual model can precisely recreate the state and movement of a robotic arm as they occur in the physical or real world.

DT-HRC systems typically consist of several key components, including human and robot models, simulation and visualization tools, and control algorithms. Human models are created by capturing the anatomy, kinematics, and dynamics of the human body, while robot models represent the physical characteristics, capabilities, and constraints of the robot. Simulation and visualization tools allow users to test and validate the HRI in virtual environments, and control algorithms enable real-time interaction between the human and the robot.

Digital twin technology has the potential to greatly enhance the use of cobots in manufacturing [85]. A digital twin is a virtual representation of a physical system, including the robot and its environment. By creating a digital twin of a cobot, manufacturers can simulate and analyze the robot's behavior in a virtual environment before deploying it in the real world. This allows for greater precision in the programming

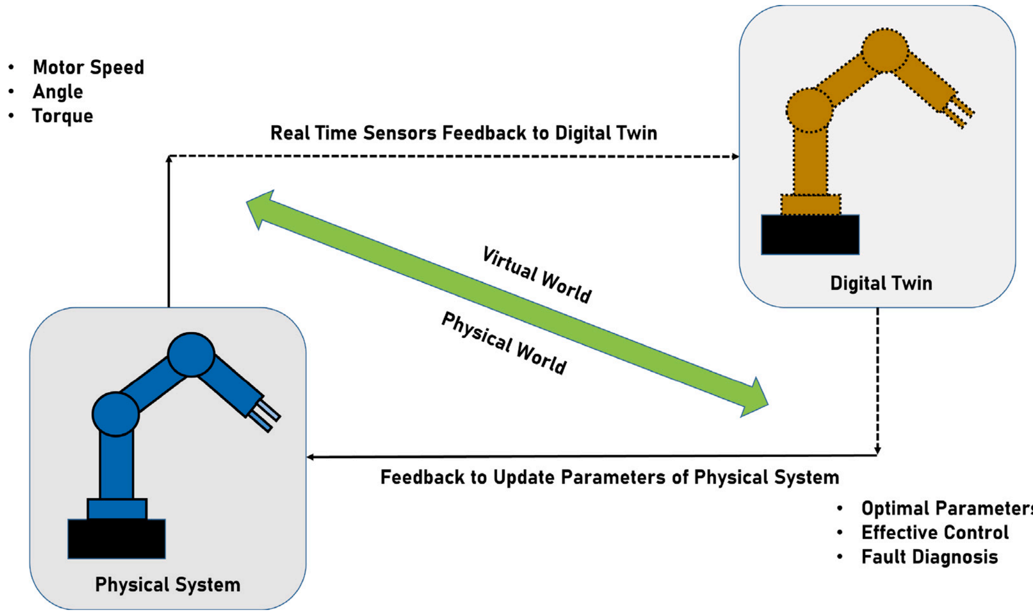

Fig. 8. Abstract representation of digital twin.

of the cobot's movements and can help to optimize its performance and efficiency. Additionally, a digital twin allows for continuous monitoring and analysis of the cobot's operation in real-time [86]. This can help to identify potential issues and improve the overall performance of the system. Furthermore, by integrating the digital twin with other systems such as manufacturing management software, manufacturers can gain a more comprehensive understanding of the entire manufacturing process and make data-driven decisions to improve efficiency and reduce costs.

The benefits of DT-HRC are numerous and far-reaching. By providing a virtual representation of the human–robot system, DT-HRC enables designers and engineers to test and optimize the system's performance and safety before deployment. This can significantly reduce the development time and costs associated with HRC systems. Furthermore, DT-HRC allows for the analysis of HRI's in real-time, enabling researchers to study and understand the cognitive, physiological, and behavioral factors that influence HRI's.

4.3. Phases of DT-HRC system

The phases of Digital Twin-based HRC refer to the steps involved in the creation, deployment, and ongoing management of a digital twin for a HRC system (Fig. 9).

1. Modeling Phase: In the modeling phase, a number of models are created, including models of the robot, its environment, and the human operator. These models may be created using a variety of simulation tools and techniques, such as computer-aided design (CAD) software, physics-based simulations, and machine learning algorithms. The models of the robot and its environment are created to accurately represent the physical system, including its mechanical structure, actuators, sensors, and other components. The model of the human operator is created to represent the human operator's physical characteristics, such as their height, weight, and reach, as well as their cognitive abilities, such as their reaction time and decision-making processes. Once the models are created, they are integrated into the digital twin of the HRC system. The digital twin is then used to simulate the behavior of the physical system, including the interaction between the human operator and the robot.
2. Simulation Phase: In the simulation phase, the digital twin is used to simulate the behavior of the HRC system, including the interaction between the human operator and the robot. This includes simulating the movement of the robot, the response of the robot to the human operator's actions, and the impact of the environment on the performance of the system. The simulation phase allows engineers and designers to test different configurations of the HRC system, including different robot designs, control algorithms, and HRC strategies. The results of these simulations can be used to make modifications to the physical system, or to the digital twin, in order to optimize the performance of the HRC system.
3. Deployment Phase: During the deployment phase, a number of tasks are performed, including the installation of sensors and other technologies for monitoring the performance of the HRC system. These sensors may include cameras, force sensors, and position sensors, among others. The data collected from these sensors is used to continuously update the digital twin, ensuring that it remains an accurate representation of the physical system. In addition to the installation of sensors, the deployment phase may also involve the implementation of control algorithms and other technologies to optimize the performance of the HRC system. This may include the development of algorithms to control the movement of the robot, to monitor the performance of the human operator, and to respond to changes in the environment. Once the deployment phase is complete, the HRC system is ready to be put into operation, with the digital twin serving as a tool for continuous monitoring and optimization of the system.
4. Monitoring Phase: The monitoring phase of Digital Twin-based HRC refers to the process of using the digital twin to continuously monitor the performance of the physical HRC system. This phase is critical for ensuring the safety and efficiency of the HRC system, as it allows engineers and designers to detect and address issues before they become major problems. In the monitoring phase, the digital twin is used to track and analyze various parameters of the HRC system, including the performance of the robot, the behavior of the human operator, and the impact of the environment on the system. This data is collected in real-time from the sensors and other technologies installed during the deployment phase. The monitoring phase may also involve the use of predictive analytics and machine learning algorithms

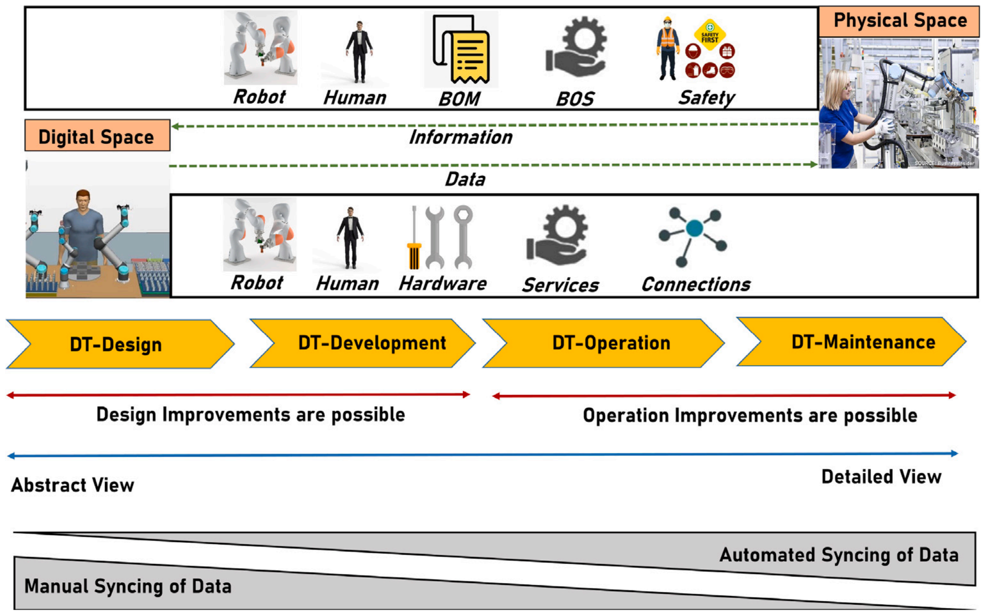

Fig. 9. DT HRC phases.

to analyze the data collected from the HRC system. These algorithms can be used to identify trends and patterns in the data, and to predict potential issues before they occur. The results of the monitoring phase can be used to make modifications to the physical system, or to the digital twin, in order to optimize the performance of the HRC system. This may include modifying the control algorithms, adjusting the placement of sensors and other technologies, or modifying the design of the robot.

