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Review

Reviewing human-robot collaboration in manufacturing: Opportunities and challenges in the context of industry 5.0

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ABSTRACT

Industry 4.0 (I4.0) has been characterized by the increasing use of automation, artificial intelligence, and big data in manufacturing. It has brought different machines, tools, robots and devices together through integration with cyber-physical systems as well as Internet of Things and computer systems. This has dramatically improved efficiency, productivity, and flexibility of automated systems, but it has also raised concerns about the impact of automation on jobs, the ethical considerations and the future of work in general. Industry 5.0 (I5.0) is the next manufacturing paradigm evolution and builds on I4.0 with the addition of 'people', in which robots will be designed to work alongside humans in a safe and efficient manner. Human-robot collaboration (HRC) is its key enabler. In manufacturing, HRC has the potential to improve safety, efficiency, and productivity by allowing humans to focus on tasks that require creativity, judgment, and flexibility, while robots perform more repetitive and dangerous tasks.

This paper explores the concept of HRC and its advancement within 21st century industry. It identifies the opportunities and challenges arising from the interactions between robots and humans in manufacturing applications, assembly, and inspection. It also highlights the significance of HRC in I4.0 and its potential in I5.0. In addition, the role of artificial intelligence, machine learning, large language models, information modelling (ontologies) and new emerging digital technologies (augmented reality, virtual reality, digital twins, cyber-physical system) in the development of HRC and I5.0 is documented and discussed adding new perspectives to the growing literature in this area.

This investigation sheds light on the emerging paradigms that have come about as parts of I5.0 and the transformative role of human-robot interaction in shaping the future of manufacturing. This critical review provides a realistic picture of manufacturing automation and the benefits and weaknesses of current HRC systems. It presents a researched view on the concept, needs, enabling technologies and system frameworks of human-robot interaction in manufacturing, providing a practical vision and research agenda for future work in this area and its associated systems.

1. Introduction

Human-robot collaboration (HRC) is an interdisciplinary field that explores the interaction between humans and robots in a shared workspace. It aims to harness the complementary strengths of both entities [1]. It integrates human capabilities, knowledge, intelligence, adaptability, ingenuity, and tactile sensibility with the efficiency and accuracy of robots for the seamless operation and quality of production processes [2]. The goal of HRC is to enable both humans and robots to work together safely and efficiently to complete different production tasks [3], with varying degrees of proximity. Fig. 1 provides an illustrative example of HRC through a human-robot collaborative 3D scanning task.

Several frameworks [5–8] have been developed consisting of three or four levels of HRC to categorize the interaction as shown in Table 1.

The existence of a standardized and globally accepted HRC interaction classification system is still lacking, leading to significant ambiguity in terminology [10–14]. However, there is a broad way of defining whether the workspace, workpiece and task are shared by the human and robot or not. This can be broadly defined under three levels, namely, coexistence, cooperation, and collaboration [15]. For coexistence, humans and robots work in their own workspace without interacting

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Abbreviations

HRC	Human-Robot Collaboration
HRI	Human-Robot Interaction
Cobot	Collaborative Robot
I1.0	Industry 1.0
I2.0	Industry 2.0
I3.0	Industry 3.0
I4.0	Industry 4.0
I5.0	Industry 5.0
AI	Artificial Intelligence
ML	Machine Learning
CI	Collaborative Intelligence
AR	Augmented Reality
VR	Virtual Reality
MR	Mixed Reality
DT	Digital Twin
RDTs	Robot Digital Twins
HDTs	Human Digital Twins
HMIs	Human-Machine Interfaces
CPS	Cyber Physical System
IoT	Internet of Things
IIoT	Industrial Internet of Things
LLM	Large Language Models
SSM	Speed Separation Monitoring
PFL	Power and Force Limiting
MG	Manual Guidance
GR	Gesture Recognition
VC	Voice Controlled
MG	Manual Guidance
HRCo	Human–Robot Co-operation
LABOR	Lean robotized assembly and control of composite aerostructures
pHRI	Physical Human robot interaction
LoC	Level of Collaboration
GiMS	Graduation Intelligent Manufacturing System
FPAI	Fixed-position assembly islands
PLM	Product lifecycle management
PPR	Product, process, resource modeling
HRCD	Human-robot collaborative disassembly
CEBMs	Circular economy business model
RALBP	Robotic assembly line balancing problem
4M	Man, Machine, Material, and Method
PAL	Parallel assembly lines
HL	Hybrid lines
FLEXHRC	Flexible human–robot cooperation
CPSS	Cyber-physical-social systems
HCPS	Human-cyber-physical system
ICT	Information and Communication Technologies
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
RGB-D	Red Green Blue-Depth
URG	United Robotics Group
DQN	Deep Q Network
GMM	Gaussian Mixture Model
HMM	Hidden Markov Model
MLP	Multi-Layer Perceptron
DNS	Dynamic Neural System
RL	Reinforcement Learning
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
VAE	Variational Autoencoder
6G	6th Generation Technology
KGs	Knowledge Graphs
RoG	Reasoning on Graphs
IT	Information Technology
ChatGPT	Chat Generative Pre-training Transformer
RoboGPT	Robot Generative Pre-training Transformer
SI	Strain Index
REBA	Rapid Entire Body Assessment
RULA	Rapid Upper Limb Assessment
TLX	NASA-Task load index
SUS	The System Usability Scale
AHP	Analytic Hierarchy Process
MSDs	Musculoskeletal Disorders
IFR	The International Federation of Robotics
O4I4	Ontology for Industry 4.0
UML	Unified Modelling Language
OWL	Web Ontology Language
RDF	Resource Description Framework
SPARQL	SPARQL Protocol and RDF Query Language
SWRL	Semantic Web Rule Language
DOLCE	Descriptive Ontology for Linguistic and Cognitive Engineering
DUL	DOLCE Ultra Lite
SUMO	Suggested Upper Merged Ontology
MPRO	The Manufacturing Process
SSN	The Semantic Sensor Network
SOSA	Sensor, Observation, Sample, and Actuator
CORA	Core Ontology for Robotics and Automation
CCORA	Collaborative CORA
OCRA	Ontology for Collaborative Robotics and Adaption
SOHO	Sharework Ontology for Human robot collaboration

