

Review

Exploring tasks and challenges in human-robot collaborative systems:
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ABSTRACT

This paper presents an in-depth exploration of Human-Robot Collaborative Systems (HRCs) within industrial environments, a dynamic field that has witnessed significant advancements due to technological innovation and the increasing integration of Artificial Intelligence (AI). As industries evolve towards more collaborative and adaptive manufacturing systems, the dynamic interaction between humans and robots becomes pivotal. This study reviews the current state of HRCs, focusing on the challenges of task allocation and skill alignment, safety, trust, and the psychological wellbeing of human workers. We review control strategies and architectural frameworks that underpin effective human-robot interactions (HRI), emphasising the critical role of AI in enhancing decision-making processes and the adaptability of collaborative efforts. Our review sheds light on the complexities involved in designing HRCs that are not only efficient but also cognisant of the human experience, advocating for a balanced approach that leverages the strengths of both human and robotic counterparts. We argue that research in and implications of HRCs should extend beyond technical considerations, touching on ethical, social, and organisational dimensions, thereby contributing to the broader discourse on the future of work in the era of Industry 4.0 and future Industry 5.0.

1. Introduction

In recent years, we have witnessed a rapid advancement in digital technology and robotics, signifying the advent of what has been coined as Industry 4.0 (I4.0) [1]. This fourth industrial revolution is reshaping traditional industries, transforming not only the processes and systems but also the very essence of work, communication, and our relationship with technology [2]. I4.0 is characterised by a pervasive digital transformation that encompasses various technologies such as Machine Learning (ML)/Artificial Intelligence (AI), Cyber-Physical Systems, Internet of Things (IoT), and Big Data Analytics [1]. These innovations are particularly evident in the manufacturing sector, where the surge in automation and robotics is driving a paradigm shift in workspace design and operational efficiency.

A significant development in industrial automation is the emergence of collaborative robots, or *cobots* [3]. Unlike traditional industrial robots - typically confined to isolated environments for mass production - collaborative robots are manufactured to operate safely alongside

human workers in shared workspaces. They are particularly suited for taking over repetitive, ergonomically hazardous tasks, while accommodating varying batch sizes, and fulfilling specific production requirements [4–6]. Critically, their operational agility - manifested in the ability to adjust to diverse workstation environments and shifting manufacturing needs - has become essential for sustaining competitiveness in dynamic industrial contexts [7,8].

In this evolving landscape, the integration of collaborative applications on the shop floor—and the potential for effective human-robot collaboration—has become a key driver of modern manufacturing processes. Collaboration, in this context, refers to the process where humans and collaborative robots work together within the same workspace, interacting symbiotically to achieve common goals [9]. However, this vision remains largely aspirational. In current manufacturing settings, human–robot interaction often falls short of true collaboration. In many cases, collaborative robots are deployed in separate areas, performing tasks independently from human workers. These typically include material handling, pick-and-place operations, packaging, and palletising

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[10]. Another work configuration includes that where cobots are integrated into sequential workflows—such as those found in automotive assembly lines [10]—executing predefined tasks that increase efficiency and precision, while maintaining a clear division of labour. More advanced forms of collaboration, where robots and human workers engage in joint problem-solving or dynamic task sharing—such as a robot anticipating and delivering tools in response to human actions—remain rare in practice in manufacturing settings [11]. Ultimately, the chosen work configuration carries significant implications for task design, safety protocols, and the role of human workers—making the selection of the collaborative setup a critical decision, closely tied to the specific requirements and constraints of the industrial application [12].

One key limitation lies in the current state of technology readiness. While advances in embodied intelligence have improved robot perception and responsiveness, the capacity to reason, anticipate human intent, and adapt to dynamically changing environments still remains limited. Some argue that achieving such capabilities borders on the realm of general artificial intelligence [13]—an ambitious objective that is unlikely to be realised in the near future. Moreover, collaborative applications within manufacturing have only been widely introduced in the past 10 to 15 years [14], and many organisations are still navigating a steep learning curve. Understanding how to fully exploit the potential of human-robot collaborative systems (HRCs) requires not just technological investment, but organisational adaptation. Currently, cobots are primarily deployed in tasks that mirror those previously carried out by humans—a “remove and replace” strategy [10]—rather than being integrated in ways that leverage their unique affordances for enhancing human capabilities or enabling new forms of work in HRCs.

Looking ahead, the integration of collaborative robots in manufacturing environments is expected to expand, and with it, so too will the emphasis on refining the quality and depth of interaction between humans and robots on the shop floor [8,15]. To enable and support such developments, early consideration of the social, ethical, and human factors challenges must become a strategic imperative. This consideration aligns with the principles set forth by the European Commission under the Industry 5.0 framework [16,17], which advocates for a more human-centric model of industrial transformation. It also represents a necessary counterbalance to the technology-driven focus that has characterised Industry 4.0—reasserting the central role of humans in shaping the future of industrial work [18].

In this regard, questions concerning the future of work and the role of human contribution are central to ongoing debates in the field. While a portion of the literature portrays human workers as passive recipients of technological change—primarily in need of reskilling and vulnerable to redeployment or job displacement [19]—a parallel and increasingly prominent body of research highlights their critical value in unlocking the full potential of industrial transformation [20–22]. While many industrial jobs will be impacted by automation—particularly through smart, intelligence-powered robotic systems capable of greater autonomy and adaptability—there is growing consensus that full automation of manufacturing processes remains unlikely. Instead, only specific tasks are expected to be automated, with others continuing to depend on human expertise [2]. In this view, human workers are not merely adapting to automation but actively shaping its implementation, as they bring resilience, contextual and tacit knowledge, and the capacity to manage production variability, perform troubleshooting, and facilitate the effective deployment of robots [23,24]. However, neglecting their role and contributions risks undermining the effectiveness, sustainability, and ethical grounding of future human-robot industrial systems.

Additional key enablers towards human-robot collaboration include safety, control strategies, and architectural frameworks. Safety is a multifaceted concept and a paramount concern. It involves deploying advanced sensors, emergency stop mechanisms, and intuitive interfaces that allow collaborative robots to operate safely alongside humans [25]. However, safety also encompasses the subjective perception of safety by

human workers. For example, considerations include whether human workers feel safe working alongside collaborative robots, particularly in scenarios where collaborative robots handle objects that could potentially cause physical harm to the human operator. Strategies to increase the subjective perception of safety may reduce the risk of accidents and ensure safe operation in HRCs. Moreover, the psychological impact of novel human-robot work dynamic requires careful analysis. Factors such as trust, robot acceptance, human autonomy and agency, and overall psychological wellbeing are under scrutiny [22,26,27].

Control strategies in HRCs go beyond traditional robotic programming by embracing flexibility and adaptability, enabling robots to interpret and respond to human actions in real-time. This dynamic interaction enhances efficiency by leveraging the strengths of both humans and robots [28,29]. At the core of these control strategies lies the ability to achieve responsive, safe, and adaptive interaction through techniques such as impedance control, shared autonomy, and real-time intent recognition, which are essential for enabling seamless human-robot collaboration in dynamic industrial settings. Additionally, the architectural framework of human-robot systems plays a crucial role in ensuring that collaborative efforts are harmonised, scalable, and resilient to evolving production demands [4]. The architectural framework serves as a key enabler by providing a modular, layered structure that integrates perception, control, and actuation, allowing seamless coordination between humans and robots. Its adaptability and scalability make it essential for deploying flexible, responsive HRCs that can evolve with changing industrial demands.

It is anticipating such future developments that this paper focuses on. With this work, we aim to propose a comprehensive HRCs framework as a conceptual tool that integrates safety, design challenges, and enabling technologies, motivated by practical applications in various industrial contexts. This is further outlined in the next Section 2. It is important to note that while a robust architectural framework is a foundational enabler for effective human-robot collaboration, the aim of this paper extends beyond merely proposing such a framework. Instead, it seeks to synthesise the broader spectrum of enablers, design challenges, safety standards, and human factors that collectively influence HRC development, thereby situating the proposed architecture within a holistic understanding of what is required to design collaborative systems that are not only technically sound and efficient, but also safe, compliant with standards, and well-aligned with human needs and expectations.

2. HRCs conceptual framework

Our framework adopts an integrated approach that combines technology-driven interventions, legal and regulatory standards, and a human-centric, bottom-up perspective. This framework is illustrated in Fig. 1.

Critically, the foundation of this framework is rooted in a stringent adherence to international safety standards, particularly within the safety dimension of human-robot collaborative environments. ISO standards such as ISO 12,100, ISO/TS 15,066, and ISO 10,218 are pivotal in guiding risk assessment, design, and implementation processes, ensuring that collaborative robots operate safely alongside human workers.

The model further addresses the core design challenges inherent in HRCs, such as ergonomic workspace design, task allocation, workers’ psychological safety, and the challenge of trusting collaborative robots. In this systems, collaborative robots are deployed to complement, rather than replace, human workers. The human operator retains control and focuses on the cognitive aspects of production, while collaborative robots handle physically demanding tasks, reducing the risk of work-related musculoskeletal disorders (WMSD) and enhancing overall workplace safety [28,30] (Black and Neumann, 2021). These aspects are critical to creating environments that are not only physically safe but also supportive of cognitive and emotional wellbeing, thereby fostering

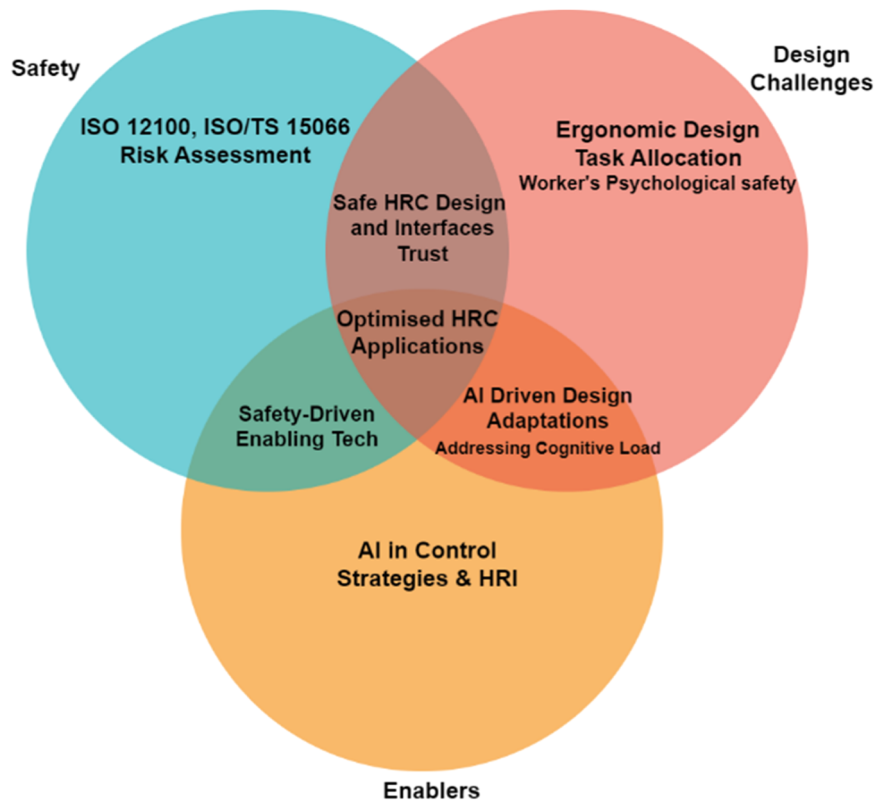


Fig. 1. HRCs Conceptual Framework.

a work environment conducive to trust and cooperation.