5. Optimization Phase: The optimization phase of Digital Twin-based HRC refers to the process of using the data collected during the monitoring phase to optimize the performance of the physical HRC system. This phase involves the analysis of the data collected from the digital twin, the identification of areas for improvement, and the implementation of changes to the system to enhance its safety, efficiency, and effectiveness. In the optimization phase, engineers and designers may use various techniques, such as predictive analytics, machine learning algorithms, and simulation models, to analyze the data collected from the HRC system. They may identify trends, patterns, and potential issues that could impact the performance of the system, and use this information to inform the design and implementation of modifications. The modifications made during the optimization phase may include changes to the control algorithms, adjustments to the placement of sensors and other technologies, modifications to the design of the robot, and improvements to the HRC workflows and processes.

4.4. Fundamental blocks of DT-HRC system

A physical environment, a digital space, data communications, and linkages are some of the parts that make up a digital twin system. Some of them – such as the digital and physical spaces – are key aspects, but the demands placed on secondary elements – such as data communications and connections – depend on what is expected of a DT system. The fundamental blocks of Digital Twin-based HRC are:

1. Digital Twin Model: This is a digital representation of the physical HRC system. The digital twin model includes all the components of the physical system, including the robot, the human operator, and the environment in which the collaboration takes place.
2. Sensors and Monitoring Technologies: These technologies are used to collect data from the physical HRC system in real-time. The data collected from sensors and monitoring technologies is used to populate the digital twin model and to monitor the performance of the system.
3. Predictive Analytics and Machine Learning Algorithms: These algorithms are used to analyze the data collected from the HRC system in order to identify trends, patterns, and potential issues. They can also be used to make predictions about the future behavior of the system, and to optimize its performance.
4. Simulation Models: These models are used to simulate the performance of the physical HRC system in a virtual environment. Simulation models allow engineers and designers to test and evaluate different design configurations, control algorithms, and human–robot interfaces before implementing them in the physical system.
5. Control Algorithms: These algorithms are used to control the behavior of the robot in the HRC system. The control algorithms can be modified based on the data collected from the digital twin model and the results of the simulation models.
6. Human–Robot Interfaces: These interfaces are used to facilitate communication and collaboration between the human operator and the robot. The interfaces may include physical controls, visual displays, and audio feedback, and can be optimized based on the data collected from the digital twin model and the results of the simulation models.

4.5. Software for DT-HRC

The design of digital twins of industrial robots can be done using both open-source and commercial software. Open-source software is free and can be modified and distributed by anyone, while commercial software is proprietary and must be purchased. Open-source software such as Coppeliasim [87], Unity3D [88] and ROS/Gazebo [89] provides a cost-effective solution for creating digital twins of industrial robots and are popular for their flexibility and customizable features. However, open-source software may not have the same level of technical support and features as commercial software. Commercial software such as PTC ThingWorx [90], GE Predix [91], MATLAB [92] and Microsoft Azure Digital Twins offer a more comprehensive solution for digital twin design [93], and typically have advanced features such as real-time data visualization, predictive analytics, and collaboration tools. Commercial software is generally more expensive than open-source software, but it also provides a higher level of technical support and can offer a quicker path to deployment. The choice between open-source and commercial software will depend on the specific needs and budget of the organization, as well as the requirements of the digital twin project. Both types of software have their advantages and disadvantages, and the best choice will depend on the unique needs of each organization and also depends on the focus, i.e., physical simulation, process, production.

Open-source cloud platforms offer a cost-effective and flexible solution for the design of digital twins of industrial robots [94]. These platforms provide a range of tools and services for creating, deploying, and managing digital twins, and are based on open-source technologies such as Linux, Docker, and Kubernetes. Some popular open-source cloud platforms for digital twin design of industrial robots include Eclipse IoT, Node-RED, OpenFog, and OpenMUC. These open-source cloud platforms provide a cost-effective solution for creating digital twins of industrial robots and can be customized and extended to meet the specific needs of each organization. However, organizations using open-source cloud platforms may need to invest more time and resources in developing and maintaining their digital twin infrastructure [95].

MATLAB and ROS are both commonly used tools for human modeling in virtual environments. MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. It can be used for human modeling in virtual environments by using its toolboxes for computer vision, robotics, and machine learning [96] . For example, the Computer Vision Toolbox in MATLAB can be used for processing and analyzing human body and hand tracking data, and the Robotics System Toolbox can be used for creating and controlling virtual human models in a simulated environment [40]. ROS (Robot Operating System) is an open-source framework for developing and deploying robot software. It provides a large number of libraries and tools for robot control, navigation, and perception, and can be used for human modeling in virtual environments by integrating with human body and hand tracking libraries [97]. For example, ROS packages such as OpenPose and OpenCV can be used for human body tracking, and ROS packages such as MoveIt can be used for controlling virtual human models in a simulated environment [42].

ROS (Robot Operating System) and Gazebo are open-source software widely used in the research community for robotics work due to their flexibility, modularity, and powerful tools for simulation and experimentation. ROS is a framework for building and managing robot software systems. It provides a suite of libraries, tools, and conventions for creating complex robot applications. ROS supports a wide range of robotic platforms, including mobile robots, manipulators, and drones. Gazebo is a multi-robot simulator for outdoor and indoor environments. It provides a realistic and customizable simulation environment for robots, including sensors, actuators, and physics. Gazebo enables researchers to test their algorithms and controllers in a virtual environment before deploying them on a real robot.

Together, ROS and Gazebo provide a powerful and flexible platform for robotics research. They enable researchers to design and test robotic systems in a virtual environment before deploying them on real robots, which can save time and reduce costs. Furthermore, their open-source nature has led to a large and growing community of developers who contribute to the systems and share their code, which can accelerate the development of new robotics applications.

Due to their effectiveness and flexibility, ROS and Gazebo have a growing community with the potential to become the de facto standard in the robotics industry. Many companies and organizations have already adopted ROS and Gazebo for their robotics research and development, including Toyota, Amazon, and NASA. The use of open-source software in the industry is also increasing, and ROS and Gazebo's open-source nature may make them particularly attractive to companies looking to build and deploy robotics applications.

The adoption of open-source and commercial software tools for the production of Digital Twin-HRC (DT-HRC) can offer several benefits and drawbacks, which can have significant implications for the overall performance and cost-effectiveness of the system.

Benefits of Open-Source Software Tools:

1. Cost-effective: Open-source software tools are usually free to use, which can greatly reduce the cost of developing DT-HRC systems.
2. Customizable: Open-source software tools are often highly customizable, which can be beneficial for developing DT-HRC systems that meet specific requirements.
3. Collaborative: The open-source community provides a platform for collaboration and knowledge-sharing, which can help accelerate the development of DT-HRC systems.
4. Extensible: Open-source software tools often provide extensible APIs and plugins, which can help to add new functionality and features to the DT-HRC systems.

Drawbacks of Open-Source Software Tools:

1. Lack of Support: Open-source software tools may not provide the same level of technical support and maintenance as commercial software tools.
2. Quality: The quality of open-source software tools can be variable, as it depends on the contributions of the community, which may be limited in scope and resources.
3. Compatibility: Open-source software tools may not be compatible with proprietary systems and tools, which can limit the integration and deployment of DT-HRC systems.

Benefits of Commercial Software Tools:

1. Technical Support: Commercial software tools usually provide technical support and maintenance, which can help to resolve any issues that arise during the development and deployment of DT-HRC systems.
2. Quality: Commercial software tools are typically of higher quality, as they are developed and maintained by professional teams with access to significant resources.
3. Integration: Commercial software tools are often compatible with proprietary systems and tools, which can help to facilitate the integration and deployment of DT-HRC systems.

Drawbacks of Commercial Software Tools:

(1) Cost: Commercial software tools are often expensive to purchase and maintain, which can significantly increase the cost of developing DT-HRC systems.
(2) Inflexibility: Commercial software tools may not be as flexible or customizable as open-source software tools, which can limit the ability to develop DT-HRC systems that meet specific requirements.

Fig. 10 shows a summary of the suggested strategy to import Human Model in ROS. In MakeHuman, the human model can be exported in a variety of file formats, including OBJ, COLLADA, and FBX. The OBJ format is a popular choice for exporting models to ROS, as it is a simple, text-based format that is easy to parse and convert.