with each other. For cooperation, humans and robots work together in the same space simultaneously but work on different tasks. For collaboration, humans and robots work together on the same tasks, with their actions affecting each other directly.

The semantics of these terms carry specific contentions. Some authors [10,16] interpret "cooperative" as denoting a higher level of interaction compared to "collaboration," while others [8,11,13] assign the opposite meanings to these terms. Other researchers opt to avoid using these terms altogether [12,14]. An analysis of literature on interaction levels in HRC and its classification is presented in Fig. 2.

Collaboration between humans and robots has been increasing as industry progresses from Industry 4.0 (I4.0) to Industry 5.0 (I5.0). There has been a gradual realisation that alongside digitalization and automation (I4.0) there is also a need to bring the 'human back-into-the-loop' (I5.0). This is increasing the flexibility of interactions and is enabling human decisions to be used to seamlessly adapt processes [17]. There have been several important papers in this area [18–20], but this review differs in the following ways: To the best of our knowledge,

- It covers and analyses the different aspect of HRC, integrating several related research areas in the context of I5.0 while introducing manufacturing applications (assembly, inspection). The role of information modelling (ontologies), machine learning (ML), augmented & virtual reality (AR/VR) and other emerging techniques and their effects on HRC are also documented and discussed. To the author's knowledge at the time of writing, there is no fixed or definitive method that comprehensively address all these different HRC aspects in a single review paper. An outline of the paper's structure is shown in Fig. 3.

- It discusses HRC communication interfaces, evaluation metrics, safety & trust aspects, handling of difficult and challenging materials, ethical considerations and socio-economic factors highlighting their benefits, and summarizing current research trends, addressing limitations, and outlining future HRC areas.
- In contrast to earlier surveys, this study is focused on recent HRC developments. Thus, it gives the reader a valuable opportunity to advance their understanding of the state-of-the-art methods.

1.1. Industry 5.0 and the emergence of HRC manufacturing paradigms

As industry has progressed from the artisan based and mechanization era (from Industry 1.0 through to Industry 3.0) to mass personalization (Industry 4.0 and Industry 5.0), the safety and flexibility demands have increased [21]. In this, HRC has played a crucial role, both in I4.0 and the emerging paradigm of I5.0 [22–24]. Fig. 4 illustrates the industrial evolution towards I5.0, indicating a move from system centric to human centric processes. It also shows the evolution of manufacturing paradigms and the core technology development areas that have had profound implications on the global economy [17].

Within the evolution of industrial paradigms, it is clear that the focus has been on technology development to increase throughput, often consisting of capturing larger quantities of data to streamline/digitalize the manufacturing process and predict potential issues. Despite this, throughout all the defined industrial revolutions (I1.0 to I4.0) the core aspect that has been missing is the 'human in the loop'. HRC, here, plays a crucial role in integrating the human factors into the system. Although the emergence started during I4.0 it has become more pronounced during the move towards I5.0. [25]. The distinction between the principles of I4.0 and I5.0 is discussed in more detail in next section.

1.1.1. Industry 4.0 and 5.0

Fig. 5 visually presents the core distinctions between the principles of I4.0 and I5.0 [26].

I4.0 aims to transform factories into intelligent environments through the integration of information, objects, and people in cyber-physical scenarios [27]. It is centred on the digitization and automation of industrial processes through machines that are interconnected and communicate with each other [28]. I5.0 builds on I4.0 by emphasizing the integration of 'the human element' into the production system, with HRC as the core collaborative work paradigm [28]. In I4.0, HRC has already shown its potential to improve efficiency, safety, and productivity in manufacturing processes [29,30]. The I5.0 paradigm aims to make production more sustainable, resilient, and human-centric by integrating human creativity and ingenuity into machines and the

Table 1
Levels of collaboration [8].