Enabling technologies, particularly those driven by AI, play a critical role in this framework. The integration of AI into HRCs enhances perception, decision-making, and adaptability, enabling collaborative robots to interact dynamically with human workers in real-time. This synergy between AI and robotic systems with human workers not only optimises task performance but also maintains a high standard of safety and efficiency.

As a conceptual foundation for the proposed HRCs framework, we invoke the emerging Industry 5.0 paradigm introduced by the European Commission, which emphasizes a transition to a more sustainable, human-centric, and resilient industrial model [31]. Industry 5.0 complements the tech-centric Industry 4.0 era by shifting focus from shareholder value to stakeholder value, placing worker well-being at the center of production while leveraging new technologies for broad societal benefit beyond mere productivity gains. In essence, it calls for integrating sustainability, resilience, and human-centricity into industrial value creation [32] – a holistic orientation that aligns technological innovation with societal needs and environmental stewardship.

Aligned with these principles, Industry 5.0 advocates a harmonious integration of smart technologies with human capabilities in pursuit of its human-centric and sustainable goals. Unlike the automation-centric ethos of Industry 4.0, the Industry 5.0 approach prioritizes human-machine collaboration, with advanced technologies augmenting human labor rather than replacing it. This paradigm leverages the respective strengths of humans (creativity, problem-solving) and intelligent machines (precision, data processing) to foster synergistic work environments that boost productivity while safeguarding worker well-being and promoting sustainable practices.

In essence, framework is characterized by a layered and modular structure that tightly orchestrates the system's perception, control, and actuation components into a cohesive whole. At the lower levels, sensor and perception modules continuously capture real-time data about the environment and human partner actions, feeding this information to

higher-level decision or control layers that interpret the context and generate appropriate robot responses; these commands are then carried out by actuation modules at the execution layer. This design establishes a continuous, low-latency data flow from observation to action, enabling the human and robot to work in synchrony and respond swiftly to each other's changes. The modular nature of the architecture not only fosters clear separation of concerns (each layer or module handles a specific set of functions) but also provides significant adaptability and scalability in dynamic industrial contexts. New sensors, algorithms, or even additional robots and tasks can be integrated as interchangeable modules with minimal reengineering, allowing the system to be reconfigured or expanded to accommodate changing production requirements while maintaining stable performance and coordinated human-robot workflows.

The subsequent sections of this paper provide a detailed exploration of each element of the framework. [Section 3](#) delves into the safety standards and protocols essential for HRC, offering a comprehensive overview of the ISO standards relevant to collaborative robotics. [Section 4](#) examines the design challenges associated with HRCs, including the considerations for creating safe and ergonomic workspaces, addressing task complexity, and ensuring psychological safety. [Section 5](#) focuses on the enablers of HRCs, such as control strategies, AI integration, and architectural frameworks that support seamless HRI. Finally, [Section 6](#) presents practical applications of HRCs, followed by an exhaustive discussion and conclusion in [Section 7](#), synthesising key insights and implications for future research and industry practices.

3. Safety

3.1. Safety standards

In HRCs, robot safety is indeed an important consideration in the design and operation of robotic systems. There are several factors which are essential to prioritise physical safety, implement systematic safety

measures, strengthen cybersecurity, ensure safe HRI, and conduct thorough risk assessments to achieve optimal robot safety.

This section will review the safety standards in the field of robotics and automation, which are used to guide the process of robot design and operation.

Type A basic safety standards: These standards provide general requirements that apply to all machinery, including robotics systems, and are intended to protect against the most significant hazards that can arise during the operation of machinery [33]. It typically covers topics such as the design and construction of machinery, the use of guards and protective devices, and the provision of safety signs and labels. Examples of Type A basic safety standards include ISO 12100 and ISO 14121.

Type B generic safety standards: These standards provide more specific requirements for the safety of machinery and control systems and are typically based on the principles and requirements outlined in the Type A basic safety standards. These standards may be developed for specific types of machinery or industries and provide a higher level of safety protection. These standards are typically developed by industry-specific organisations or committees and are based on the specific risks and hazards associated with a particular type of machinery [33, 34]. They may include requirements for the design and construction of the machinery, as well as requirements for the use and maintenance of the machinery or industries. They are further divided into B1 and B2 sub-category, B1 address specific safety aspect whereas B2 covers safety aspect of safeguarding and provide specific requirements for the safety of conveyors and human-machine interfaces, respectively. Examples include ISO 13849 and IEC 61508 [33].

Type C machine safety standards: These standards may be specific to a particular model or make of robot or robotic device. These standards provide detailed requirements for the safety of a particular robot or robotic device and may include requirements for design, construction, use, and maintenance. These standards are intended to be used in conjunction with Type A basic safety standards and Type B generic safety standards to provide a higher level of safety protection for specific models or makes of machinery. These standards for robotics are typically developed by the manufacturer of the robot or robotic device and are based on the specific risks and hazards associated with that particular model or make of machinery. They may include requirements for the design and construction of the robot or robotic device, as well as requirements for the use and maintenance of the machinery. Examples of Type C machine safety standards include ISO 13849 (safety of machinery control systems or specific models of industrial robots) and IEC 61508 (functional safety of electrical/electronic/programmable electronic safety-related systems) [33,34].

In addition to these, there are several categories of safety standards that are commonly used in the field of robotics: Functional safety standards: These standards focus on the safe operation of a system, including the safe performance of functions and the prevention of accidents. Examples include ISO 13849 and IEC 62061. Safety-related control systems standards: These standards focus on the design and construction of safety-related control systems, including the use of safety-related sensors and actuators. Examples include ISO 13849 and IEC 61508. HRI standards: These standards focus on the design and operation of robots in the presence of humans, including the safe physical interaction between humans and robots. Examples include ISO 10218 and ISO/TS 15066 (these are introduced in the next section). Safety of machinery standards: These standards focus on the design and construction of machinery, including the use of safety-related control systems. Examples include ISO 12100 and ISO 14121. Cybersecurity standards: These standards focus on the protection of automation systems from cyber-attacks and the maintenance of system integrity. Examples include ISO/IEC 62443 and NIST 800-82 [34–36].

There are various safety standards developed by International Organization for Standardization (ISO) or and IEC (International Electrotechnical Commission) that apply to robotics, depending on the specific industry and application of the robotics technology. Some common

standards falling under type A, type B and type C safety standards for robotics safety (Table 1).

It is important for manufacturers and users of robotics technology to be aware of and adhere to the relevant safety standards to ensure the safe operation of their robotics systems. There are several types of safety standards that are commonly used in the field of robotics Collaborative Robot Operations.

Collaborative robots are designed to work alongside humans in a shared workspace. There are four main types of Safety control modes in HRCs systems (Table 2):

The existing safety standards for HRCs, such as ISO 10218, ISO/TS 15066, and IEC 61508, interact with each other in ways that can sometimes create challenges for seamless implementation [11]. While these standards provide a comprehensive framework for ensuring safety in robotics, their overlap, particularly between Type B and Type C standards, can lead to redundancies and confusion over which requirements take precedence. There are significant overlaps between Type B and Type C standards in safety-related control systems, protective measures, risk assessment, and human-machine interfaces. These overlaps can cause duplication in safety assessments, conflicts in implementation, and confusion over which standards to prioritise, leading to potential inefficiencies in the safety validation process [37].

Additionally, the sequential application of these standards, where general principles are first established before moving to specific machine requirements, may not adequately address the dynamic nature of modern robotics, especially when AI is involved [38]. Traditional regulatory mechanisms struggle to keep pace with the dynamic nature of AI systems, necessitating new approaches to ensure safe and ethical deployment. This creates a need for more integrated and adaptive frameworks that can accommodate the continuous real-time safety assessments required by AI-driven systems.

Despite their comprehensiveness, these standards reveal significant gaps when faced with emerging technologies in robotics [37]. AI and machine learning, for instance, introduce new challenges that existing standards do not fully account for, such as the unpredictable behaviour of robots that learn and adapt in real time. Similarly, cybersecurity, a growing concern in interconnected robotic systems, is not sufficiently integrated into the safety standards, leaving potential vulnerabilities that could compromise physical safety. Moreover, the current standards do not adequately address the HF involved in HRCs, such as the psychological impact on workers, which is increasingly important as robots become more pervasive in industrial environments.

The limitations of these standards are further highlighted by their static nature, which does not align well with the dynamic capabilities of modern robotic systems [37,38]. Many of these standards were developed with traditional, non-autonomous robots in mind and struggle to keep pace with advancements like autonomous robots and AI. This lag in

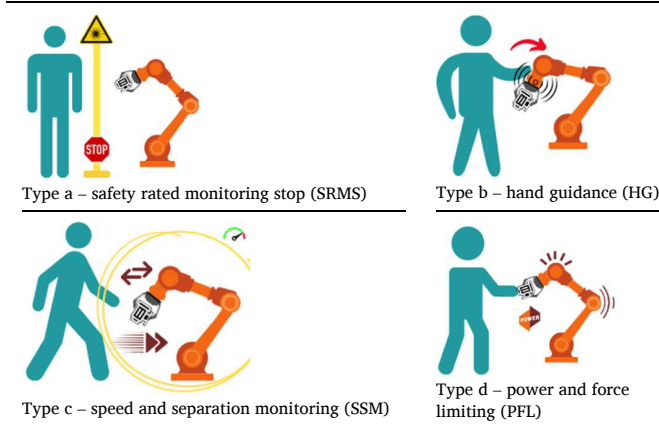
Table 1
Safety standards and their classification.

Standard	Type	Description
ISO 12100	A	This standard provides safety principles for the design of machinery, including robotics systems. The standard is type A standard and applies a general framework for risk management process and provides guidelines for minimising risks of injury to operators and other people who may come into contact with the machinery.
ISO 14121	A	This standard that provides a process for identifying hazards, evaluating risks and selecting measures to reduce the risks for machinery, including robotics systems.
ISO 14119:2013	B	Safety of machinery - Interlocking devices associated with guards - Principles for design and selection
ISO 14120:2015	B	Safety of machinery - Safety distances to prevent danger zones being reached by the upper and lower limbs - Part 2: Minimum gaps to avoid crushing of parts of the human body

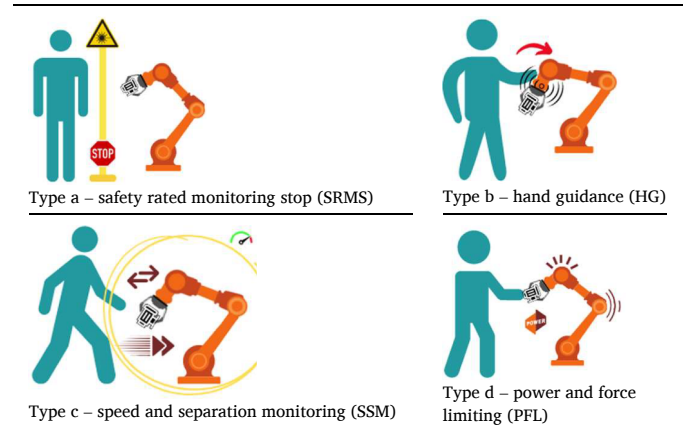
*Complete table available in appendix.

Table 2

Types of collaborative safety control modes– visual description.