4.6. Benefits of DT-HRC system

Digital twin based HRC (DT-HRC) systems offer a range of benefits, including:

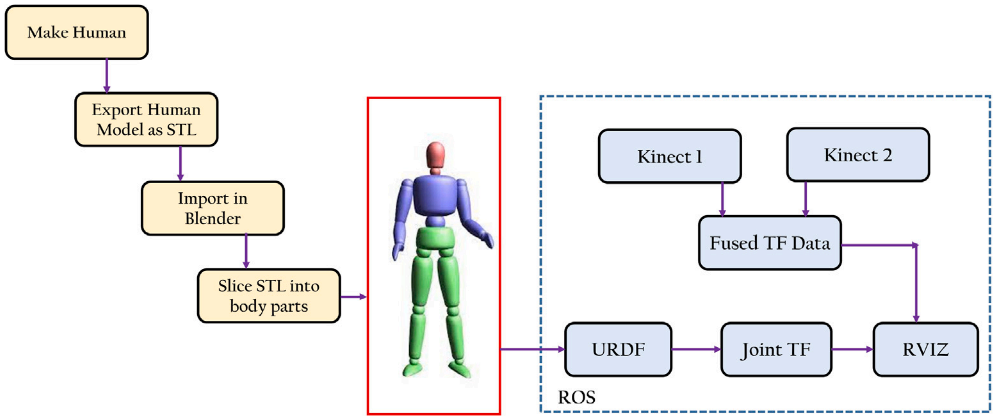

Fig. 10. Process of creating a human model for visualization in RViz.

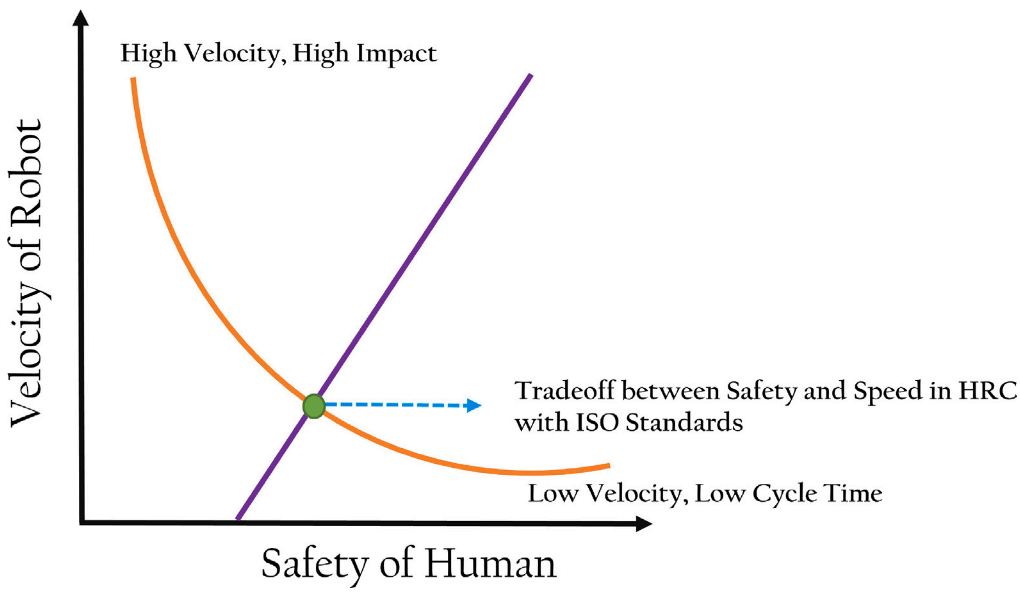

Fig. 11. The robot joint in HRC is traded off between safety and speed for the benefit of both production and a safe HRC.

1. Improved safety: DT-HRC systems allow for real-time monitoring and control of HRI's, reducing the risk of accidents and injury. This is achieved through the use of safety-rated monitored stops, power and force limiting, and other safety features that are built into the digital twin. The level of safety and trust in a collaborative setting, on the other hand, is determined by the programmer who programs the robot. In the HRC environment, one difficulty is the trade-off between robot velocity and safety. Fig. 11 illustrates this trade-off. The higher the pace of the robot, the faster a task may be completed, however this results in less trust and increased risk for the operator. It is possible to figure out the best way to ensure safety while reducing task cycle time using the DT.
2. Collision Tests: This enables the testing of different scenarios and configurations to assess the risk of collisions and prevent accidents before the system is deployed in a real-world setting. Additionally, DT-HRC systems can monitor HRI's in real time, providing real-time feedback and control over the system to reduce the risk of collisions. By incorporating safety features such as safety-rated monitored stops and power and force limiting, DT-HRC systems can significantly improve the safety of HRI's and enhance the reliability and effectiveness of collision testing.
3. Increased flexibility: DT-HRC systems provide a flexible platform for HRC, allowing for the integration of new technologies, the addition of new tasks, and the adaptation of the system to changing requirements.
4. Ergonomic Analysis: This enables designers and engineers to optimize the design of the robot to reduce the risk of repetitive strain injuries and other types of work-related musculoskeletal disorders. DT-HRC systems can also provide real-time feedback on the human body's movements, allowing for the identification and correction of any ergonomic issues that may arise during HRI's. By incorporating human models into the digital twin, DT-HRC systems can provide an accurate representation of the human body, improving the accuracy of ergonomic analysis and reducing the risk of work-related injuries [98].
5. Control of Robots: Developing efficient robot control algorithms involves significant human effort in robotic applications [99]. DT-HRC enables designers and engineers to optimize the robot's control program and test different scenarios in a simulated environment before deploying the robot in a real-world setting. DT-HRC systems can also monitor the robot's performance in real-time and provide real-time feedback, allowing for the identification and correction of any control issues that may arise during HRI's. By incorporating human models into the digital twin, DT-HRC systems can also take into account the human's movements and actions, allowing for the development of more efficient and safe control programs. The use of DT-HRC systems

Table 3
Overview of literature for the benefits of DT-HRC.

Application	Ref.	Summary
Safety	[100]	For flexible robotized warehouses, this research suggests a ToM-based human intention estimation system. Using generalized Voronoi diagram-based path planning, this observes human motion, or worker motion, and validates it in relation to the goal locations. The proposed hidden Markov model framework then processes these data in order to estimate worker intentions in an online manner that can adapt to changing circumstances. Experiments were conducted with a worker using Microsoft Hololens augmented reality glasses in a real-world laboratory warehouse to evaluate the proposed intention estimation.
	[101]	A robot system can predict the planned activities of human workers in an HRC environment by classifying standing postures from standing-pressure photographs, according to the current study. In order to achieve this, it investigates deep learning based on standing-posture recognition and a way of fusing many recognition algorithms for HRC. Ten experimental subjects stood on a pressure-sensing floor that was covered in thin-film pressure sensors in order to collect data on pressure distribution. Each participant provided the pressure data for nine different standing positions. Seven classification methods were used to differentiate between the human standing positions.
	[102]	This article suggests a kinematic control technique that upholds safety while preserving the robot's highest degree of production. The (potentially redundant) robot's final motion is produced by an optimization-based real-time method, where safety is viewed as a difficult constraint to satisfy. A dual-arm concept robot with seven degrees of freedom (DOF) per arm executing a manipulation task is used to empirically evaluate the methodology.
Task planning	[40]	It is suggested and integrated inside the Robot Operating System (ROS) framework to use an intelligent decision-making approach that permits the assignment of human–robot tasks. The suggested approach makes it possible to assign sequential tasks to a robot and a human in distinct workplaces. In order to raise the level of automation in manual or even hybrid assembly lines, the emphasis is instead placed on the coexistence of humans and robots during the performance of sequential tasks. A human interacts with a robot using body motions for controlling and directing purposes. The suggested framework is used to a scenario involving an automotive industry's manual assembly lines. The construction of a hydraulic pump is the main focus of an early design for a hybrid assembly cell.
	[103]	The innovative idea put out in this paper is that a manufacturing cell's production resources will be automatically planned and coordinated by a digital twin created from a digital product description. In contrast to the general services provided by the manufacturing cell, which make few assumptions about the type of product that will be constructed, the digital product description is created by collaboration between an OEM designer and automated services provided by possible manufacturers.
	[104]	In this study, we introduce a cyber–physical testbed designed to let a team of humans and robots work together on a shared task in a common area. A typical HRC situation, tabletop manipulation, can be implemented on the testbed. The testbed combines aspects from the real and virtual worlds. In this study, we present the conclusions we reached after investigating task planning and execution for human–robot teams and putting them into practice.
Testing and training	[105]	The usage of a virtual reality digital twin of a physical layout is discussed in this research as a way to better understand how people respond to both predictable and unanticipated robot motions. The usefulness of the Virtual Reality environment is examined and validated using a variety of recognized measures as well as a newly created Kinetic Energy Ratio metric. It is hoped that virtual reality digital twins would let future factories safely deploy human–robot collaborative tactics.
	[106]	The proposed approach first maps the DTs of industrial robots to actual robots so that users can see them in their AR glasses. To synchronize the status of the robots in the twin, a multi-robot communication mechanism is being created and implemented in the meantime. The robot motion planning also incorporates a reinforcement learning method to swap out the standard kinematics-based robot movement with appropriate target placements.

can significantly improve the reliability and safety of the control program and enhance the overall performance of the robot.

Furthermore, the detailed summary of the literature on benefits of DT-HRC is shown in Table 3.