References	Levels of Collaboration
Michalos *et al.*, 2015 [5]	Three levels based on the task shared: • A common task and workspace • A common task and a separate workspace • A shared task and workspace (one inactive at a time)
Pini *et al.*, 2015 [6]	Three levels of workspace sharing: • Fixed safety fence • Exclusive motion zone (physical contact only with standing robots) • Shared workspace (contact allowed during simultaneous motions)
Behrens *et al.*, 2015 [9]	Four levels based on shared workspace, simultaneous co-work and physical contact: • Coexistence (existing together at the same time, separate workspaces) • Sequential cooperation (successive actions on same workpiece; robot is stopped when human is working on the same workspace) • Parallel cooperation (working simultaneously towards a common goal; no physical contact) • Collaboration (joint action, working hand-in-hand, physical contact allowed, possibility for hand-guiding)
Bauer *et al.*, 2016 [7]	Four levels based on interaction: • Coexistence (workspace not shared) • Synchronized (only one present at a time) • Cooperation (shared workspace, non-simultaneous tasks, separate object) • Collaboration (simultaneous work on same product)
Aaltonen *et al.*, 2018 [8]	Four levels based on interaction: • No coexistence: physical separation • Coexistence: human works in (partially or completely) shared space with the robot with no shared goals • Cooperation: human and robot work towards a shared goal in (partially or completely) shared space • Collaboration: human and robot work simultaneously on a shared object in shared space

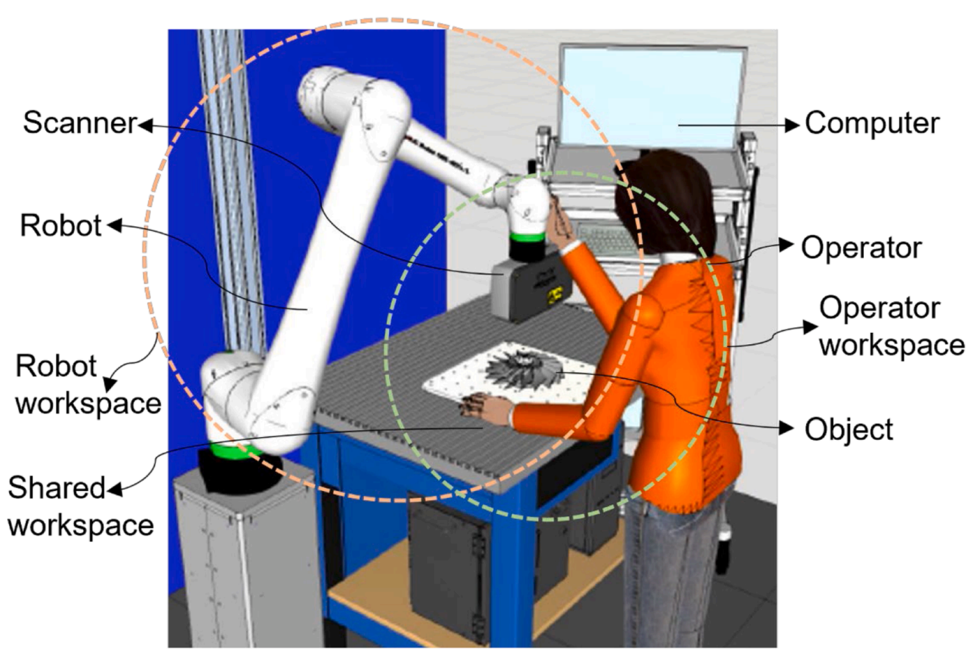

Fig. 1. A Collaborative 3D scanning operation, Adapted from Fluently [4].