Types	SRMS	HG	SSM	PFL
Description	Safety rated monitored stop: In this safety mode, the robot immediately stops its movements when a human operator enters a defined safety area. This mode prevents collisions and ensures the safety of human operators working alongside robots [36].	Hand guidance: This mode allows human operators to manually manoeuvre the robot without external force. It enhances flexibility and adaptability, enabling precise adjustments and closer collaboration between humans and robots. []	Speed and separation monitoring: This mode limits the robot's force and speed within designated safety zones to prevent collisions or accidents. Sensors monitor distance and trigger a safety stop if robot gets too close to the human operator [36].	Power and force limiting: This node restricts the amount of force and torque exerted by the robot, keeping it within safe limits to prevent injury or material damage. It ensures the robot can work safely alongside human operators [35].
Application Type	This is suitable when the robot works mostly independently with occasional human interaction.	It is used for path teaching or hand-guiding the robot.	It uses laser scanners, light curtains, or vision systems to track the worker's position.	Robot works alongside a human without additional safety devices.
Operation	When a human enters a predefined restricted area, the robot comes to a complete stop (servo on, brakes applied). It resumes motion only after safety parameters are reset (e.g., human leaves the safety scanner's red zone).	The human switches the robot to TEACH mode for path teaching, and the robot operates with safety guards in PLAY mode during regular operation.	The robot operates within predefined safety zones, adjusting speed or stopping when a human is detected within these zones.	The robot monitors external forces applied to its body and takes action (e.g., stop, retreat) to ensure safety.
Robot Setup	Standard industrial robot.	Standard industrial robot with an additional sensing device	Standard industrial robot with additional safety sensing	Non-standard industrial robot, with special force-

Table 2 (continued)

Example	Human performs a secondary operation on a workpiece while the robot holds it.	Quick and easy path teaching, robot guiding during seat assembly in the car body.	for hand guiding.	devices (e.g., safety scanner or light curtain).	limiting features and rounded shapes for force dissipation in case of impact.
		Loading jigs, removing finished products.			Machine tending, picking, and packing, assembly, etc

standardisation means that by the time new standards are published, they may already be outdated, failing to address the latest technological developments. Additionally, the testing and validation procedures outlined in these standards are often insufficient for ensuring the safety of cutting-edge technologies, particularly in validating the safety of AI-driven decision-making processes. These aspects are summarised in Table 3.

A more forward-looking perspective emphasises the need for dynamic and adaptive safety standards that can evolve in real-time, mirroring the technologies they regulate [39]. The traditional sequential approach, where basic safety principles are established before moving on to specific machine requirements, may not fully address the complexities inherent in modern, AI-driven HRCs systems [38]. As AI enables robots to learn and adapt their behaviours in real-time, there is a

Table 3

Critical Interactions, Gaps, and Limitations in HRCs Safety Standards.

Aspect	Key Issues	Impact
Interaction Between Standards	Overlaps between Type B & C standards, Sequential application, Inadequate for dynamic AI-driven systems	Redundancies, Confusion in compliance, Challenges in real-time safety assessments
Gaps in Standards	Lack of AI/ML integration, Insufficient cybersecurity measures, Inadequate focus on HF and psychological impacts	Increased risks in AI applications, Vulnerability to cyber-attacks, Neglect of worker well-being
Limitations of Standards	Static nature, Lag in responding to advancements, Inadequate testing/ validation for cutting-edge technologies	Outdated standards, Inadequate safety measures, Barriers to adopting new technologies
Global Harmonisation Issues	Inconsistent regional requirements, Complicated compliance, Potential inhibition of global innovation	Compliance complexity for multinationals, Fragmented global deployment, Stifled innovation

corresponding need for safety protocols to transition from static, one-time assessments to continuous, real-time evaluations. This evolution could involve the development of AI-driven safety monitors that dynamically adjust to changes in both the environment and robot behaviour, thereby providing an additional layer of protection.

Furthermore, as robots become increasingly interconnected within industrial networks, the potential for cyber-attacks grows, necessitating a more comprehensive integration of cybersecurity measures within HRCSSs safety standards. Future safety protocols must ensure that HRCSSs systems are resilient to both physical hazards and digital threats [37]. This includes implementing encrypted communications, robust access controls, and continuous monitoring for cyber threats as essential components of the safety certification process.

In addition to physical and digital safety, it is also crucial to consider the psychological safety of human workers. Future safety standards should incorporate specific guidelines that address the cognitive and emotional well-being of workers interacting closely with robots [40]. This includes designing robots with user-friendly interfaces and implementing measures to mitigate anxiety or stress that may arise from working alongside machines operating with near-human autonomy. By addressing these factors, safety standards can better support the overall well-being of workers, fostering a more effective and harmonious HRCSSs.

3.2. Monitoring HRCSSs

To ensure safe operations and prevent physical contact between robots and workers in the shop floor, safe HRCSSs implementations have incorporated various technologies, including real-time collision avoidance systems [41–43]. These systems provide warnings and take preventive measures to avoid any potential collisions that could cause harm to humans [44]. One of the challenges in implementing a safety distance-related constraint in task allocation is to design tasks in a way that adjusts the collaborative robot speed based on the proximity to the operator. By incorporating this constraint, the collaborative robot's speed can be decreased when it is closer to the operator, ensuring a safe distance. By reducing the speed of collaborative robots, the likelihood and severity of potential accidents can be significantly reduced [45,46]. As the distance increases, the speed can be increased, thus improving system performance and safety. This approach allows for a dynamic adjustment of speed based on the proximity between humans and collaborative robots, ensuring both efficient task completion and the well-being of the operators involved. However, it's important to note that reducing motion speed can have a trade-off with production efficiency and overall performance [47,48].

Cybersecurity is critical in robotics design since robots and automation systems become potential targets for cyber-attacks as they are increasingly connected and integrated with the digital infrastructure. Implementing secure communication protocols, data encryption, and intrusion detection systems safeguards against unauthorised access [49–51] (Table 4).

Safe collaboration of operators and industrial robots is also achieved

Table 4

Key ISO Standards Governing Safety Requirements for Industrial and Collaborative Robots.

Standard	Description
ISO 10218-1:2011	Safety requirements for industrial robots. Covers design, construction, and performance of robots, safety requirements for integration, and risk assessment.
ISO 10218-2:2011	Safety requirements for industrial robots. Focuses on robot systems and integration.
ISO/TS 15066:2016	Technical specification for collaborative robots. Defines processes for the safe integration of collaborative robots into HRCSSs systems and protection of human operators.

* Complete table available in appendix

by detecting the human-robot positions and interaction in the manufacturing processes. A key aspect of HRCSSs tasks is the ability of the robot to perceive and understand its environment in order to perform tasks effectively [52–55]. It may also be possible to adapt system performance, based on physiological measures (such as muscle fatigue [56] and to reinforce positive and safe behaviour during HRCSSs through nudges [57] if the system has such awareness. Perception systems play a vital role in enabling this by providing the robot with the ability to detect, recognise, and understand objects and other elements in the environment [58–60]. However, developing effective perception systems for HRCSSs tasks comes with several challenges, such as the need for accurate and reliable object detection and recognition, real-time performance, robustness to environmental conditions, and integration with other systems [61–64]. In this section, we will briefly discuss these challenges, explore some of the existing research questions related to perception systems in HRCSSs tasks, and highlight the importance of these systems for enabling effective and efficient task performance.

Developing effective perception systems for HRCSSs tasks presents several challenges that must be addressed. The first challenge is the need for accurate and reliable object detection and recognition. Perception systems must accurately detect and recognise objects of different shapes, sizes [61], and materials [65] while handling occlusions and variations in lighting and background [53,66,67]. The second challenge is real-time performance, which is necessary in many industrial settings where robots need to perform tasks quickly and efficiently. The large amounts of data that must be processed can make real-time performance a challenge [61,68,69]. The third challenge is robustness to environmental conditions. Industrial environments are often challenging due to variations in lighting, temperature, humidity, and other factors that can affect the performance of perception systems [70–74]. Perception systems must be robust enough to handle these variations and continue to operate effectively. The fourth challenge is integration with other systems. Perception systems must be integrated with other systems such as motion planning, control, and task execution to perform tasks effectively [63,68,70]. This requires careful design and coordination of the different systems to ensure smooth and efficient operation.

Effective and efficient task performance in HRCSSs tasks heavily relies on perception systems. However, developing these systems can be challenging due to several factors. Perception systems need to detect and recognise objects of various shapes, sizes, and materials while handling occlusions and variations in lighting and background accurately and reliably. Furthermore, these systems need to operate in real-time to meet production demands, be robust enough to withstand environmental conditions, and integrate seamlessly with other systems such as motion planning, control, and task execution to ensure smooth operation.

4. Section 4 – design challenges

This section reviews the relevant challenges at the task level in HRCSSs. The list is not meant to be exhaustive but aims to present the current scientific debates. The technical dimensions, including health and physical safety issues and control systems (including perception) were discussed in the previous section. Here, we focus on some socio-organisational considerations that take into account the human and psychological experience of workers with collaborative robots, which are critical for creating a positive and productive work environment, where workers feel comfortable and empowered while working alongside collaborative robots.

4.1. Issues of perceived and psychological safety

As described in the previous section, ensuring physical safety in HRCSSs is paramount and involves designing robots that do not pose a risk of physical harm to humans. I.5.0 places significant importance on adopting a human-centric approach when designing safe HRCSSs and promoting worker comfort and wellbeing (L. Li & and Duan, n.d.) [75].

This approach ensures that the design of such systems prioritises the physical and ergonomic aspects, considering factors such as workstation layout, equipment design, and ergonomic considerations to minimise physical strain and reduce the risk of injuries [58].

Safety is not only physical—it is also perceived and psychological [76]. The subjective perception of safety by human workers refers to how humans perceive and interact with collaborative robots on a personal or emotional level, beyond just their functional capabilities. The Human Factors (HF) literature has extensively investigated the socio-technical factors that can influence the psychological and emotional states of workers. Factors such as trust, user experience, and acceptance of collaborative robots as operational aids on the shop floor are pivotal—particularly across diverse tasks and human-robot work configurations [77–79].

In recent research on integrating ethical principles into the design of HRCs, Callari et al. [22] argue that ensuring both physical and psychological safety requires a comprehensive approach. This entails not only complying with regulatory safety standards and embedding safety features into the design of collaborative robots but also fostering a safety culture where psychological wellbeing is a priority. Such a culture should encourage the continuous reporting of incidents without fear of reprisal, while also addressing concerns related to surveillance, performance pressure, and mental health [22]. Ethical principles must be embedded into organisational practices to create a human-centric environment that balances technological progress with workers' cognitive and emotional needs [80].

However, the psychological impact of HRCs on workers is still underexplored [25,34,44,49–51,81,82]. Notably, HRCs have the potential to engender psychological harm, including increased levels of stress, burnout, or anxiety among workers [83,84]. Similarly, recent research is attempting to comprehend the role of emotions and embodied experiences associated with a subjective perception of HRCs, aiming to provide valuable insights into this multifaceted domain. Arguably, this stream of research requires additional consideration and investigation (van Wynsberghe, Ley and Roeser, 2022).

Working alongside collaborative robot systems could present psychological challenges for workers in terms of performance expectations. The distinctive attributes of collaborative robots and ML/AI systems, characterised by their precise timing and movements, can create psychological pressure on human workers to replicate a similarly precise and efficient mechanical performance that is not inherent to human nature. Consequently, employers may expect such high-performance levels from human workers, observing the efficiency with which automation carries out its designated tasks [85]. This phenomenon, driven by the pursuit of heightened productivity and cost reduction, has the potential to contribute to an increased dehumanisation of work within factory settings (e.g., Foxconn) or logistics hubs (e.g., Amazon) [28], consequently giving rise to inevitable psychological challenges. On the contrary, when the motion of collaborative robots is excessively slow due to safety measures, it may evoke feelings of frustration among workers and potentially hinder their situation awareness.