4.7. Control methods of HRC

Over time, there have been significant changes in how humans and robots interact. They began with straightforward physical interactions utilizing simple devices like a mouse or keyboard, progressing to the usage of touch screens as interactive interfaces later on. Thanks to their increasing autonomy and the development of new software and hardware capabilities over the past few years, robots have begun to communicate with humans without difficulty using gestures or voice [107].

As robots become more intelligent coworkers, their interactions with people have gradually transformed to more closely mirror human–human interactions [108]. Robot control techniques have been impacted by this progression as well. Additionally, the incorporation of hybrid teams into industrial manufacturing processes has raised the demand for more effective interfaces. There are several methods for controlling robots for HRC, including:

1. Task-level control: This method involves controlling robots to perform specific tasks, such as grasping and moving objects, based on predefined rules and conditions [109].
2. Motion control: This method involves controlling robots to plan and execute safe and efficient motions to achieve a desired task, taking into account the presence and movements of humans in the workspace [110].
3. Imitation learning: This method involves controlling robots to learn from human demonstrations, either through kinesthetic teaching or by observing human actions in the environment [111].
4. Reinforcement learning: This method involves controlling robots to learn from trial-and-error by receiving rewards or penalties for actions, which are used to improve their performance over time [112].
5. Natural language programming: This method involves controlling robots using natural language instructions, such as spoken or written commands, to perform tasks in a more intuitive and user-friendly way [113].
6. Model Predictive Control (MPC): This method involves controlling robots to continuously optimize their actions based on a predictive model of the environment, taking into account constraints and goals. This allows for real-time adaptation to changes in the workspace [114].
7. Hybrid Position/Force Control: This method involves controlling robots to use both position control, to ensure safe and precise motion, and force control, to respond to unexpected contact or interactions with humans [115].
8. Shared Autonomy: This method involves programming robots to perform tasks in collaboration with humans, allowing both

parties to share control and contribute their unique abilities and expertise [116].
9. Human-Aware Motion Planning: This method involves controlling robots to take into account human comfort, safety, and preferences when planning their motions and actions. This helps to ensure that humans feel comfortable and safe when working with the robot [117].
10. Multi-Agent Systems: This method involves controlling multiple robots to work together in a coordinated manner, allowing for more complex and efficient HRC scenarios [118].

5. State of the art hardware for HRC systems

The success of HRC also depends on the quality and type of hardware used to build the robots. In this review, we will discuss the current state of the art hardware for HRC.

5.1. Manipulators

Manipulators, also known as robotic arms, are the most commonly used hardware for HRC. They are designed to assist human operators in performing tasks that are physically demanding, dangerous, or repetitive. Manipulators are versatile tools that can be used in a variety of applications, ranging from manufacturing and assembly to material handling and inspection. In this section, we will discuss the current state of manipulators for HRC in detail.

1. Actuation system: The actuation system is a crucial component in robotic manipulators that facilitates movement by converting electrical or mechanical signals. It consists of various elements such as the motor, transmission system, and the end-effector, which connects the robot to the object it is manipulating. Two main types of actuators used in robotic manipulators are rigid and soft actuators. Rigid actuators, typically made of hard materials, deliver high force and precision in their movements. Electric motors, hydraulic, and pneumatic actuators are some common examples of rigid actuators used in robotic manipulators. In contrast, soft actuators, made of compliant and deformable materials, have lower stiffness and are more versatile in their movements. Examples of soft actuators include pneumatic artificial muscles, dielectric elastomer actuators, and shape-memory alloys. These soft actuators are becoming increasingly popular in robotic manipulators because they can mimic human muscles' movements, enabling natural and safe interactions with humans. Ultimately, the selection of rigid or soft actuators depends on the specific application's requirements.
2. Degrees of freedom: The degrees of freedom (DoF) of a manipulator refers to the number of independent directions in which it can move. The current state of manipulators for HRC includes high degrees of freedom, ranging from 6 to 12 DoF, which allow for greater flexibility and precision in task performance.
3. Precision: Precision is a critical factor in HRC, as it directly affects the quality of the task being performed. The current state of manipulators for HRC includes high precision, with repeatability in the order of tens of micrometers, which allows for accurate and consistent task performance.
4. Safety features: Safety is a key concern in HRC, as the presence of human operators in close proximity to the robot increases the risk of injury. The current state of manipulators for HRC includes improved safety features, such as torque sensors and obstacle detection systems, which allow the robot to respond to changes in its environment and avoid potential hazards.
5. Collaborative capabilities: Collaborative capabilities refer to the ability of the manipulator to interact and respond to the human operator in real-time. The current state of manipulators for HRC includes the development of collaborative robots, also known as cobots, which have been designed specifically for interaction with human operators. Cobots have been equipped with safety features and advanced control algorithms that allow for a safer and more natural interaction between the human and the robot.

There are several types of manipulators that can be used in HRC, each with its own strengths and weaknesses. Some of the most common manipulators used in HRC include:

1. Articulated manipulators: Articulated manipulators, also known as robotic arms, are the most commonly used type of manipulator in HRC. They consist of several joints, allowing for a wide range of motion and flexibility [119].
2. SCARA (Selective Compliance Assembly Robot Arm) manipulators: SCARA manipulators are specialized manipulators that are commonly used in assembly and pick-and-place applications. They are known for their high precision and speed, making them ideal for tasks that require repetitive movements [120].
3. Parallel manipulators: Parallel manipulators consist of several parallel links that are connected to a fixed base. They are known for their high rigidity, making them ideal for heavy-duty tasks [121].
4. Mobile Robots: Mobile robots, equipped with wheels or tracks for locomotion, are pivotal in HRC for their ability to navigate and interact in diverse and dynamic environments. These robots often incorporate advanced sensing and navigation systems, enabling them to adapt to changing surroundings and collaborate with humans across various tasks. Their mobility makes them suitable for scenarios where tasks are spread across different locations or involve navigating through cluttered spaces, offering a flexible and versatile solution [122].
5. AGVs: AGVs represent a specialized category of mobile robots designed for the efficient transport of materials within industrial settings. These vehicles follow predefined paths or respond to environmental cues, enhancing their precision and reliability in material handling tasks. AGVs are particularly prevalent in manufacturing and logistics, contributing to the automation of material transport processes. The integration of AGVs in HRC scenarios emphasizes their role in streamlining workflows and collaborating with human operators to optimize operational efficiency [123].

5.2. Wearables

Wearable technology (Wearables) is an emerging technology that provides more immersive experiences when interacting with technology, be it wristwatches, headsets or glasses. Wearable technology is increasingly being used in HRC (HRC) to enhance the interaction between humans and robots. The state-of-the-art wearables for HRC include:

1. Exosuits: Exosuits are wearable robots that provide mechanical assistance to the wearer. They are commonly used in HRC to augment human strength and endurance, allowing the human operator to perform tasks that would otherwise be too physically demanding [124].
2. Virtual Reality (VR) Head-Mounted Displays (HMDs): VR HMDs are used to provide the human operator with a virtual environment that they can interact with. In HRC, VR HMDs can be used to provide the operator with a sense of presence and enhance their ability to collaborate with the robot [125].
3. Augmented Reality (AR) Head-Mounted Displays (HMDs): AR HMDs are used to display information and graphics in the wearer's field of view. In HRC, AR HMDs can be used to provide the human operator with information about the task, such as instructions and real-time feedback, as well as to enhance their ability to collaborate with the robot [126].

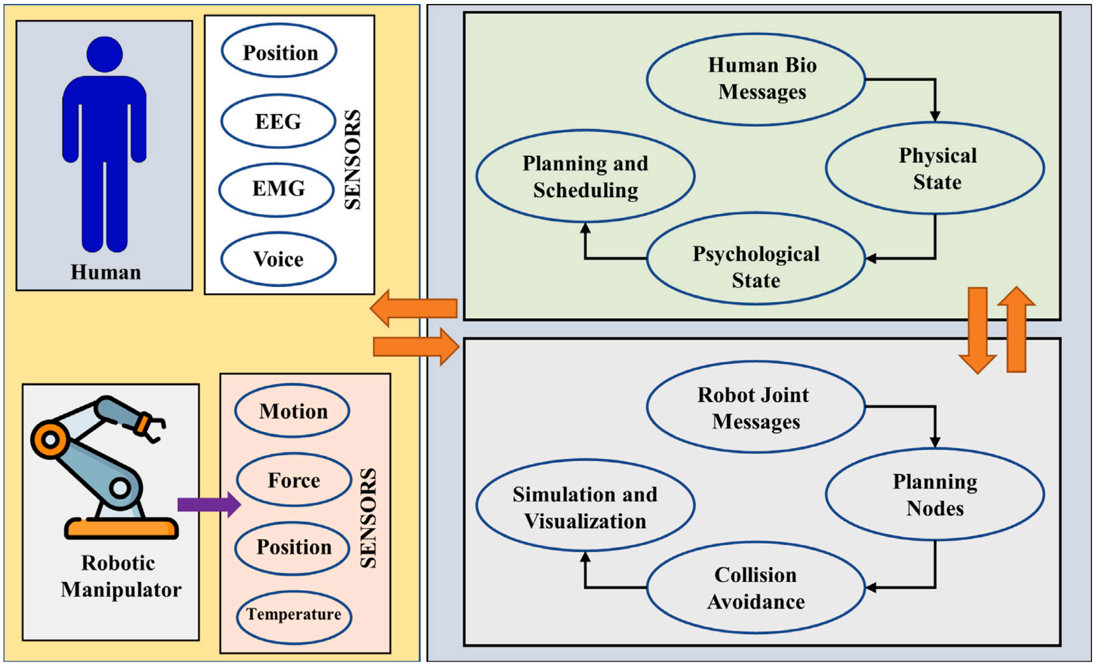

Fig. 12. HRC Framework for Wearable Sensors.