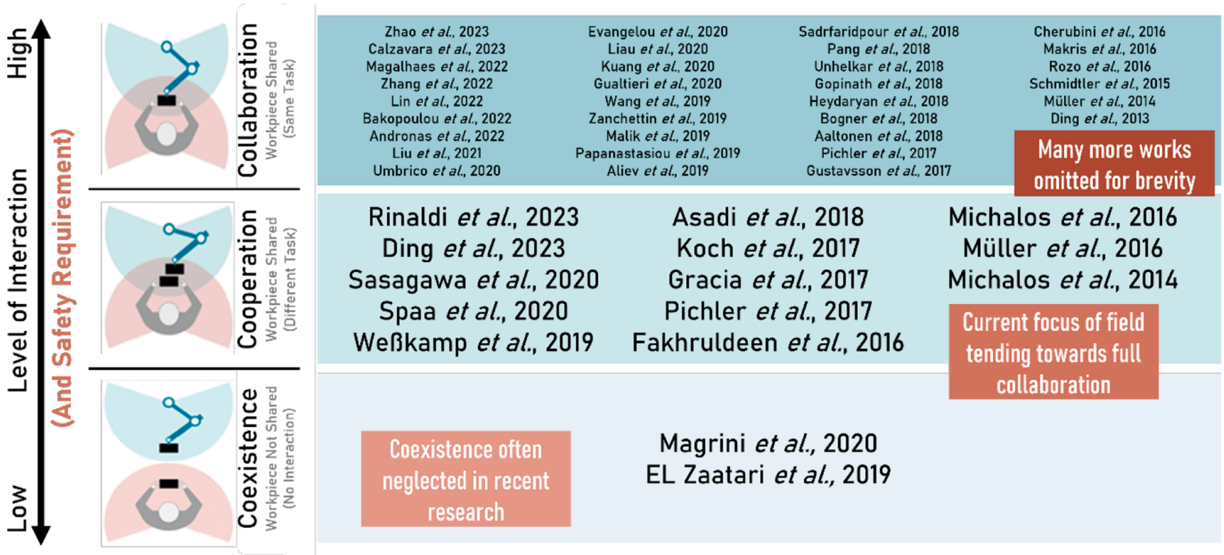

Fig. 2. Different levels of HRC interaction.

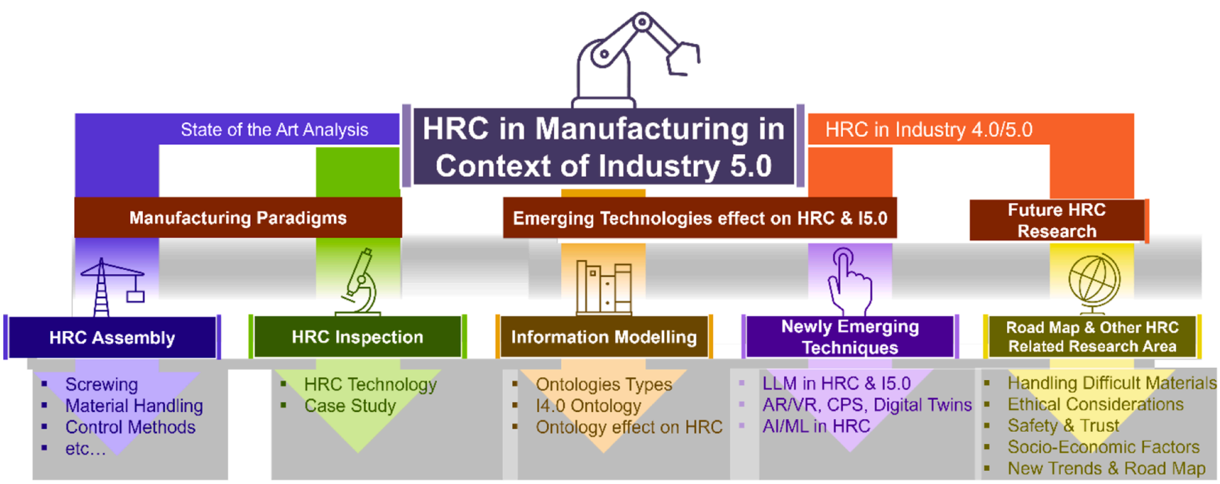

Fig. 3. An outline of the paper's structure.

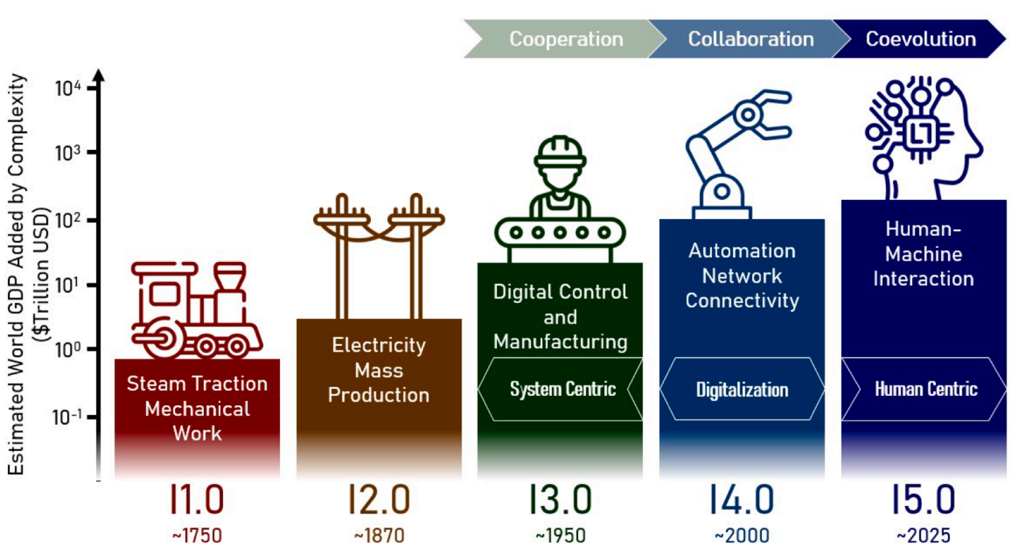

Fig. 4. Illustration of industrial evolution towards I5.0.