Recent studies [43,86,87] have examined the psychological perception of social distancing in the context of regulating the spatial interaction between humans and collaborative robots. The aim is to create work environments where humans feel more comfortable when collaborating closely with robots. It is argued that proxemic behaviours should consider individual characteristics, such as gender and prior experience with robots, in order to maximise human comfort during close collaboration [88]. These considerations are particularly crucial in industrial settings, where the trajectories of robots have the potential to cause psychological discomfort for workers [89].

Trust is a multifaceted concept, and can refer to workers' cognition and perceptions during actual collaboration with robots on the factory floor [90,91]. This includes concerns related to mistrust or over-trust in the capabilities and reliability of robots, examining workers' cognition and perceptions regarding actual collaboration with robots on the

factory floor [92]. Critically, if these aspects are not properly addressed, they can lead to detrimental consequences such as work-related stress, burnout, or depression [56].

According to Lu and colleagues' review [89], safety awareness is identified as a critical psychological aspect within HRCs [89]. Critically, safety awareness refers to the workers' understanding of potential hazards related to the location, activities, and status of Collaborative robots in the shared workspace. Research indicates that higher stress levels can lead to decreased situation awareness, potentially increasing the likelihood of incidents. Therefore, they suggest countermeasures to enhance situation awareness and promote a safer working environment within HRCs. These include ensuring that workers are continuously informed and kept in the loop through warnings before engaging in high-risk activities. Additionally, they recommend implementing visual and audible signals to effectively communicate information about collaborative robot motion to the workers.

4.2. Task complexity and allocation

Traditionally, industrial robots and workers have operated separately on production lines due to safety considerations. As anticipated in the Section1, HRCs' configurations regard: in *coexistence* configurations, collaborative robots complete processes on their own without human intervention or monitoring, therefore, with 'human out of the loop' processes; 'semiautonomous' or 'human in the loop' where tasks between human and collaborative robots are performed sequentially or simultaneously, such as in synchronous work configurations; in cooperation work configurations, both the worker and the cobot work on separate tasks within the same process, and in such processes, humans are 'on the loop' and can perform monitoring and supervisory roles [93, 94].

While all three paradigms can maximize operational efficiency from a company's perspective, the semiautonomous "human in the loop" model is particularly attractive because it combines robotic precision and repeatability with human cognition and adaptability. However, identifying tasks that allow for truly seamless and natural interaction is challenging. Recent reviews of human–cobot task allocation highlight that neglecting task trade-offs can harm workers: when collaboration cannot run in parallel, human idle time increases costs and may lead to unbalanced physical and mental workloads [95].

Early approaches to human-centric task assignment often relied on a linear resource-utilization model, aiming primarily to reduce physical fatigue or stress (Tsarouchi et al., 2016). Ergonomics-driven designs sought to relieve operators of the most strenuous activities [96], and the proliferation of advanced sensors has accelerated collaborative robotic system adoption [97]. Yet even today, many robot systems are conceived from a purely task-focused perspective, without fully considering the operator's routine or acceptance of new technology ([98]; Tsarouchi et al., 2016),

Emerging frameworks instead evaluate workplace workflows and operator habits to determine where automation can enhance (and not replace) human roles. By engaging users early, these approaches foster greater acceptance of collaborative robotic systems and promote more effective collaboration ([99]; Tausch & Kluge, 2022).

All of this means that the consideration of allocating tasks is one that must be done carefully, with a variety of aspects in mind and a recognition that such allocation may be required to change dynamically. There are a number of approaches that can support such activities, outlined below.

4.2.1. Task allocation as a function of performance optimisation

Task allocation in HRCs regards the strategic assignment of specific tasks between humans and robots to optimise the performance and efficiency of the collaborative system [100]. This process involves considering factors such as the complexity of the task, the physical requirements, the level of automation, and the overall goal of the

collaborative work environment [80].

Physical tasks that are repetitive, dangerous, or demand high precision are typically entrusted to robots, which can exploit their superior speed, accuracy and endurance. This not only enhances throughput but also mitigates the risk of musculoskeletal injuries—such as strains, sprains or repetitive-stress disorders—among human workers [101]. Furthermore, robots can perform tasks with greater precision and consistency, reducing the likelihood of human error and operator incidents. This can include situations where operating heavy machinery or handling dangerous substances may pose a risk to human operators.

Conversely, tasks that rely heavily on human cognitive skills—such as decision-making, problem-solving and real-time adaptation—are allocated to human operators. While this division aims to optimize resource utilization, it does not always account for the ergonomic or cognitive load imposed on the human, potentially increasing mental workload and reducing process efficiency [29].

Recent Industry 4.0—and emerging Industry 5.0—research has begun to integrate ergonomic and physical-fatigue considerations into the allocation process. Instead of fully offloading all strenuous activities, these approaches focus on assistive interventions, such as adaptive ergonomic support, to improve human comfort and performance [102, 103]. Some systems now incorporate real-time physiological data from operators—heart rate, muscle activity or posture—to dynamically reassign tasks in response to growing physical fatigue, thereby enhancing both comfort and productivity [104,105]. Although these developments show promise for reducing physical strain, their effects on cognitive workload and long-term benefits remain under investigation through longitudinal studies.

Task complexity regards the distribution of both physically and cognitively demanding activities between humans and robots [95]. An optimal allocation framework must therefore balance these dual aspects—leveraging robotic strengths in speed and precision while preserving critical human involvement in tasks requiring judgment and flexibility—to achieve a truly efficient and ergonomic collaborative process.

4.2.2. Task allocation as a function of responsibility distribution

A complimentary consideration, and in some cases stand-alone approach, is determining who is responsible for robot operation contribute to task complexity as the distribution of responsibilities affects the level of coordination and cooperation between humans and robots [100]. Decisions need to be made regarding who has primary control over the robot and who is responsible for supervising its actions [106]. This includes considering whether the human operator is actively controlling the robot's movements or if the robot operates autonomously under certain conditions, and cooperates with the worker in several tasks. Critically, collaborative tasks in HRI often require humans to engage in anticipatory thinking and decision-making. This may involve predicting the robot's actions, understanding its intentions, and making decisions accordingly. The cognitive workload associated with these processes can vary depending on the complexity of the task, the level of automation, and the degree of uncertainty involved. Managing the cognitive workload effectively is crucial for maintaining situational awareness and ensuring efficient collaboration. In fact, studies show that greater responsibility allocation to human counterparts, results in greater task completion in particular taking into account their cognitive workload and spare mental capacity [107]. This indicates that clarity and responsibility allocation towards operator can improve their psychological wellbeing, at the same time improving task efficiency. However, as such allocation would not take into account dynamically changing situations, the long term effects are debatable.

4.2.3. Task allocation as a function of user routines

From the sections above it is evident that the assignment and collaborative modes depending on the process steps has received the most attention over the recent years [55,98,108], less often it was

investigated the task allocation in the systems where the cognitive demands increase due to monitoring collaborative robot would be accounted for and integrated into task performance [109] and teaching/educating programmes of efficient allocation and overall organisation impact [97]. Regardless of the analytical depth - whether focusing solely on the immediate process or incorporating an organizational perspective - these methods consistently depend on analyzing agent capabilities and task characteristics.

The main drawbacks of the task allocation depending on the agent capabilities and task requirements is the decrease in independence and self-determinism, which can have impact on operator engagement and acceptance according to the Self Determination Theory [110]. In the cases where operators have limited control of process change and their working environment, it can result in greater rejection rates/ decreased trust as well as decreased psychological safety [111]. The potential solution is designing of the system fitting within operator performed processes and routines [112].

Recent research [113] has expanded on responsibility attribution by evaluating task performance when task allocation considers human operator preferences. These studies show improved efficiency through adaptive task planning; however, identifying the operator's preference for leading or following roles prior to task execution remains critical. By aligning task allocation with individual user preferences and routines, system performance and user satisfaction can be significantly enhanced. Furthermore, recent studies have examined autonomous role allocation in human-robot teams that dynamically considers human preferences and capabilities [114]. This approach has demonstrated high usability, as indicated by participant feedback.

A thorough understanding of the user routines and cognitive steps, decision-making points allows to introduce automation where the help is meaningful for the user and is going to contribute towards the decreased cognitive workload and greater engagement of the new process [99]. Afterall, when agency and autonomy to decide task allocation is dependent on the needs of operator or even left to themselves to allocate, increase the acceptance and satisfaction with the new process (Tausch & Kluge, 2022).

4.3. Workforce skill alignment in HRCSS

Questions of task allocation influence workforce skills and skilling. In Industry 4.0 much of the debate around workers' skills has been framed through a narrow, technocentric lens that focuses on the 'skills gap' [19, 115]. This narrative often positions workers as lagging behind technological progress, thus necessitating intervention to acquire digital and STEM-related skills [116]. Within this framing, the rapid deployment of automation, artificial intelligence, and smart manufacturing technologies is frequently associated with a risk of large-scale unemployment unless workers are retrained or reskilled to meet new technological demands [117]. However, technological transformation has brought not only new digital demands but also a growing complexity of skills. Workers are now expected to develop hybrid competencies that blend technical proficiency, digital literacy, and cognitive flexibility [118]. Skill complexity involves not just knowing how to operate new systems, but also understanding and managing integrated workflows, anticipating disruptions, and collaborating effectively with increasingly autonomous machines [12,21].

Workers' reskilling and upskilling are key towards Industry 5.0. In the literature, reskilling refers to acquiring entirely new competencies to transition into different roles as a response to workplace changing dynamics and conditions and adoption of new technology [118,119]. The emergence of collaborative robotics, in particular, necessitates a nuanced understanding of system behaviour, safety protocols, troubleshooting procedures, and production flow dynamics [120]. Critically, manufacturing demands workers capable of overseeing complex, semi-autonomous systems, maintaining situational awareness, and exercising critical judgement in real-time. Thus, the skills required in

smart factories are not merely additive; they are integrative, blending cognitive, technical, and experiential forms of knowledge into new constellations of practice [12,121]. Within this context, upskilling is about deepening or expanding current skills, and includes developing systemic understanding and the ability to manage process continuity, quality assurance, and human–robot collaborative workflows—functions central to future operational resilience [12,118].

The deployment of collaborative robots in manufacturing raises concerns regarding the phenomenon of deskilling—where technology simplifies or reduces workers' tasks [122]. Evidence shows that their integration can inadvertently simplify job tasks, diminishing the complexity and autonomy traditionally associated with certain roles [12]. Deskilling can be found in early stages of human-cobot interaction, particularly in coexistence and synchronisation configurations where robots perform repetitive or monotonous activities independently or sequentially with minimal human involvement [12]. In such settings, workers can be reassigned to peripheral monitoring or support tasks that require less decision-making, technical complexity, or creative engagement. This simplification risks eroding not only technical competences but also the workers' sense of professional agency, pride, and meaning in their work [123].

4.4. The question of designing usable robots

Designing technologies that ensure positive user experiences (UX) in HRI is critical for the acceptance and success of robotic technologies. Positive UX is not only about safety and acceptability but also about creating a beneficial and enjoyable interaction. If users have negative experiences, they may be reluctant to engage with robots, hindering the acceptance of future technologies. Human-friendly design can balance the safety and optimal performance requirements of collaborative robots with psychologically acceptable design principles that address workers' expectations through ergonomic and user-friendly interfaces, thereby helping to mitigate psychological distress on the shop floor [124–126].