4. Gesture-Tracking Devices: Gesture-tracking devices, such as gloves and hand-held controllers, are used to detect the movements and gestures of the human operator. In HRC, gesture-tracking devices can be used to provide the robot with information about the operator's intentions and movements, allowing it to respond to their actions and collaborate with them [127].
5. Wearable Sensors: Wearable sensors, such as accelerometers and gyroscopes, are used to detect the movements and position of the human operator. In HRC, wearable sensors can be used to provide the robot with information about the operator's movements, allowing it to respond to their actions and collaborate with them [128].

The wearable sensors based framework for HRC system is presented in Fig. 12. As, Wearable technology is highly useful in enhancing the interaction between humans and robots in HRC (HRC) as it provides real-time information about the human operator's movements and intentions. This information allows the robot to respond to their actions, avoid potential hazards and augment their strength and endurance. The use of wearables such as exosuits, VR/AR head-mounted displays, gesture-tracking devices, and wearable sensors enhances the ability of the human operator to collaborate with the robot and perform tasks more efficiently. In conclusion, wearables play a crucial role in HRC by providing a new level of interaction between humans and robots, making the collaboration more effective and safe.

5.3. Sensors

In HRC, sensors play a critical role in ensuring the safety and accuracy of the task being performed. The state-of-the-art sensors for HRC include:

1. Force/Torque Sensors: Force/torque sensors are used to detect the force and torque being applied by the robot, allowing it to respond to changes in its environment and avoid potential hazards. These sensors provide real-time feedback to the robot's control system, allowing it to adjust its movements accordingly.
2. Vision Sensors: Vision sensors, such as cameras and lidars, are used to provide the robot with a visual representation of its environment. They allow the robot to detect obstacles, track human operators, and perform tasks that require visual recognition, such as inspection and assembly.
3. Proximity Sensors: Proximity sensors, such as infrared sensors and ultrasonic sensors, are used to detect the presence of objects and humans in the vicinity of the robot. These sensors are critical for ensuring the safety of the human operator, as they allow the robot to respond to changes in its environment and avoid potential hazards.
4. Tactile Sensors: Tactile sensors, also known as touch sensors, are used to detect physical contact with objects and humans. These sensors provide the robot with a sense of touch, allowing it to respond to physical interactions and perform tasks that require a delicate touch, such as material handling and manipulation.
5. Motion Sensors: Motion sensors, such as accelerometers and gyroscopes, are used to detect the motion of the robot and its environment. These sensors provide the robot with information about its orientation and movements, allowing it to respond to changes in its environment and maintain its stability.

5.4. Human–robot interfaces

Human–robot interfaces (HRIs) are the methods and technologies that enable humans and robots to communicate and interact with each other. HRIs are critical in HRC (HRC) as they allow the human operator to control the robot and provide it with information about its environment. The following are some of the key components of HRIs in HRC:

1. Input Devices: Input devices are the methods by which humans can communicate their intentions and actions to the robot. Examples of input devices in HRC include buttons, joysticks, keyboards, and gesture-tracking devices.
2. Output Devices: Output devices are the methods by which the robot communicates its status and information to the human operator. Examples of output devices in HRC include displays, lights, audio, and haptic feedback.
3. Human–Machine Interfaces (HMIs): HMIs are the graphical interfaces that enable humans to interact with the robot. HMIs can

be as simple as a few buttons or as complex as a full-fledged graphical user interface.

4. Robotics Operating Systems (ROSs): ROSs are the underlying software systems that manage the communication between the human operator and the robot. ROSs provide the necessary infrastructure for HRC, including the ability to transmit and receive information, manage sensor data, and control the robot's movements.
5. Natural Language Processing (NLP): NLP is the technology that allows the human operator to communicate with the robot using natural language, such as speech or text. NLP enables the human operator to interact with the robot in a more intuitive and user-friendly manner.

In conclusion, the current state of hardware for HRC is constantly evolving, with a focus on improving safety, precision, and the quality of HRI. However, there is still much room for improvement, particularly in the areas of safety, usability, and cost-effectiveness. As HRC continues to gain popularity, it is likely that we will see further advancements in the hardware used for this field.

6. Artificial intelligence and machine learning

The key learning mechanisms used by the publications reviewed in this study are briefly discussed in the section that follows. The majority of machine learning (ML) and its applications are based on the three methodologies that have been outlined. Following a brief introduction, examples of several HRC applications in industry that have been documented in literature are used to survey various learning methodologies.

6.1. Supervised learning

Supervised learning is a type of machine learning where the algorithm trains on a labeled dataset, consisting of input/features and their corresponding outputs. The goal of the algorithm is to learn the mapping between inputs and outputs in order to make accurate predictions on new, unseen data. This is achieved by minimizing the difference between the predictions made by the algorithm and the actual outputs in the training data [129].

Convolutional neural networks (CNN) [101,130], decision trees [131], k-nearest neighbors [132], and recurrent neural networks (RNN) [130] are examples of common supervised learning techniques used in digital twins. Data labeling can be an expensive operation in real life. To produce a model with high prediction accuracy, the majority of supervised learning algorithms need a significant amount of labeled data during the training phase. In general, more data are required to give useful conclusions the more complicated the design is. The choice of feature vectors and the precision of labeling affect the outcomes of supervised learning algorithms.

6.2. Unsupervised learning

Unsupervised learning is a type of machine learning where the algorithm trains on an unlabeled dataset, meaning that the desired outputs or "labels" are not known. The goal of unsupervised learning is to identify patterns or structures in the data without the guidance of labeled outputs. This is useful for exploring and understanding complex datasets, as well as for dimensionality reduction and data visualization [133].

Principle-component-analysis (PCA) [134,135], k-means [136], generative adversarial network (GAN) [137], and autoencoders [138] are all clustering algorithms that use unlabeled data at the training stage and are therefore considered to be a form of unsupervised learning. The fact that the number of clusters is frequently unknown a priori presents one of the difficulties in employing unsupervised learning techniques. Euclidean, cosine, and Gaussian distance are the three metrics used in clustering algorithms to evaluate similarity, but it is not always clear which one is the best fit for a particular task.

6.3. Reinforcement learning

Reinforcement learning is a type of machine learning where an agent learns to make decisions by performing actions in an environment and receiving feedback in the form of rewards or penalties. The goal of the agent is to maximize its cumulative reward over time. In reinforcement learning, the learning process is driven by trial-and-error, where the agent learns from its experiences and improves its decision-making strategy over time [139].

To improve the process of making decisions for conveyor systems, box sorting, and other DT scenarios, researchers have implemented algorithms of reinforcement-learning such as Q-learning [140], deep q-learning [141,142]. The accuracy of data logging and the selection of reward structures typically have a significant impact on the effectiveness of a reinforcement learning system. During training, logging to the wrong references could corrupt the data and cause the system to crash.

6.4. Applications of AI/ML in HRC systems

The goal of HRC is realized by the human and robot agents having good communication. Through the exchange of forces, there is explicit and intentional physical involvement in physical HRC. In order to anticipate human intents, the robot measures these pressures and modifies its speed, trajectory, and movements accordingly. No deliberate physical contact is made during contactless collaboration; instead, communication for task coordination is accomplished through direct methods like gestures and vocal commands as well as indirect methods like human motion intention prediction [143].

For direct communication, there are numerous input channels, or modalities, including eye contact, gestures, vocal commands, and facial expressions [144]. Communication is more dependable and the system as a whole is more robust when there are complementary input modes that are human-derived. These inputs provide the robot with signals for the task at hand, allowing it to learn it more quickly or correct itself. For improved HRC and Human prediction, multi-modal fusion has been investigated [145,146]. In a collaborative situation, semantics (labeling items in the robot environment) is a useful input for the robot [147].