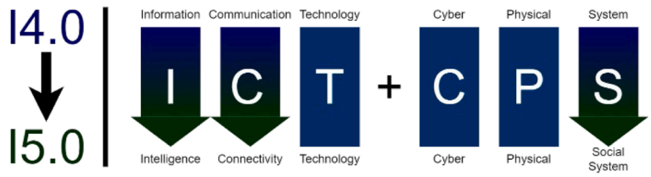

Fig. 5. I4.0 vs I5.0 (based on Wang *et al.*, 2023 [17]).

production environment. This is the core development of I5.0 differentiating it from prior forms of industry paradigms [31].

A study by the International Federation of Robotics found that HRC has the potential to increase manufacturing-based productivity by up to 30% [32]. Another study by the World Economic Forum found that HRC could help to create up to 9 million new jobs in the manufacturing sector by 2025 [31]. Wang *et al.* [33] highlighted the importance of I5.0 through different case studies in building smart societies through a smooth transition from I4.0 to CPSS-based I5.0 for a better world which is Safe in physical spaces, Secure in cyberspaces, Sustainable in ecology, Sensitive in individual privacy and rights, Service for all, and Smartness of all (6S). As the transition to I5.0 advances, HRC's significance is expected to grow even further, promoting safer and more sustainable work environments while empowering human workers with the assistance of advanced robotic technologies [34]. In this paper we explore HRC within the context of I5.0. The subsequent section details the article searching and selection criteria followed in this work.

2. Article search and paper selection process

Fig. 6 details the method used for the article searching and selection process. The potential articles were searched by typing suitable keywords in electronic databases (Web of Science, IEEE Xplore and Scopus). These keywords were determined based on the recent research trends in HRC, particularly manufacturing [35]. A total of 2073 potential articles relating to the HRC Manufacturing field from the years 2013–2023 were identified from the different electronic databases. Only 397 have been included in the study. The included articles were selected after removing duplicates (referred to as phase 1). After this, in phase 2 track articles (not matching with the keywords HRC) were screened. While this approach guided the study, some articles which did not exactly match with the keyword HRC but conveyed the same meaning were selectively retained. The papers related to HRC (specifically to ontology, ML, metrices & evaluations) were the principle focus of this exception. The additional papers which do not fulfil the matching criteria were separately evaluated in phase 3 (Fig. 6). This criterion is selected based upon relation mapping of different combinations of the selected keywords (HRC Manufacturing, HRC in I5.0, HRC in Smart manufacturing, ML in HRC, HRC Ontology, HRC emerging techniques) which simplify the literature search mapping and evaluation.

Fig. 7 shows that significant research has occurred between the years 2013–2023 in HRC [35]. It does, however, show that less research has been found in the HRC manufacturing field in context of I5.0. This subsection has also been growing, and the reduction is expected as I5.0 is an emerging and evolving research area. This paper strives to address these gaps by providing a comprehensive review of this field of research.

3. State-of-the-art analysis of HRC review papers (Years 2013–2023)

In this section, the core focus is on identifying and analysing HRC review papers in manufacturing published between the years 2013–2023. This particular time period has been chosen to cover most of the recent works in I5.0 and HRC as this field advances rapidly. These reviews are summarized in Table 2 by indicating the coverage parameters: Low (L), Medium (M), High (H) and Not Applicable (NA) to the corresponding HRC aspects [36]. It documents industrial use cases, ontologies (within an information modelling context), the role of AI, I4.0/I5.0, HRI matrices & tools, and future research directions in HRC.

Table 2 shows that this papers coverage of the different HRC aspects is considered be high (H) when compared to other similar review papers in which not all the cells have high coverage (H). As far as the authors are aware, there are currently no academic papers that comprehensively cover all the various aspects of HRC. The review articles (indicated in Table 2) based on their identified HRC aspects are analysed below.

Schlenoff *et al.* [37] have provided a thorough review of existing sensor network ontologies for manufacturing applications and suggested possible future work in exploring the requirements, standardization, extension, and refinement of the manufacturing perception sensor ontology (ontology of sensors, sensor networks, sensor capabilities, environmental objects, and environmental conditions). In this paper they better define and anticipate the wide range of perception systems needed to perform the required tasks. Olivares-Alarcos *et al.* [42] reviewed the use of ontologies for autonomous robot applications and compared the ontologies in terms of scope and cognitive capabilities.