Systematically designing and evaluating UX is essential, particularly for social robots, where positive user experiences underpin their societal proliferation. According to ISO 9241-11 the usability is “The extent to which a product can be used by specified users to achieve specified goals, with effectiveness, efficiency and satisfaction in a specified context of use.” [127]. The information exchanges between humans and robots while performing any given task are performed through an interface that includes all commands to enable this interaction (ISO 8373:2012, ISO 11064-5:2008) [128]. Communication modalities within interaction modes can include speech, facial expressions, displays, and augmented reality.

Traditionally, this interaction has been made possible through a

programmable controller, where the user requires specific training to be able to make the robot move in a certain sequence. That sequence is created by recording/saving several robots poses that are executed cyclically in a predefined order to perform a task, sometimes taking into account external signals to be able to have a basic interaction with the surrounding environment of the robot [30]. Even though this kind of interaction is not intuitive and requires the user to be trained, it has been useful for industrial environments to automate repetitive tasks. Nevertheless, with the widespread adoption of robotics in other fields where the environment and workspace of the robot is less structured, such as the surgical field, this kind of interaction is not enough. Table 5 provides a clear overview of the various challenges in HRI design, the approaches taken to address these challenges, the goals of each stage, key activities involved, and the specific challenges each approach addresses (Table 6).

Research highlights four key trends in HRI UX. Firstly, UX is crucial and often used to argue for the positivity of certain features or aspects, though it can be superficial without addressing deeper complexities. Secondly, UX aspects are frequently neglected in favour of robot-centric studies, which may result in less valuable research outcomes. Thirdly, UX evaluations typically occur post-interaction, which might bias responses as participants reflect on their experiences after the fact. Lastly, there is a significant need for better theoretical and methodological knowledge about evaluating UX in HRI, as many robot developers lack awareness of established methodologies [129].

4.5. Trust

Trust in HRCs will need ongoing work as the systems develop and as our understanding and familiarity develops. Trust can have a critical impact on success due to its impact on acceptance and adoption of systems, but work is still needed to understand different aspects of trust [130].

In an industrial setting, establishing and maintaining a connection between humans and robotic systems is crucial for harnessing the anticipated advantages offered by both parties (for instance, time and cost savings from the robotic agent, as well as the human agent's reasoning, creativity, and decision-making abilities), all while ensuring that essential non-functional requirements like reliability and safety are met. To ensure the successful deployment of systems, it is necessary to comprehend the human agent and design systems based on our understanding of human cognition and decision-making processes.

The establishment of trust in such systems is widely acknowledged as a crucial factor for their full adoption by end users. Without trust, the systems may not be utilised to their maximum potential and could potentially compromise both system and human safety [111]. Human trust in automated systems can be conceptualised as a continuum,

Table 5
Challenges and approaches in designing user-centered HRI.

Challenges	Understanding user needs	Designing for emotional needs	Prototyping and testing	Evaluating and refining designs	Managing expectations
Description	Identifying and understanding users' practices and needs through interviews and observations.	Creating interactions that are emotionally fulfilling, addressing feelings of loneliness, etc.	Developing and testing various prototypes to identify the best features and designs.	Continuously evaluating designs to identify and correct UX issues.	Ensuring that user expectations are aligned with the robot's capabilities.
Approach	Field data collection, user interviews, and observations.	Designing features like face-tracking and communication.	Exploring different design options (anthropomorphic, zoomorphic, etc.).	Using formative and summative evaluation methods.	Transparent communication of the robot's capabilities.
Goals	Understanding specific user needs in different contexts.	Translating user needs into specific UX goals and design concepts.	Managing and adjusting user expectations before finalising the design.	Refining robot features and interaction capabilities based on feedback.	Achieving realistic and achievable user expectations.
Key Activities	User research, needs assessment.	Conceptual design, emotional interaction design.	Iterative prototyping, user testing.	Continuous feedback loops, usability testing.	Expectation management, user education.
Challenges Addressed	Misunderstanding user needs, designing irrelevant features.	Creating meaningful interactions, addressing loneliness.	Identifying the most suitable interaction models and features.	Ensuring the robot meets user expectations and goals.	Preventing negative user experiences due to misaligned expectations.

ranging from complete system abandonment (disuse) to complete system reliance and dependency (misuse) [131,132], with neither extreme being ideal.

We can consider the impact of trust in different dimensions, such as performance, process and purpose [133]; the impact on trust of individual differences, such as personality traits [81,134,135], culture [81,135–137], mood [138,139] and self-confidence [140,141]; and recognise that, in human automation systems, trust is recognised to have both affective and cognitive features [142–144].

There is a widely held belief that human trust in automated systems consists of two distinct components: general (propensity) trust and specific (dynamic) trust. Both components are influenced by various factors that impact how humans trust automated systems. General trust, or propensity to trust, refers to an individual's overall inclination to trust any automated system. It is developed by considering past experiences with different types of automated systems, both similar and dissimilar, and reflects their judgments and assumptions based on prior knowledge and experiences across a wide range of technologies and situations. On the other hand, specific trust, or dynamic trust, is the trust an individual has in a particular automated system. It is based on the judgment that the automated system possesses appropriate characteristics to successfully perform a specific task within a specific context, even when there is a possibility of adverse consequences. This type of trust is specific to the given automated system and the situation at hand [145].

Trust can have clear impacts on technology acceptance, but impact on trust can also have a lasting impact on the people involved in the system. It is something that can be gained and lost and will be dynamic across the life of the system.

The relationship between a human and a robot (or similar system), the development of understanding within the system, supporting affinity and development of social cues will impact the success and acceptance of the system. What is perhaps less clearly understood is the impact that this will have on the human, their wellbeing and psychological safety.

5. Enablers

The successful implementation of HRCs relies on the seamless integration of safety, design, and control strategies, making it essential to address each aspect holistically. Safety standards form the bedrock of HRCs systems, establishing the necessary protocols to protect both humans and robots during their interactions. These standards are not just regulatory requirements; they are vital for creating environments where robots can work alongside humans without compromising safety. Implementing advanced safety measures such as collision detection, emergency stop mechanisms, and real-time monitoring ensures that the physical interaction remains secure, reducing the risk of accidents.

Beyond physical safety, the design of HRCs systems must also consider the psychological well-being of human workers [76]. An ergonomic workspace, combined with intuitive interfaces, is crucial to fostering trust and reducing cognitive load. When workers feel safe and confident in their interactions with robots, they are more likely to engage effectively, leading to higher productivity and lower stress levels. This human-centered design approach is necessary to address the psychological challenges that can arise, such as anxiety or mistrust, which could otherwise undermine the collaboration.

Moreover, advanced control strategies and AI integration are critical enablers that enhance the adaptability and efficiency of HRCs systems [146]. These technologies allow robots to dynamically respond to changes in the environment and human behaviour, ensuring that the collaboration remains smooth and effective even in complex, unpredictable scenarios. By prioritising safety, ergonomic design, and adaptive control, HRCs systems can achieve a balanced and sustainable integration of robots into human workspaces, fostering both innovation and worker well-being.

5.1. Control strategies

Collaborative robots are designed with the intention of being easily manoeuvred and exhibiting a certain level of flexibility in their positional stability, thereby fostering a receptive environment for human interaction. Achieving this objective necessitates the utilisation of control techniques that deviate from traditional tight-position controllers. Instead, control approaches such as direct torque control, selective position control, hybrid control, and their respective variants such as impedance control, robust control, and adaptive control, are employed. These alternative control strategies enable the robot's joints to operate in a manner that accommodates human interaction while maintaining the desired level of collaboration.

Control strategies in the context of HRCs are pivotal elements that underpin the effective and safe interaction between humans and robots in collaborative environments. These control strategies are essential to orchestrate seamless cooperation while considering the presence of human operators and ensuring the overall safety and efficiency of tasks. The following control strategies are commonly employed in HRC:

First, safety-critical control strategies prioritise safety by incorporating measures such as collision detection and avoidance, monitoring forces and torques, and implementing emergency stop mechanisms to prevent harm to both humans and robots during interactions [147]. Second, shared control strategies strike a balance between human expertise and robot precision, allowing both entities to contribute to task execution effectively while maintaining safety. Third, compliance control strategies endow robots with compliance and adaptability during interactions to minimise the risk of injury or damage by responding to external forces. Task-level control strategies focus on high-level task goals rather than individual motions, improving task efficiency, while adaptive control strategies enable robots to adjust behaviour in real-time, addressing dynamic and unpredictable situations. Haptic feedback control enhances user situational awareness by providing tactile sensations during interactions. Human intent inference algorithms enable robots to anticipate user actions and respond proactively [146]. Motion planning and trajectory generation strategies ensure efficient and collision-free robot movements during task execution. Force and impedance control strategies regulate forces and torques, ensuring safe interactions during physical contact. Multi-robot coordination is crucial in scenarios with multiple robots, preventing conflicts and ensuring efficient task execution [148]. Additionally, user-friendly control interfaces facilitate effective communication and cooperation between humans and robots. Lastly, control mode switching allows users to transition between different control modes depending on task requirements and trust levels in robot capabilities. These control strategies are selected and fine-tuned to align with specific collaborative application needs, ultimately ensuring safe and efficient HRCs across various domains such as manufacturing, healthcare, and service robotics.

The choice of control strategy depends on the specific application and the level of collaboration between humans and robots. Successful HRCs systems carefully select and integrate control strategies to optimise performance, safety, and user experience.

Common parameters in robotics control strategies, including those utilised in HRCs, encompass a diverse range of factors tailored to specific control approaches and application contexts. These parameters, pivotal to optimising robot performance and ensuring safety, constitute fundamental elements of control system design as illustrated in Fig. 2. Among these parameters are **set points**, dictating desired values or states for the robot to attain, **gains** that govern control system responses, and **trajectory parameters** for defining the robot's motion characteristics. **Force thresholds**, **safety margins**, and **collision detection** parameters are indispensable in ensuring safe physical interactions and avoiding accidents. **Control time constants** influence the robot's responsiveness and stability, while joint limits preserve mechanical integrity. In HRCs, parameters related to HRI, such as **reaction times**, **force limits** during contact, and allowable joint torques, are pivotal for

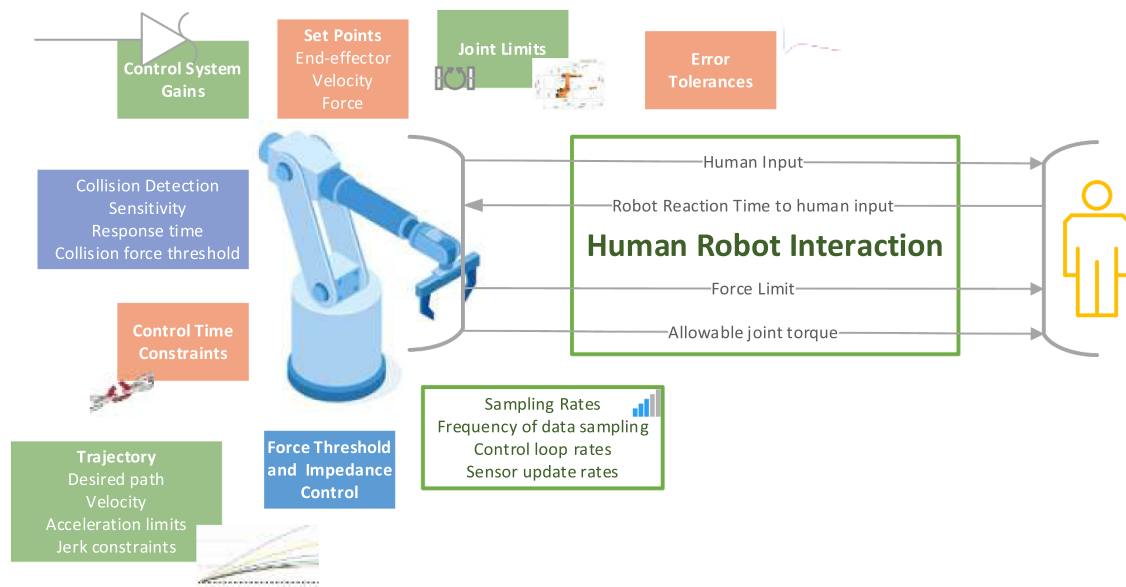


Fig. 2. Human Robot Interaction generic architecture for control strategies.

safety and comfort. Moreover, the selection of control modes, error tolerances, and adaptation rates play significant roles in shaping the robot's behaviour and performance. These parameters are meticulously adjusted and fine-tuned throughout the robot's development and deployment to align with specific application requirements and safety standards, ensuring optimal and secure operation.