1. Hand Gestures: Due to the fact that hand gestures are a common and natural way for people to express themselves and can be distinguished from human poses, they are a powerful and effective form of input from the human operator for a robot in an industrial setting [148]. For a straightforward collaborative assembly activity, the study [149] employing the hand gesture-based robot program builder software MEGURU exceeded the usage of the conventional teach pendant in terms of command simplicity and operating time. The classification of gestures in HRC according to utility is shown in [150]. A framework of the modules needed for the detection and recognition of human gestures is presented in the surveys [151,152].
   Hand gesture recognition has been done using neural networks [153,154], neurofuzzy inference system-based classifiers [155], and [156] scenarios built for HRC. Gesture mapping is the last phase, in which gestures are identified, converted into instructions or feedback, and then communicated to the robot.
2. Voice Command: In the process of learning by demonstration, a human operator performs a task or activity, which the robot then observes and imitates. Natural language commands, according to researchers in [145], would significantly boost the effectiveness of the order to the robot since they are intuitive for the operator while also being able to include complex instructions and parameterizations.
   Using sequence-to-sequence learning, researchers created a novel bidirectional mapping between human motion and natural

language [145]. Mater Motor Map was used to represent the motion of the entire human body in joint space (MMM). The mapping could produce semantically rich and syntactically accurate descriptions of motions that were seen in people, as well as produce distinct motions from descriptions in plain language. Researchers [157] created a semantic multimodal translator for the H2020 FourByThree project that merged gesture- and voice-based requests through a "fusion engine" to provide trustworthy instructions for a cooperative deburring operation. The authors of [158] demonstrated that speech and gesture inputs together had a greater detection rate (91%) than each of the modes alone (56% gesture and 83% voice). HMMs were used to recognize gestures, and SVM was used in the fusion engine to combine modes and categorize inputs.

3. Gaze: When a robot and a human partner are working together on a job, the robot may use clues from the human partner's gaze to help predict their intentions and take turns. This technique is known as visual focus of attention (VFOA). Due to the high cost, intrusive nature, and general lack of natural engagement with eye tracking equipment, it is challenging to detect and analyze eye movements. A method for recognizing gaze is through head posture detection and interpretation using machine vision; for instance, HMMs are used to interpret gaze in a specific situation [159]. A dynamic mapping of gaze used previous head postures.
   While the robot's gaze can be utilized as an input to facilitate collaboration, the opposite was investigated by employing a reinforcement learning (RL) framework based on neural networks to control the robot's gaze in a busy environment where many people are speaking [160].
4. AR/VR: Virtual Reality (VR) and Augmented Reality (AR) technologies have shown great promise in enhancing the control of robots in Human–Robot Collaboration (HRC). In VR-based control, a human operator can wear a VR headset that provides them with a 3D virtual environment [161]. This environment can be used to simulate the manufacturing process, allowing the operator to interact with the robots in a natural and intuitive way. The operator can manipulate objects in the virtual environment, and the movements are transferred to the real-world robot in real-time. AR-based control, on the other hand, involves the use of cameras and sensors that track the operator's movements and provide them with visual feedback through an AR headset. The technology can also be used to overlay useful information, such as instructions, machine settings, and other relevant data, onto the real-world environment. VR/AR-based control of robots in HRC can improve the operator's situational awareness, enhance their ability to control the robot, and reduce the need for complex programming or manual input [162]. This can improve the efficiency and effectiveness of the manufacturing process while reducing the risk of errors or accidents.

7. Integrated synergy of digital twin, collaborative robots, augmentation and AI in industry 5.0

The exploration of integrative synergies in Industry 5.0, as highlighted in the paper, presents a groundbreaking shift in manufacturing paradigms. This shift is not merely technological but fundamentally human-centric, intertwining advanced digital capabilities with a profound respect for human skills, creativity, and ethical considerations.

- Deepening Human–Machine Collaboration The evolution of manufacturing in the Industry 5.0 era is characterized by a nuanced synergy between humans and machines. Unlike previous industrial phases where machines often replaced human labor, Industry 5.0 envisions a collaborative ecosystem. In this setting, machines, especially collaborative robots (cobots), are designed not just to execute tasks but to augment human capabilities. This collaboration goes beyond physical assistance; it encompasses cognitive and creative synergies where human decision-making is enhanced by AI's analytical prowess. This interplay significantly uplifts the production process, making it not only more efficient but also more intuitive and adaptable to human needs and creativity.
- Elevating the Role of Humans in Technological Narratives A central tenet of Industry 5.0 is its emphasis on human involvement and experience in technological narratives. The approach diverges from viewing technology as a standalone driver of progress to seeing it as a tool that must serve and enhance human potential. In this context, humans are not passive recipients of technological innovation but active participants and shapers of technological ecosystems. This human-centric focus ensures that technological advancements align with enhancing the quality of life, work satisfaction, and overall wellbeing, thereby fostering an inclusive and sustainable industrial future.
- Bridging Digital and Physical Realms through Digital Twins Digital twins represent a cornerstone technology in realizing these synergies. By creating dynamic virtual models of physical systems, digital twins enable a deep understanding of complex manufacturing processes. This understanding is crucial for optimizing human–robot interactions, facilitating predictive maintenance, and enhancing overall system resilience. Digital twins serve as a bridge between the digital and physical worlds, offering a platform where human workers can interact with complex data and simulations in a user-friendly manner, thus democratizing access to advanced technological insights.
- Sustainable and Ethical Considerations The integrative approach of Industry 5.0 also firmly embeds sustainability and ethics into the manufacturing process. By leveraging smart technologies and AI, this new industrial model seeks to minimize environmental impacts, promote resource efficiency, and support circular economy principles. This approach extends beyond environmental considerations to encompass ethical manufacturing practices, ensuring fair labor practices and prioritizing the wellbeing of workers. Such an approach not only aligns with global sustainability goals but also enhances the social license to operate for businesses in a world increasingly conscious of environmental and ethical issues.
- Dynamic Adaptability to Emerging Challenges The dynamic nature of Industry 5.0, underpinned by its integrative synergies, positions the manufacturing sector to rapidly adapt to changing global challenges, market demands, and consumer preferences. This adaptability is essential in an era of rapid technological change and global uncertainties. The fusion of human creativity with machine efficiency creates a manufacturing landscape that is not only resilient but also capable of innovating and responding to new challenges and opportunities with agility.

8. Discussion and future directions

Smart manufacturing involves the integration of advanced technologies to optimize the manufacturing process. Digital twin, HRC, and machine learning are key technologies in industry 5.0 that can contribute to the realization of smart manufacturing. When these technologies are combined, they create a powerful synergy that can enhance manufacturing operations in a number of ways.

Digital twin technology involves the creation of a virtual replica of a physical product, system, or process. This technology allows manufacturers to simulate and optimize the performance of their products and processes in a virtual environment. By creating a digital twin of a manufacturing system, manufacturers can monitor and control the system's performance, predict potential issues, and optimize the system's efficiency. In addition, digital twin technology can be used to create virtual models of products, which can be used for testing and validation before physical prototypes are produced.

HRC involves the integration of robots into the manufacturing process, while working alongside human workers. This collaboration can enhance the efficiency, safety, and quality of manufacturing operations. Robots can handle repetitive and dangerous tasks, freeing up human workers to focus on more complex and creative tasks. In addition, robots can work in hazardous environments, reducing the risk of workplace injuries. HRC can also increase productivity, as robots can work continuously without the need for breaks.

Industry 5.0 is a manufacturing paradigm that emphasizes the integration of advanced technologies with human workers. This paradigm aims to enhance the capabilities of human workers, while leveraging the power of advanced technologies. Industry 5.0 emphasizes the importance of human skills, such as creativity, problem-solving, and decision-making, in the manufacturing process. This paradigm involves the use of advanced technologies, such as robotics, artificial intelligence, and the Internet of Things (IoT), to enhance the productivity, quality, and efficiency of manufacturing operations.

Machine learning is a subset of artificial intelligence that involves the development of algorithms that can learn from data and improve their performance over time. Machine learning can be used in the manufacturing process to optimize operations, reduce waste, and improve quality. Machine learning algorithms can analyze data from sensors and other sources to identify patterns and anomalies in the manufacturing process. This information can be used to optimize the performance of machines, predict maintenance needs, and reduce downtime.

The synergy of these technologies in smart manufacturing can produce a number of benefits. By using digital twin technology, manufacturers can simulate and optimize their processes before they are implemented, reducing the risk of costly mistakes. HRC can enhance the efficiency and safety of manufacturing operations, while Industry 5.0 can leverage the skills and expertise of human workers to improve the performance of advanced technologies. Machine learning can optimize the manufacturing process by identifying patterns and anomalies that can be used to improve efficiency and quality.