Manzoor, S. *et al.* [58] wrote a systematic review of ontology-based

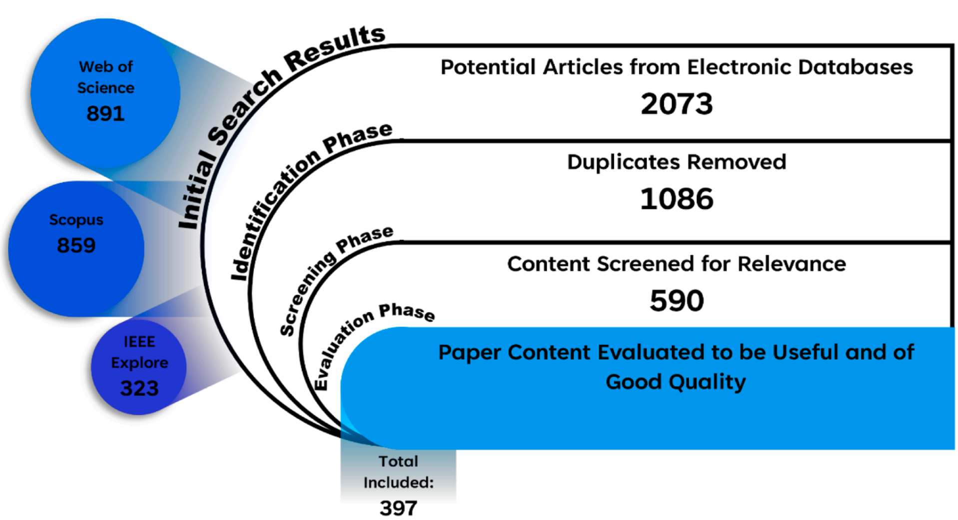

Fig. 6. Article searching and paper selection process
(Article Searching: Title AND/OR Abstract AND/OR Keywords "Human-Robot Collaboration in Manufacturing" OR "in Industrial application" OR "in Industry 4.0/ Industry 5.0″ OR "in Digital/Smart Manufacturing" from Year 2013 to 2023).

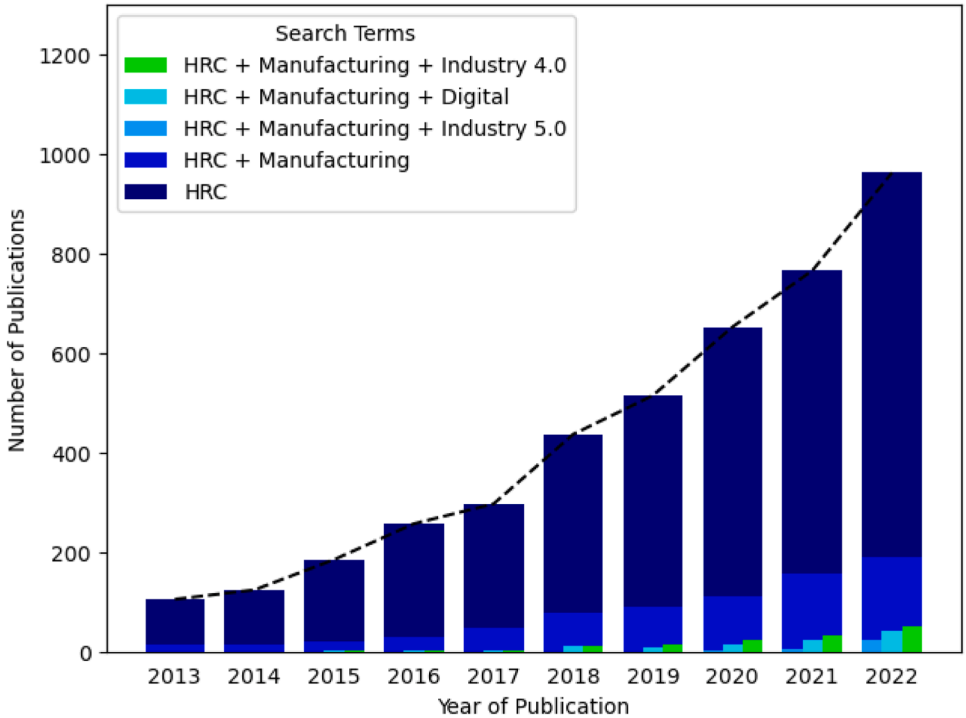

Fig. 7. Relevant publication in HRC targeting Manufacturing.

and knowledge-based systems for autonomous social robots. New insight from this was put into recent research developments in robotics in domestic, hospital, and industrial environments. A lack of development of the ontology mechanism in the field of knowledge representation and development of efficient queries that might be applied to many distributed ontologies with limited resources were noted features of their study. It was concluded that further work is required to achieve a viable solution to these ontological problems.