5.2. AI in HRCs

The integration of AI in HRCs has brought significant advancements and improvements in various collaborative tasks. By leveraging AI techniques for perception and sensing, action and motion planning, and HRCs, robots can work alongside humans more effectively, enabling enhanced productivity, safety, and efficiency.

Accurate perception and sensing capabilities are crucial for robots to understand their environment and interact with humans effectively. AI techniques, such as computer vision and object recognition, enable robots to identify and interpret objects, gestures, and human actions in real-time [72]. Through sensor fusion and environment modelling, robots integrate data from different sensors (e.g., cameras, depth sensors) to create a comprehensive representation of their surroundings. Advancements in speech and natural language processing allow robots to understand and respond to human commands, enabling seamless communication [149].

Efficient action and motion planning are essential for robots to perform tasks collaboratively with humans. AI-driven path planning and collision avoidance algorithms help robots navigate dynamic environments safely and efficiently [15,46]. Task planning and scheduling algorithms, as discussed in Section 4.1, assist robots in allocating and coordinating tasks effectively, considering dependencies, resource availability, and human preferences. Reinforcement learning and adaptive control further empower robots to improve their decision-making over time through continuous interaction and feedback [4,150].

Effective interaction between humans and robots is central to successful collaboration. Gesture and emotion recognition algorithms allow robots to interpret human expressions and emotions, supporting more intuitive and natural interactions [34,151,152]. Dialog systems and language understanding tools help robots comprehend and generate human language, facilitating clear task coordination [4].

The integration of AI in HRCs directly supports the principles of HF

by making interactions more intuitive, reducing cognitive load, and fostering a user experience that is both efficient and user-friendly. The ability of AI to dynamically adapt to the environment and learn from interactions not only enhances the technical performance of HRCs systems but also builds trust—a critical aspect of HF—by ensuring that robots operate safely and reliably in collaboration with humans.

Furthermore, AI contributes to the psychological safety of human workers by enabling robots to respond to emotional cues and personalise interactions based on individual user preferences. This personalisation is closely tied to HF, as it ensures that the system is responsive to the unique needs and capabilities of each user, leading to higher user satisfaction and better performance outcomes. By monitoring and responding to the emotional states of human operators, AI helps create a supportive and empathetic interaction environment, addressing the emotional and psychological dimensions of HF.

However, there are still challenges to overcome and opportunities for further research and development. HRCs continues to evolve, presenting exciting research opportunities such as cognitive abilities and context awareness, multimodal collaboration and shared autonomy, human-centered design, user experience, and scalability and generalisation in AI-enabled collaboration. These research directions aim to address existing challenges, enhance the capabilities of collaborative systems, and ensure the seamless integration of humans and robots in various domains. The synergy between AI and HF paves the way for a future in HRCs where technological innovation and human-centered design work in concert to create safe, efficient, and supportive collaborative environments.

The challenges presented in HRCs necessitate a comprehensive approach that goes beyond isolated technical solutions, requiring an integration of human-centered design, control strategies, and ergonomic considerations. Ensuring physical safety in collaborative environments is paramount, but it cannot be the sole focus. As this paper has explored, the psychological safety and well-being of human workers must be equally prioritised. The success of HRCs systems hinges on the development of trust between humans and robots, which is influenced by the design of intuitive interfaces, transparency in robot behaviour, and the adaptability of control systems.

The enablers discussed, particularly advanced control strategies and AI integration, are crucial in addressing these challenges. For instance, adaptive control mechanisms that respond in real-time to human actions not only enhance physical safety but also reduce cognitive load,

fostering a work environment where human operators feel secure and supported. Similarly, AI-driven perception systems play a dual role in improving task performance while ensuring that the interaction remains intuitive and natural, thus supporting both technical efficiency and psychological comfort.

This interdisciplinary approach, which merges insights from robotics, human factors, psychology, and industrial design, is essential for the development of HRCs systems that are not only effective but also sustainable in real-world applications. By addressing the physical, cognitive, and emotional dimensions of HRI, the proposed control strategies and AI integrations pave the way for a future where robots and humans collaborate seamlessly. This multi-faceted strategy, which balances technical innovation with a deep understanding of human needs, is critical for advancing HRCs in a manner that truly enhances both productivity and the human experience.

6. Applications

The practical applications of HRCs show how integrating safety protocols, ergonomic design, and advanced control strategies ensures seamless, efficient, and safe interactions. These elements work together to create HRCs systems that are adaptable, secure, and user-friendly, enhancing productivity across various real-world industrial settings. Robots have become indispensable in the manufacturing industry, particularly in performing repetitive tasks like welding, painting, and assembly [153,154]. Collaborative robots, for instance, in pick and place applications, a human operator guides the robot to pick up objects and place them in specific locations, which finds application in packaging, palletising, and machine loading/unloading tasks [155]. An example is the LWR-III robot used for bin picking, equipped with a camera for object detection, and generating accurate environment models using the DLR 3D modeller [156].

Collaborative robots play a vital role in inspection and quality control processes during manufacturing. These robots can be programmed to measure and inspect product dimensions, identify defects, and detect variations in quality. They assist human operators in ensuring high product standards. Furthermore, in maintenance and repair tasks, collaborative robots prove invaluable. They excel at inspecting and repairing equipment located in challenging or inaccessible areas, such as high ceilings or pipelines [75,157]. This collaboration between robots and human operators streamlines maintenance operations and enhances workplace safety.

Logistics and warehousing applications have also benefited significantly from the use of collaborative robots. Companies like Amazon and Ocado employ robots in picking and placing items in warehouses or transporting goods between locations ("Robots Handling the Groceries," [158]). This integration has resulted in improved efficiency and reduced labour costs in these sectors. Similarly, collaborative robots find increasing utilisation in medical and pharmaceutical fields. They perform tasks such as surgery, rehabilitation, as well as packaging and inspection, working alongside human operators to ensure precision and efficiency [159].

In the automotive and aerospace industries, collaborative robots assist human operators in various tasks [160]. For instance, Audi introduced HRCs in their production process, known as PART4you, where robots and humans work together without any safety barriers [156,161]. In this application, robots raise components from boxes and hand them over to workers in an ergonomically designed manner. Similarly, in BMW plants, door assembly is carried out without safety fences. Robots with roller heads seal doors with maximum precision, protecting the electronics housed within [156].

Lastly, collaborative robots are increasingly employed in agriculture and forestry. They perform tasks such as planting, harvesting, and pruning, enhancing productivity and efficiency in these sectors [159]. Overall, collaborative robots have revolutionised manufacturing processes, offering improved efficiency, reduced costs, and enhanced

product quality in various industries [154].

7. Discussion and conclusion

This paper has presented a comprehensive examination of the issues and challenges associated with the design and implementation of HRCs on the manufacturing shop floor, particularly within the evolving Industry 4.0 and future Industry 5.0 paradigms. As explored, collaborative robots are designed for easy maneuverability and flexibility, creating an environment conducive to seamless interaction with humans. However, the effective implementation of HRCs necessitates addressing considerations at both technical/engineering and HF/sociological levels [6, 28]. The ongoing research into strategies, precision, safety, and adaptability underscores the importance of a human-centric approach in ensuring that HRCs can meet the diverse demands of real-world applications.

The proposed framework introduced in Section 2 provides a structured approach to address these multifaceted challenges. This framework is essential in guiding the integration of smart and intelligent (i.e. with embodied AI) technologies while maintaining a focus on the social and design challenge that are critical for effective collaboration in HRCs. Control strategies, as discussed, play a pivotal role in fostering effective and safe collaboration between humans and robots. Various control techniques—including safety-critical, shared, compliance, task-level, adaptive, haptic feedback, human intent inference, motion planning, trajectory generation, force and impedance control, multi-robot coordination, user-friendly interfaces, and control mode switching—are instrumental in orchestrating collaborative efforts across diverse domains [34]. The careful selection and integration of these control strategies are tailored to specific applications and collaboration levels, ensuring optimised performance, safety, and a positive user experience [25,34].

Moreover, this framework can be effectively applied to the emerging I.5.0 paradigm. I.5.0 emphasises a more human-centric approach, where technology enhances human capabilities rather than replacing them, focusing on sustainability, resilience, and the well-being of workers. The integration of HRCs within this context aligns perfectly with the goals of I.5.0. The framework's focus on safety, ergonomic design, and psychological well-being is crucial in creating environments that are not only efficient but also supportive of the human workforce [114]. The use of AI and adaptive control strategies, as discussed in the framework, supports the dynamic and evolving nature of I.5.0 environments, where real-time adaptability and human-centered design are critical.

The recent integration of AI techniques further transforms the organisation of labour involving human and collaborative robotic systems. AI empowers these systems with the ability to perceive, reason, learn, and communicate with humans, fostering enhanced interaction and coordination in collaborative tasks. Accurate perception, facilitated by AI techniques like computer vision and object recognition, enables robots to interpret real-time environmental cues. AI-driven improvements in action and motion planning ensure robots navigate dynamically while prioritising safety, and AI's role in task planning, scheduling, and reinforcement learning enhances robots' adaptability and decision-making capabilities [145]. Moreover, safety protocols and ergonomic design are seamlessly integrated with AI to guarantee optimal collaborative environments. However, challenges and research opportunities persist, particularly in addressing cognitive abilities, context awareness, multimodal collaboration, shared autonomy, human-centered design, user experience, and scalability in AI-enabled collaboration [162,163].

The proposed framework's multidisciplinary approach is crucial in this context, as it ensures that the integration of AI and control strategies within HRCs systems is aligned with human-centered design principles. A critical discussion of current safety standards in HRCs reveals significant gaps and limitations, especially when considering the dynamic capabilities of modern robotic systems and AI integration. The overlap between Type B and Type C safety standards can lead to redundancies

and confusion, while the sequential application of these standards may not fully address the complexities inherent in AI-driven HRCs systems [34,40]. These challenges highlight the need for more dynamic and adaptive safety standards that can evolve in real-time, mirroring the technologies they regulate. Furthermore, the integration of cybersecurity measures within HRCs safety standards is essential to protect against the growing risk of cyber-attacks in interconnected robotic systems [81]. The future of HRCs safety protocols must ensure that systems are resilient to both physical hazards and digital threats, with continuous real-time safety assessments and a strong focus on human-centered design [160]. Addressing these gaps is critical for ensuring that HRCs systems can achieve both high performance and safety in increasingly complex and dynamic environments.