8.1. Benefits

The synergy of the digital twin, HRC, and machine learning in industry 5.0 can offer numerous benefits to smart manufacturing. Here are some ways in which this synergy can be useful:

1. Optimize Manufacturing Operations: By using digital twin technology, manufacturers can simulate and optimize their processes before they are implemented. This allows them to identify potential issues, and test different scenarios without risking the costly mistakes that might occur in a physical environment. This can help manufacturers improve the efficiency and productivity of their processes, and minimize errors and rework.
2. Improve Quality: Machine learning algorithms can be used to analyze data from sensors and other sources to identify patterns and anomalies in the manufacturing process. This information can be used to optimize the performance of machines, predict maintenance needs, and reduce downtime. The use of digital twin technology can also help manufacturers identify potential quality issues early on, allowing them to take corrective actions to prevent defects and improve overall product quality.
3. Enhance Safety: HRC can help reduce the risk of workplace injuries by allowing robots to handle repetitive and hazardous tasks. This can free up human workers to focus on more complex and creative tasks that require human expertise. By integrating safety protocols and sensors, robots can work safely alongside human workers, reducing the risk of accidents and injuries.
4. Improve Productivity: By combining the power of advanced technologies with the skills and expertise of human workers, Industry 5.0 can help manufacturers improve their productivity. Human workers can leverage their skills in creativity, problem-solving, and decision-making to work alongside robots and optimize manufacturing operations. This can increase throughput, reduce lead times, and lower costs.
5. Predictive Maintenance: The use of machine learning algorithms in conjunction with sensors can help predict when maintenance will be required for machines. This can help to reduce downtime and improve the efficiency of the manufacturing process. The information obtained from predictive maintenance can be used to optimize the performance of machines, predict maintenance needs, and reduce downtime.
6. Continuous Improvement: The combination of digital twin technology, Industry 5.0, and machine learning can help manufacturers achieve continuous improvement in their manufacturing processes. By analyzing data from sensors and other sources, machine learning algorithms can identify areas of the process that can be optimized. These optimizations can then be implemented in the digital twin, and the resulting improvements can be tested and validated before they are implemented in the physical manufacturing process.

8.2. Challenges

While the synergy of digital twin, HRC, and machine learning in industry 5.0 offers many benefits for smart manufacturing, there are also some challenges that need to be addressed. Here are some of the challenges that manufacturers may face when implementing these technologies:

1. Data Security: The use of digital twin technology, machine learning, and Industry 5.0 involves the collection and storage of large amounts of sensitive data. Manufacturers must ensure that the data is properly secured and protected from unauthorized access or cyber-attacks.
2. Integration: Integrating these technologies with existing manufacturing processes and systems can be challenging. This may require significant changes to the manufacturing processes, hardware, and software.
3. High Initial Investment: The initial investment required to implement these technologies can be significant. This can be a major hurdle for small and medium-sized manufacturers who may not have the financial resources to make such investments.
4. Skill Gaps: The successful implementation of these technologies requires skilled professionals who can operate and maintain the systems. However, there is a shortage of skilled workers in these areas, and the cost of hiring and training such personnel can be high.
5. Standardization: As these technologies are still relatively new, there is a lack of standardization in terms of data formats, protocols, and interfaces. This can make it difficult to integrate different systems and technologies.
6. Ethical Considerations: The use of robotics in the workplace raises ethical considerations, such as job displacement, and the need to protect human workers from accidents and injuries. These issues must be addressed to ensure that the implementation of these technologies is socially responsible.
7. Resistance to Change: The introduction of new technologies can meet resistance from workers who are used to traditional ways of working. Workers may feel threatened by the prospect of automation and may require significant training to adapt to the new technologies.

8.2.1. Data security

In the context of Industry 5.0, the challenge of data security is multifaceted, given the extensive collection, transmission, and storage of sensitive information associated with digital twin technology, human–robot collaboration (HRC), and machine learning. The sheer volume of data, encompassing proprietary manufacturing processes, product designs, and operational parameters, presents a substantial risk if not adequately protected. Unauthorized access, cyber-attacks, and breaches could lead to severe consequences, including intellectual property theft and operational disruptions.

The solution to this challenge involves a comprehensive and proactive approach. Robust encryption mechanisms must be implemented to safeguard data both in transit and at rest, complemented by strict access controls that restrict data access to authorized personnel based on their roles. Network security measures, including firewalls and intrusion detection systems, are critical to monitor and secure communication channels. Regular security audits and vulnerability assessments are imperative, accompanied by timely application of security patches and updates. Employee training on cybersecurity best practices is vital, emphasizing secure password management and recognition of phishing attempts. Additionally, having a well-defined incident response plan ensures a swift and effective response in case of a security breach. Data backups, secure third-party collaborations, regulatory compliance, continuous monitoring, and fostering a security culture within the organization further contribute to a robust data security framework. Embracing these measures collectively establishes a resilient defense against potential threats and aligns with the evolving landscape of technological advancements and regulatory requirements.

8.2.2. Integration

The integration challenge in the Industry 5.0 landscape arises from the necessity to harmonize digital twin technology, human–robot collaboration (HRC), and machine learning with existing manufacturing processes and systems. This complexity stems from the diverse nature of these technologies, each with its unique requirements and interfaces. The risk lies in the potential disruption of established workflows and the need for substantial changes in hardware, software, and operational procedures. The solution to the integration challenge demands a meticulous and phased approach. First and foremost, manufacturers should develop a well-thought-out integration plan that outlines the step-by-step incorporation of new technologies. Collaboration with technology providers and experts is essential to ensure a seamless integration process. This might involve the deployment of modular solutions that allow incremental changes, reducing the overall impact on operations.

Moreover, organizations should invest in comprehensive training programs for their workforce to facilitate a smooth transition. Training initiatives should encompass both technical aspects, ensuring that employees can operate new technologies effectively, and soft skills to manage the cultural shift associated with technological adoption. Continuous communication and feedback loops between management and employees are crucial to address concerns and facilitate a collaborative approach to change. Considering the potential financial burden of integrating these technologies, manufacturers can explore phased implementation strategies to manage costs. This involves prioritizing critical components and gradually expanding integration efforts over time. Government incentives and funding opportunities may also alleviate the financial strain, particularly for smaller manufacturers. Ultimately, successful integration requires a holistic perspective that considers not only the technical aspects but also the organizational culture and human factors. By strategically planning, collaborating with experts, investing in training, and adopting a phased implementation approach, manufacturers can overcome the integration challenge and unlock the full potential of Industry 5.0 technologies.

8.2.3. High initial investment

The high initial investment required for the implementation of digital twin technology, human–robot collaboration (HRC), and machine learning in Industry 5.0 poses a significant hurdle for manufacturers, especially for small and medium-sized enterprises (SMEs) with limited financial resources. The comprehensive nature of these technologies, involving hardware, software, training, and infrastructure upgrades, can strain budgets and deter potential adopters. To address this challenge, manufacturers can explore several strategic approaches. Firstly, careful financial planning and analysis are essential. This includes conducting a thorough cost–benefit analysis to identify areas where the initial investment can yield the most significant returns. Prioritizing technology adoption based on immediate business needs and long-term strategic goals allows for a phased implementation, reducing the immediate financial burden.

Collaboration with government agencies, industry consortia, and research institutions can provide access to funding, grants, and incentives aimed at promoting the adoption of advanced manufacturing technologies. Governments often recognize the importance of technological innovation in boosting economic growth and may offer financial support to organizations embracing Industry 5.0 initiatives. Additionally, manufacturers can consider alternative financing models, such as leasing or partnerships with technology providers. Leasing allows organizations to access the latest technologies without the burden of outright purchases, spreading costs over time. Partnerships with technology vendors can involve shared investments, with the vendor having a stake in the successful implementation of their solutions. Furthermore, fostering a culture of innovation within the organization can encourage employees to contribute ideas for cost-saving measures and efficiency improvements. Incentivizing innovation and efficiency gains can result in creative solutions that reduce the overall financial impact of adopting Industry 5.0 technologies.

8.2.4. Skill gaps

The challenge of skills gaps in the context of implementing digital twin technology, human–robot collaboration (HRC), and machine learning within Industry 5.0 is a critical concern. The successful deployment of these technologies necessitates a workforce equipped with specialized skills in data science, artificial intelligence, robotics, and advanced manufacturing. However, there is a notable shortage of professionals with expertise in these areas, presenting a barrier to effective implementation. To address the skills gaps challenge, proactive measures are essential. First and foremost, organizations should invest in comprehensive training programs for existing employees. This includes upskilling initiatives to enhance the proficiency of the current workforce in emerging technologies. Collaborating with educational institutions and training providers can facilitate tailored programs that align with the specific needs of the industry.