Spoladore *et al.* [74] reviewed existing domain ontologies on disabilities. Their focus was on healthcare 5.0 which promotes patient-centric AI solutions for disabilities. While sensory, cognitive, and physical impairments are largely addressed, chronic illness-induced disabilities are less represented. Ferrer *et al.* [57] wrote a comparison study between ontologies and databases in manufacturing systems, focusing on product lifecycle management (PLM) and product, process, resource (PPR) modelling. The qualitative and quantitative analysis of their strengths and weaknesses was captured by this study, however there was limited analyses and comparison of the two technologies for common applications in the context of PLM and PPR.

The review by Liu *et al.* [39] focused on four significant issues when applying CPS techniques in smart warehouses: efficient CPS data collection, accurate and robust localization, human activity recognition and multi robot collaboration. They highlight challenging issues (blockchain-based bookkeeping subsystem, shelf-life prediction with multi-source data fusion, multi-robot collaboration via reinforcement learning) in the future CPS-based smart warehouses, which could open new research directions. Borboni *et al.* [71] authored a review on cobots to enable direct communication without barricades and investigated how AI can enhance the cobots' responsiveness and improve the user experience. In addition, this review discussed the outcomes of accuracy, safety issue, time delay, training process, and robot ability and provided recommendations for the interaction between the cobots and the AI domain.

Chuengwa *et al.* [73] studied human-robot collaborative assembly scenarios, machine vision, and digital twins for task evaluation and identification of human characteristics affecting team dynamics. Ajoudani *et al.* [40] explored human-robot interfaces, control modalities, system stability, benchmarking, and use cases. Hentout *et al.* [19] reviewed major recent works on human-robot interactions using industrial collaborative robots and created a classification of these interactions into several categories and sub-categories. These reviews demonstrated that challenges and several open issues for highly advanced HRI in industrial cobotics need exploration.

Losey *et al.* [41] reviewed shared control architectures for physically coupled Physical Human robot interaction (pHRI) tasks. Their focus was on intent detection, arbitration, and feedback. Kolbeinsson *et al.* [43] provided a theoretical foundation for the LoC (levels of collaboration) tool in HRC. The proposed LoC tool helps to identify appropriate collaboration levels. However, understanding human cognition for HRC and visualizing scale effects user prioritization in terms of the activities and tasks that place excessive demands on either humans or robots when working independently. It can arise from physically demanding tasks for humans leading to injuries, or from tasks that require finesse in fitting parts together that robots lack. Thus, collaboration should be designed to address the limitations of each.

Matheson *et al.* [44] investigated industrial case studies and economic convenience of collaborative robots in manufacturing tasks. However, there was no unique classification or terminology used in the analysis of industry use cases. The review by Demir *et al.* [25] was on the impact of human-robot coworking in businesses, information security challenges, and the importance of secure robot maintenance and upgrades. They found that evolutions in organizational behaviour, structure, workflow, legal, psychological, social, ethical issues, and work environment need to be addressed for effective human-robot coworking. Additionally, acceptance of robots in workplaces, discrimination, privacy and trust in a human-robot co-working environment, redesign of the workplaces for robots, education, and training are issues that need to be addressed and are subjects for further discussion, investigation, and experimentation.

Dobra and Dhir [46] worked on the prevailing status of HRC: human factors, complexity/programming, safety, collision avoidance, instructing the robot system, measuring the degree of collaboration, integrating human robot cooperation into teamwork theories, effective functional relocation of the robot, and product design for HRC. Arents *et al.* [47]