From a social and design perspective, this review has considered the perceived experience of human workers when interacting with collaborative robots. Creating intuitive interaction interfaces that facilitate natural communication is crucial. Managing cognitive workload to prevent overload for both humans and robots is a delicate balancing act, building trust through transparent behaviour, and addressing ethical concerns are vital aspects of successful collaboration [22,26]. The proposed framework in this paper emphasises these aspects by ensuring that AI and control strategies are implemented in a way that supports human cognitive and emotional needs. To deepen our understanding of the psychological ramifications of HRCs, it is essential to extend our focus to broader organisational and societal implications, such as educational programmes, changes in employment dynamics, and job roles in the evolving landscape of human labour amid escalating automation [56]. This involves integrating ethical considerations into HRCs to foster a culture of responsible robotics, promoting the development of guidelines and frameworks that facilitate ethical decision-making throughout the implementation and operation of HRCs [22,162].

Ethical considerations towards Industry 5.0 are paramount, particularly as collaborative robotic systems become more integrated into industrial settings [22]. In these configurations, humans must retain a central role not only in task execution but also in overseeing, guiding, and adapting collaborative processes. Human autonomy and agency are essential; robots should be conceptualized not as replacements but as aids that extend human capabilities without diminishing human discretion or control [12]. The moral dimensions of workforce skilling also demand attention, including the provision of inclusive, accessible pathways that respect different learning needs, protect the dignity of ageing workers, and support diverse contributions across the workforce [22]. Skilling initiatives must affirm individuals as knowledgeable, adaptable agents within evolving production ecosystems. To ensure effective integration of HRCs, a collaborative design approach is critical. Involving workers directly in the design of human-robot tasks—particularly concerning usability, safety, and workflow adaptation—supports the development of systems that are not only technically efficient but also ethically sustainable. Such participatory engagement is key to safeguarding human agency, enhancing system usability, and fostering environments where technological innovation strengthens, rather than undermines, meaningful human work [164].

In conclusion, the future of HRCs in industrial settings is promising but fraught with challenges that necessitate a holistic approach. The

successful implementation of HRCs systems will require not only advancements in robotic technologies and AI but also a concerted effort to address the human and ethical dimensions of collaboration [34,114]. The proposed framework provides a comprehensive structure for integrating these elements, ensuring that safety, trust, and intuitive interaction are prioritized in the development of collaborative environments. Achieving a balance between technical innovation and the human experience is essential for the sustained success of HRCs. This balance calls for a comprehensive examination of the socio-economic landscape, promoting interdisciplinary discussions that span psychology, sociology, and economics to understand the extensive impacts of collaborative robotics on individuals and societies.

Future research should continue to explore the complex interplay between technology and HF in HRCs, with an emphasis on developing frameworks that support the sustainable and responsible integration of robots into the workforce. A task-oriented approach, which considers stakeholders’ goals and essential requirements, such as reliability, maintainability, and supportability, is critical. This method streamlines workflows and aids in creating an environment that encourages the acceptance and integration of technology. Delving into the crucial enablers of HRCs, including AI-driven decision-making, adaptive control strategies, and advanced safety protocols, will be essential for shaping intuitive and effective human-robot partnerships. By embracing a broad, multidisciplinary approach, it is possible to fully capture the complex interplay between the technical and social dimensions characteristic of advanced HRCs, ensuring that the integration of robots into the workforce enhances both productivity and the human experience [44, 165].

Collaborative robot case studies

<https://research.aimultiple.com/Collaborative-Robot/>.

CRedit authorship contribution statement

Seemal Asif: Writing – original draft, Resources, Investigation, Conceptualization, Writing – review & editing, Supervision, Methodology, Funding acquisition. **Tiziana C. Callari:** Writing – review & editing, Methodology, Writing – original draft. **Fahad Khan:** Writing – original draft, Methodology. **Iveta Eimontaite:** Writing – original draft. **Ella-Mae Hubbard:** Writing – review & editing, Writing – original draft. **Masoud S. Bahraini:** Writing – original draft. **Phil Webb:** Funding acquisition. **Niels Lohse:** Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Seemal Asif reports financial support was provided by Engineering and Physical Sciences Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. : Safety Standards and their classification

Standard	Type	Description
ISO 12100	A	This standard provides safety principles for the design of machinery, including robotics systems. The standard is type A standard and applies a general framework for risk management process and provides guidelines for minimizing risks of injury to operators and other people who may come into contact with the machinery.

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Standard	Type	Description
ISO 14121	A	This standard that provides a process for identifying hazards, evaluating risks and selecting measures to reduce the risks for machinery, including robotics systems.
ISO 14119:2013	B	Safety of machinery - Interlocking devices associated with guards - Principles for design and selection
ISO 14120:2015	B	Safety of machinery - Safety distances to prevent danger zones being reached by the upper and lower limbs - Part 2: Minimum gaps to avoid crushing of parts of the human body
ISO 14121:2007	A	Safety of machinery - Risk assessment - Part 1: Principles
ISO 14122-1:2016	B	Safety of machinery - Permanent means of access to machinery - Part 1: General requirements
ISO 14123-1:2015	B1	Safety of machinery - Safety distances to prevent danger zones being reached by upper and lower limbs - Part 1: Principles, selection of values
ISO 13849	B1	This standard provides guidelines for the design, installation, and maintenance of control systems including safety-related control systems used in machinery such as robotics systems.
IEC 62061	B1	This standard defines criteria and recommendations for the design, development, integration and validation of safety-related control systems (SCS) in machinery.
IEC 61508	A	This standard provides guidelines for the functional safety of electrical, electronic, and programmable electronic safety-related systems.
ISO 10218	C	This standard provides safety requirements for industrial robots and robotic devices, it covers design, construction, and performance of robots, safety requirements for integration and risk assessment and reduction in robotic systems.
ISO 10218-1:2011	C	Robots and robotic devices - Safety requirements for industrial robots - Part 1: Robots
ISO 10218-2:2011	C	Robots and robotic devices - Safety requirements for industrial robots - Part 2: Robot systems and integration
ISO/IEC 62443	NC	This is a standard that provides guidelines for industrial control systems cybersecurity. It covers the design, implementation, operation, and maintenance of secure industrial control systems. It also provides guidance on threat modeling, security risk assessment, security policies, and incident response.
ISO 13482	C	This standard provides safety requirements for personal care robots, focused on safety for human operators and other people who may come into contact with them.
ISO 8373:2021	C	This is a standard that provides safety requirements for industrial robots. It covers the design, construction, commissioning, installation, use, and maintenance of robots, as well as measures to protect people during the operation and maintenance of robots, and integration of robots into a larger system.
ISO 8373:2012	C	Robots and robotic devices - Safety requirements for industrial robots
ISO/TS 15066	C	This standard is a technical specification for collaborative robots, or Collaborative Robots. It defines a process for the safe integration of Collaborative Robots into a human-robot collaboration (HRC) system. This also covers protection of people during the operation of Collaborative Robots.
ISO 14159	B	This standard is a standard that provides safety requirements for conveyors. It covers the design, construction, installation, commissioning, operation, maintenance, and decommissioning of conveyors, as well as measures to protect people during the operation and maintenance of conveyors.
ISO 11064	B	This is a standard that provides guidelines for the design of human-machine interfaces. It covers topics such as ergonomics, layout, visibility, and operation of human-machine interfaces.
NIST 800-82	NC	This is a guideline issued by the National Institute of Standards and Technology (NIST) that provides recommendations for securing industrial control systems, including robotics systems. It covers topics such as risk management, incident response, security controls, and assessment methods.
ANSI/RIA R15.06	B	An American standard for industrial robot safety, it also covers measures to protect people during the operation and maintenance of robots.
UL 60730	A	This provides safety requirements for electronic control products for appliances and other robotic devices; includes requirements for the testing, evaluation, and listing of control products.
ISO 10218	B	This standard specifies the safety requirements for industrial robots, including the design and construction of robots, as well as their integration into work environments.
ISO 13482	C	This standard is specific to personal care robots and covers the safety requirements for robots that are intended to interact with people in domestic or similar environments.
ISO/TR 20218-1:2018	C	This standard focuses on ensuring the safe interaction between humans and robots during collaborative operations. It is a Technical Report (TR) that provides guidelines for the safety of collaborative industrial robot systems.
ISO 19649:2017	B	This standard is for the safety of mobile robots and helps in minimizing risks associated with mobile robot operation and enhancing safety in various applications.
ISO 18646:2016		These standard addresses safety requirements for non-industrial robots, including service and medical robots, to ensure safe and reliable use.
ISO 14539:2000		This standard defines methods for measuring the energy consumption of robots, helping assess their efficiency and promote sustainability.
ISO/TR 13309:1995		This standard offers safety guidelines for industrial robots, including risk assessment and protective measures.
ISO 11593:1996		This standard specifies requirements for robot positioning performance, evaluating accuracy and repeatability.
ISO 9946:1999		This standard provides guidelines for programming industrial robots to standardize and enhance efficiency.
ISO 9787:2013		This specifies graphical symbols for industrial robots, facilitating communication and safety.
ISO 9409:2004		In this standard it defines dimensions and mounting flange interface of robot wrists for compatibility with end-effectors.
ISO 9283:1998		It offers guidelines for determining robot repeatability and accuracy in specific tasks.

*NC is not categorised

Table 6

Available commercial collaborative robots.

ROBOT	Payload	DOF	Reachability	Repeatability	Speed	Weight	Collaboration**	Application*
ABB – Yumi – IRB 14000	0.5 kg	7	559 mm	±0.02 mm	1500 mm/s 185°/s - 400°/s	38 g	A, D	
ABB GoFa 5	5 kg	6	950 mm	±0.02 mm	2200 mm/s	28 kg	A, C, D	4, 20, 24, 32, 37
ABB GoFa 12	12 kg	6	1270 mm	±0.02 mm	2000 mm/s	48 kg	A, C, D	4, 20, 24, 32, 37
ABB GoFa 10	10 kg	6	1520 mm	±0.02 mm	2000 mm/s	51 kg	A, C, D	4, 20, 24, 32, 37
ABB SWIFTI CRB 1100 – 4	4	6	580 mm	±0.01 mm	5050 mm/s	21 kg	A, B, C	4, 20, 21, 32, 28, 13, 37
ABB SWIFTI CRB 1300 - 11	11 kg	6	900 mm	±0.08 mm	6200 mm/s	75 kg	A, B, C	4, 15, 32, 20, 21, 24
ABB SWIFTI CRB 1300 - 10	10 kg	6	1150 mm	±0.04 mm	6200 mm/s	77 kg	A, B, C	4, 15, 32, 20, 21, 24
ABB SWIFTI CRB 1300 - 7	7 kg	6	1400 mm	±0.07 mm	6200 mm/s	79 kg	A, B, C	4, 15, 32, 20, 21, 24
Aubo i5	5 kg	6	880 mm	±0.05 mm	2800 mm/s	24 kg	A, B, C, D	4, 5, 10, 15, 17, 25, 12, 28, 30, 33, 34, 22, 23, 19
Bosch (fanuc) APAS	2 kg	6	911 mm	±0.03 mm	500 mm/s	230 kg		23

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Table 6 (continued)