In addition to upskilling, organizations should focus on attracting new talent with the required expertise. This involves reevaluating recruitment strategies to identify candidates with backgrounds in data science, artificial intelligence, and robotics. Offering competitive salaries, benefits, and a stimulating work environment can make manufacturing industries more appealing to skilled professionals. Furthermore, fostering a culture of continuous learning within the organization is crucial. Encouraging employees to engage in ongoing professional development, attend workshops, and pursue relevant certifications ensures that the workforce remains adaptable to evolving technological landscapes. Partnerships with academic institutions, research organizations, and industry consortia can facilitate the development of specialized training programs. These partnerships not only provide access to a pool of skilled individuals but also contribute to the overall growth and development of the industry.

8.2.5. Standardization

The challenge of standardization in the integration of digital twin technology, human–robot collaboration (HRC), and machine learning within Industry 5.0 is a pivotal concern. The lack of uniformity in data formats, communication protocols, and interfaces hinders interoperability between various systems and technologies. This fragmentation can lead to inefficiencies, increased development complexity, and obstacles in achieving seamless connectivity across the manufacturing ecosystem. To overcome the standardization challenge, industry stakeholders must collectively work towards establishing common frameworks and guidelines. Engaging in collaborative efforts with industry associations, standardization bodies, and technology consortiums can pave the way for the development of universally accepted standards. These standards should address data formats, communication protocols, and interfaces, ensuring compatibility and ease of integration between different technologies and systems.

Furthermore, industry leaders and organizations can actively participate in the standardization process. Sharing insights, best practices, and lessons learned from practical implementations contribute to the formulation of standards that are both practical and effective. Advocating for the adoption of these standards within the industry helps create a common language for technology integration. The establishment of open standards encourages innovation and competition while mitigating the risks associated with proprietary solutions. Manufacturers should prioritize technologies that adhere to or contribute to established standards, fostering an ecosystem where diverse solutions can seamlessly coexist. Continuous monitoring and adaptation are essential as technology evolves. Regular reviews and updates of standards ensure they remain relevant and effective in addressing emerging challenges. As technologies advance, industry stakeholders should actively contribute to the evolution of standards, ensuring they keep pace with the dynamic nature of the Industry 5.0 landscape.

8.2.6. Ethical considerations

In the era of Industry 5.0, the seamless integration of digital twin technology, human–robot collaboration (HRC), and machine learning brings forth a set of ethical considerations that demand careful navigation. The foremost challenge revolves around the potential job displacement caused by increased automation. This raises concerns about job insecurity and economic disparities. Simultaneously, the deployment of robots and autonomous systems introduces safety risks in the workplace, necessitating thoughtful strategies to prevent accidents and injuries. To address these challenges, organizations must invest in reskilling programs, ensuring employees acquire competencies that complement and enhance automated processes. Additionally, stringent safety protocols and risk assessments are paramount to safeguard human workers. Another ethical concern arises from the extensive use of data in Industry 5.0, prompting questions about privacy, consent, and responsible data handling. Robust data governance frameworks and privacy policies are essential, emphasizing transparency in data collection, storage, and usage. Employing anonymization and encryption techniques ensures the ethical treatment of sensitive information, aligning with data protection regulations such as GDPR.

In terms of social responsibility, organizations must consider the broader societal impact of their actions. This involves addressing worries related to income inequality, access to opportunities, and the ethical deployment of advanced technologies in different communities. Adopting ethical frameworks prioritizing fairness, transparency, and accountability is crucial. Engaging with local communities and seeking diverse stakeholder input ensures that technological deployment aligns with societal values and needs. Transparency and explainability in decision-making processes of machine learning systems present another challenge. The opacity of advanced algorithms raises concerns about accountability. Therefore, prioritizing explainable AI models and transparent practices in algorithmic decision-making enhances accountability and builds trust among employees and the public.

8.2.7. Resistance to change

A significant challenge in the implementation of digital twin technology, human–robot collaboration (HRC), and machine learning within Industry 5.0 is the resistance to change that often manifests among the workforce. The introduction of these new technologies disrupts familiar workflows, instilling apprehension and fear of job displacement among employees. To address this challenge, organizations need a multifaceted approach to change management. Clear and inclusive communication is paramount, elucidating the rationale behind the technological shift, outlining the associated benefits, and assuring employees of the support mechanisms in place. Actively involving employees in decision-making and seeking their input fosters a sense of ownership and diminishes resistance. Additionally, comprehensive training programs are essential to equip the workforce with the necessary skills, addressing concerns related to unfamiliarity and uncertainties about adaptation. A focus on not just technical aspects but also the broader implications of the changes helps bridge the skills gap and mitigate resistance. The organizational culture plays a pivotal role, and leadership must cultivate an environment that values innovation, experimentation, and staying at the forefront of technological advancements. By implementing changes gradually, through phased strategies, and incorporating feedback mechanisms, organizations can create an environment where employees feel empowered, valued, and motivated to embrace the transformative technologies associated with Industry 5.0.

8.3. Future directions

This paper provides a strong foundation for advancing research and exploration into the possibilities and application areas of Industry 5.0 technologies. However, there remain open questions and challenges that warrant further investigation. On the data security front, future work can involve designing comprehensive governance frameworks addressing the volume and velocity of data associated with digital twins, cobots, and AI systems. Encryption mechanisms tailored for manufacturing data need to be developed, along with access controls, employee training, and prompt security updates. Additionally, overcoming integration complexities across legacy equipment, emerging modular solutions, proprietary systems, and standardized protocols requires a concerted focus. Research into plug-and-play architectures, extensible APIs, and adaptable interfaces can aid integration. Collaboration with industrial consortia is key for harmonizing standards central to interoperability.

Regarding the skills gap, nuanced workforce development initiatives through public–private partnerships are imperative. Navigating job transitions and advancing digital/technical literacy via immersive training environments can alleviate displacement risks and widen talent pools. Supporting reskilling/upskilling needs of incumbent workforces is equally essential. Moreover, ethical dimensions regarding human–AI trust, algorithmic accountability, and collaborative autonomy necessitate further analysis. As machine intelligence intensifies, maintaining holistic wellbeing of human partners emerges as a priority. Exploring the adjustable autonomy spectrum and human-centered ML can unlock symbiotic potentials. Additionally, emerging capabilities in augmented environments, wearable interfaces, and visualization technologies present promising opportunities. Virtual simulations, digital workflows, multi-modal interactions, and AR/VR spaces can elevate human creativity and oversight across production cycles. Capitalizing on these areas can smoothen Industry 5.0 transformations.

9. Conclusions

In this work, a systematic review was presented which explores the synergies between collaborative robots, digital twins, augmentation, and industry 5.0 for smart manufacturing. To the best of the author's knowledge, this is the first attempt in the literature to give a full overview of the symbiosis between Industry 5.0's different components.

First, a detailed review was outlined on HRC which includes the complexities of manufacturing, collaborative robots, barriers of HRC systems, the complexity of HRC systems, and how digital twin will address these complexities. After that, industry 5.0 was discussed in detail. A detailed review was presented of applications in Industry 5.0 and enabling technologies of Industry 5.0. In the next step, a review was discussed on the digital twin-driven HRC system with phases, fundamental blocks, and software for digital twin-based HRC systems. Also, a review of the control methods of HRC was given.

Successively, a state-of-the-art review was presented on the hardware requirements for the accomplishment of HRC systems. These hardware requirements include manipulators, wearables, sensors, and human–robot interfaces. After that, a detailed review of artificial intelligence and machine learning in HRC was provided. Finally, a discussion on the benefits and challenges was provided. In particular, the potential benefits of these technologies include improved efficiency, productivity, and cooperation, as well as an increased product quality and personalized customization. Nevertheless, implementing Industry 5.0 poses difficulties, such as the need for upskilling and reskilling of the workforce, cybersecurity issues, and ethical questions related to the use of AI and robotics. Overall, the human-centered approach of Industry 5.0 presents a potential route towards a sustainable and inclusive manufacturing future. Future research may expand on the insights offered in this analysis to better investigate the possibilities of Industry 5.0 and solve the challenges that may occur during its implementation. This study aims at broadening worldwide efforts to realize the wide range of application possibilities given by Industry 5.0, as well as to provide an up-to-date reference as a cornerstone for future research and development in this domain.

CRediT authorship contribution statement

Muhammad Hamza Zafar: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. **Even Falkenberg Langås:** Investigation, Resources, Software, Writing – original draft, Writing – review & editing. **Filippo Sanfilippo:** Funding acquisition, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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All authors claim that there is not any conflict of interest regarding the above submission. The work of this submission has not been published previously. It is not under consideration for publication elsewhere. Its publication is approved by all authors and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

Data availability

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

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