ROBOT	Payload	DOF	Reachability	Repeatability	Speed	Weight	Collaboration**	Application*
Comau - Aura	170 kg	6	2790 mm	±0.1 mm	2000 mm/s 500 mm/s*	1615 kg	A, B, C, D	7, 4, 3, 9, 20, 24, 32
Doosan M0609	6 kg	6	900 mm	±0.3 mm	1000 mm/s	27.5 kg	A, B, C, D	4, 20, 12, 35, 10, 25, 24, 27, 28
Doosan M0617	6 kg	6	1700 mm	±0.1 mm	1000 mm/s	35.5 kg		4, 20, 12, 35, 10, 25, 24, 27, 28
Doosan M1013	10 kg	6	1300 mm	±0.5 mm	1000 mm/s	34 kg		4, 20, 12, 35, 10, 25, 24, 27, 28
Doosan M1509	15 kg	6	900 mm	±0.3 mm	1000 mm/s	33 kg		4, 20, 12, 35, 10, 25, 24, 27, 28
Denso Wave Collaborative Robotta	6 kg	6/7	908 mm	±0.03 mm	2100 mm/s	NA	A, B, C, D	4, 12, 1, 27, 29
Denso Wave Collaborative Robotta Pro	12 kg	6/7	1303 mm	±0.04 mm	2500 mm/s	NA	A, B, C, D	4, 12, 1, 27, 29
Fanuc CR-35iA	35 kg	6	1813 mm	±0.03 mm	750 mm/s	386 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CR4iA	4 kg	6	550 mm	±0.01 mm	1000 mm/s	48 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CR7iA	7 kg	6	717 mm	±0.01 mm	1000 mm/s	53 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CR-7iA/L	7 kg	6	911 mm	±0.01 mm	1000 mm/s	55 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CR-14iA/L	14 kg	6	911 mm	±0.01 mm	500 mm/s	55 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CR-15iA	15 kg	6	1441 mm	±0.02 mm	800 mm/s	255 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CRX-5iA	5 kg	6	994 mm	±0.03 mm	1000 mm/s	25 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CRX-10iA/L	10 kg	6	1418 mm	±0.04 mm	1000 mm/s	40 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CRX-20iA/L	20 kg	6	1418 mm	±0.04 mm	1000 mm/s	41 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Fanuc CRX-25iA	25 kg	6	1889 mm	±0.05 mm	1000 mm/s	135 kg	A, C, D	4, 20, 11, 13, 37, 24, 25, 27, 5
Festo – BionicCollaborative Robot	1.5 kg	7	NA	±1 mm	NA	6 kg		31, 20, 8, 2
Festo Collaborative Robot	3 kg	6	670 mm	±0.3 mm	NA	~ 17 kg		31, 34, 8, 20, 18, 16
Franka Emika	3 kg	7	855 mm	±0.1 mm	20000 mm/s	18 kg		20, 4, 12, 29, 31, 6, 10, 28, 33, 15
Hanwha HCR-12A	12 kg	6	1300 mm	±0.05 mm	1200 mm/s	53 kg	NA	20, 18, 4, 12, 35, 11, 17, 13
Hanwha HCR-5A	5 kg	6	915 mm	±0.05 mm	1500 mm/s	21 kg	NA	20, 18, 4, 12, 35, 11, 17, 13
Hanwha HCR-3A	3 kg	6	630 mm	±0.05 mm	1000 mm/s	13 kg	NA	20, 18, 4, 12, 35, 11, 17, 13
Kassow KR810	10 kg	7	850 mm	±0.1 mm	1800 mm/s	24 kg	NA	4, 17, 35, 11, 28, 31, 23, 26, 36
Kassow KR1018	18 kg	7	1000 mm	±0.1 mm	2400 mm/s	34 kg	NA	4, 17, 35, 11, 28, 31, 23, 26, 36
Kassow KR1205	5 kg	7	1200 mm	±0.1 mm	1800 mm/s	25 kg	NA	4, 17, 35, 11, 28, 31, 23, 26, 36
Kassow KR1410	10 kg	7	1400 mm	±0.1 mm	2400 mm/s	35 kg	NA	4, 17, 35, 11, 28, 31, 23, 26, 36
Kassow KR1805	5 kg	7	1800 mm	±0.1 mm	2400 mm/s	38 kg	NA	4, 17, 35, 11, 28, 31, 23, 26, 36
Kawasaki CL103N	3 kg	6	590 mm	±0.02 mm	200°/s	NA		
Kawasaki CL105N	5 kg	6	800 mm	±0.02 mm	200°/s	NA		
Kawasaki CL108N	8 kg	6	1300 mm	±0.02 mm	200°/s	NA		
Kawasaki CL110N	10 kg	6	1000 mm	±0.02 mm	200°/s	NA		
Kinova Link 6 Collaborative Robot	6 kg	6	1000 mm	±0.1 mm	2000 mm/s	23.45 kg		11, 20, 9, 4, 21, 1, 35
KUKA LBR IIWA 7	7 kg	7	800 mm	±0.1 mm		22.3		12, 4, 21, 9, 35, 20, 24
KUKA LBR IIWA 14	14 kg	7	820 mm	±0.15 mm	90 – 180 °/s	29.5 kg		12, 4, 21, 9, 35, 20, 24
Kuka LBR iisy 3 R760	3 kg	6	760 mm	±0.1 mm		22.8 kg		12, 4, 21, 9, 35, 20, 24
Kuka LBR iisy 6 R1300	6 kg	6	1300 mm	±0.05 mm		NA		12, 4, 21, 9, 35, 20, 24
Kuka LBR iisy 8 R930	8 kg	6	930 mm	±0.05 mm		43.2 kg		12, 4, 21, 9, 35, 20, 24
Kuka LBR iisy 11 R1300	11 kg	6	1300 mm	±0.05 mm		46.3 kg		12, 4, 21, 9, 35, 20, 24
Kuka LBR iisy 15 R930	15 kg	6	930 mm	±0.05 mm		43.2 kg		12, 4, 21, 9, 35, 20, 24
MABI Robotics - Speedy 6	6 kg	6	800 mm	±0.1 mm	145 – 275 °/s	28 kg	NA	
MABI Robotics - Speedy 10	10 kg	10	1384.5 mm	±0.1 mm	120 – 180°/s	28 kg	NA	
MABI Robotics - Speedy 12	12 kg	12	1250 mm	±0.1 mm	75 – 275°/s	35 kg	A, B, C, D	
Mitsubishi ASSISTA	5 kg	6	910 mm	±0.03 mm	1000 mm/s	20 kg		21, 4, 3
MRK Systems KR5 SI	5 kg	6	1423 mm	±0.04 mm	NA	NA	SRMS	18, 20
Omron TM5 700	6 kg	6	700 mm	±0.05 mm	1100 mm/s	22.1 kg	A, B, C, D	4, 22, 9, 29, 20, 12, 8, 33
Omron TM5 900	4 kg	6	900 mm	±0.05 mm	1400 mm/s	22.6 kg		4, 22, 9, 29, 20, 12, 8, 33
Omron TM12	12 kg	6	1300 mm	±0.1 mm	1300 mm/s	32.8 kg		4, 22, 9, 29, 20, 12, 8, 33
Omron TM14	14 kg	6	1100 mm	±0.1 mm	1100 mm/s	32.5 kg		4, 22, 9, 29, 20, 12, 8, 33
Omron TM16	16 kg	6	900 mm	±0.1 mm	1100 mm/s	32.2 kg		4, 22, 9, 29, 20, 12, 8, 33
Omron TM20	20 kg	6	1300 mm	±0.1 mm	1300 mm/s	33 kg		4, 22, 9, 29, 20, 12, 8, 33
Productive Robotics – OB7	5 kg	7	1000 mm	±0.1 mm	2000 mm/s	24 kg		20, 3, 21, 17, 35, 24, 31, 4, 13, 10
Rethink Robotics –Sawyer	4 kg	7	1260 mm	±0.1 mm	1500 mm/s	19 kg	A, B, C, D	17, 13, 31, 12, 30, 35, 20
Siasun SCR5	3 Kg	7	600 mm	±0.2 mm	800 mm/s	18 kg		18, 19, 4, 3
Siasun SCR5	5 kg	7	800 mm	±0.2 mm	1000 mm/s	33.8 kg		18, 19, 4, 3
Staubli – TX2touch-60	4.5 kg	6	920 mm	±0.03 mm	8.4 m/s	51 kg	A, B, C, D	
Staubli – TX2touch-90XL	10 kg	6	1450 mm	±0.04 mm	11.6 m/s	116 kg	A, B, C, D	
Techman TM5–900	4 kg	6	900 mm	±0.05 mm	1400 mm/s	22.5 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM5- 700	6 kg	6	700 mm	±0.05 mm	1100 mm/s	22.1 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM12	12 kg	6	1300 mm	±0.1 mm	1300 mm/s	32.8 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM14	14 kg	6	1100 mm	±0.1 mm	1100 mm/s	32.5 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM16	16 kg	6	900 mm	±0.1 mm	1100 mm/s	32 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM20	20 kg	6	1300 mm	±0.1 mm	1100 mm/s	32.8 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM5S	5 kg	6	900 mm	±0.03 mm	180 – 225°/s	22.1 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM7S	7 kg	6	700 mm	±0.03 mm	180 – 225°/s	22.1 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM12S	12 kg	6	1300 mm	±0.03 mm	1300 mm/s	32.8 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM14S	14 kg	6	1100 mm	±0.03 mm	1100 mm/s	32.5 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Techman TM25S	25 kg	6	1902 mm	±0.05 mm	1100 mm/s	32.8 kg	A, B, C, D	3, 20, 31, 10, 18, 3, 34, 27, 8
Universal Robots – UR3	3 kg	6	500 mm	±0.1 mm	1000 mm/s	11 kg	A, B, C, D	21, 5, 20, 22, 11, 35, 4, 7
Universal Robots – UR5	5 kg	6	850 mm	±0.1 mm	1000 mm/s	18.4 kg	A, B, C, D	21, 5, 20, 22, 11, 35, 4, 7
Universal Robots –UR10	10 kg	6	1300 mm	±0.1 mm	1000 mm/s	28.9 kg	A, B, C, D	21, 5, 20, 22, 11, 35, 4, 7

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Table 6 (continued)

ROBOT	Payload	DOF	Reachability	Repeatability	Speed	Weight	Collaboration**	Application*
Universal Robots –UR16	16 kg	6		±0.1 mm			A, B, C, D	21, 5, 20, 22, 11, 35, 4, 7
Universal Robots –UR20	20 kg	6		±0.1 mm			A, B, C, D	21, 5, 20, 22, 11, 35, 4, 7
Yaskawa Motoman HC10	10 kg	6	1200 mm	±0.1 mm	130 – 250°/s	45 kg	A, B, C, D	4, 11, 38

Available commercial collaborative robots.

Chart with date (x) and Payload Y

** A – SRMS, B – SSM, C – HG, D – PFL.

* Application:

1. Additive Manufacturing
2. Air blowing
3. AGV/AMR
4. Assembly
5. Bagging
6. CNC Machine
7. Depowdering
8. Dispensing
9. Finishing
10. Gluing
11. Grinding
12. Healthcare
13. Inspection
14. Insertion
15. Kitting
16. Labelling
17. Laser cutting
18. Loading
19. Machining
20. Machine tending
21. Material handling
22. Mobile manipulation
23. Moving
24. Palletizing
25. Packaging
26. Patrol Robot
27. Pick and Place
28. Polishing
29. Processing
30. Scientific research
31. Screwing
32. Screwdriving
33. Soldering
34. Sorting
35. Tagging
36. Testing
37. Welding.

Data availability

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

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