Table 2
Summary of important relevant reviews on HRC Manufacturing

Ref.	HRC Manufacturing	Applications/ Use cases	Ontology & AI role & Challenges	I4.0/ I5.0 & Enabling technologies	HRI Metrics, Modes and Tools	Research Directions	Remarks/Focus on
[37]	L	M	H	L	NA	H	Sensor network ontologies for manufacturing applications
[18]	L	M	L	L	H	M	Challenges for the human factors research in HRI
[38]	NA	H	NA	L	NA	L	Optimised assembly sequences for manufacturing process
[39]	M	M	L	H	NA	M	Applying CPS techniques in smart warehouses for I4.0
[40]	NA	H	NA	L	M	L	Human-robot interfaces, modalities, system stability, and use cases
[19]	M	H	M	M	M	M	Human-robot interactions in industrial collaborative robots
[41]	L	L	L	L	H	L	Intent detection, arbitration, and feedback for physically coupled HRI
[42]	L	H	H	L	L	M	Ontologies for autonomous robot applications and capabilities
[43]	M	NA	NA	NA	M	L	Theoretical foundation for the level of HRC tools
[44]	H	M	L	NA	NA	L	Industrial case studies and collaborative robots in manufacturing
[25]	M	L	L	H	NA	M	Human-robot coworking, information security challenge and I5.0
[45]	NA	L	L	M	NA	L	Assembly 4.0 for graduation intelligent manufacturing systems
[46]	M	L	NA	NA	M	L	HRC in production, human factors, safety, collision avoidance
[47]	L	NA	NA	NA	M	L	Safety action, standards used for HRC modularity and operability
[48]	L	L	NA	NA	M	M	Role of human in HRC and effects on job quality, cognitive workload, and trust
[49]	L	L	NA	NA	M	L	Safety, contact mitigation, and ergonomics in industrial collaborative robotics
[50]	L	M	NA	H	L	M	Cobots in I4.0 considering modern social practice on HRC
[51]	M	L	NA	M	NA	M	HRC techniques in I4.0 challenges and opportunities
[52]	L	H	NA	H	NA	M	Industrial revolution 4.0 and cutting-edge technologies like AI and IoT
[53]	L	L	NA	H	NA	M	Sustainability of coexistence, evolution of I5.0 from I4.0
[54]	M	H	NA	NA	M	M	HRC interaction levels, safety and control modes for manufacturing applications
[55]	M	H	NA	NA	NA	M	Trends, progress, and importance of collaborative robot applications & improvement
[56]	L	M	NA	M	NA	L	HRC technologies to reduce work-related musculoskeletal disorders in I4.0
[57]	L	L	H	NA	NA	L	Ontologies and databases comparison and analysis in manufacturing systems
[58]	L	H	H	NA	NA	M	Ontology-based KB systems for autonomous social robots toward applications
[59]	M	L	NA	NA	H	L	HRC in industry contexts handover and metrics, quality, safety, and ergonomics
[60]	M	M	NA	NA	H	M	Human comfort factors, measurements, and improvements in HRC
[61]	L	L	NA	NA	M	L	HRI in manufacturing and human behaviour modelling attitudes, anxiety
[26]	L	H	NA	H	NA	M	I5.0, enabling technologies and application healthcare, cloud manufacturing
[62]	M	M	NA	NA	NA	L	Landscape of human-robot collaborative disassembly, circular economy models
[63]	L	M	NA	M	L	H	Human-technology integration in smart manufacturing and logistics work design 4.0
[64]	L	L	L	H	NA	L	I5.0 in society human-centric solutions, challenges, and research areas
[65]	L	L	NA	H	H	L	Focus on evaluating quality in HRI factors, measures and metrics towards I5.0
[66]	H	L	NA	M	L	L	HRC in smart manufacturing and improving production lines
[67]	M	L	NA	H	L	L	Human-centric manufacturing towards I5.0, bi-directional empathy

(*continued on next page*)

Table 2 (*continued*)

Ref.	HRC Manufacturing	Applications/ Use cases	Ontology & AI role & Challenges	I4.0/ I5.0 & Enabling technologies	HRI Metrics, Modes and Tools	Research Directions	Remarks/Focus on
[68]	L	L	NA	NA	L	M	Robotic assembly line balancing, types of layouts and the 4M concept
[69]	L	L	NA	H	L	L	Human-machine interaction towards I5.0 human-centric smart manufacturing
[70]	L	M	NA	H	NA	L	I5.0 revolution in trauma and orthopaedics, implants and tools
[71]	L	M	NA	H	M	L	AI in cobots for industrial applications, challenges in cognitive and dexterity tasks
[72]	M	L	NA	H	L	M	Technological advancements to human-machine collaboration in I5.0
[29]	L	M	NA	H	L	L	I4.0 and industrial robots, study from manufacturing company employees
[73]	M	M	NA	M	L	L	Collaborative assembly, machine vision and digital twins for task evaluation
[74]	L	M	H	M	L	L	Domain ontologies for disability representation healthcare 5.0
[75]	L	L	NA	H	L	L	Network automation for IIoT in I5.0 technologies and standardizations
[76]	M	M	NA	L	M	M	Micro-ergonomic human-robot collaboration in industry, workplace risk factors
[77]	L	M	NA	M	L	L	Augmented reality-based guidance in product assembly and maintenance/ repair
[78]	M	L	NA	L	M	L	Evaluation identifying methodologies and factors of user experience affecting HRI
[79]	L	L	NA	L	H	M	Integration of complex techniques from cognitive robotics and AI-metrics, and tasks
[80]	L	M	NA	L	L	L	Proactive HRC integrates robotic automation and human cognition challenges
[20]	M	L	NA	H	L	L	I5.0 enhancing HRC with supporting technologies include IoT, AI, and XR
[81]	L	L	NA	L	H	M	Advancements in multimodal human robot interaction research progress
This paper	H	H	H	H	H	H	A comprehensive survey of HRC in manufacturing applications towards I5.0, role of ontology and new emerging AI tools in HRI with future research directions

L: Low Coverage; M: Medium Coverage; H: High Coverage; NA: Not Applicable.

reviewed safety action and standards used for HRC in HRC work cells. Baltrusch *et al.* [48] primarily reviewed the role of humans in HRC, its effects on aspects of job quality, cognitive workload, collaboration fluency, trust, acceptance, and satisfaction. Gualtieri *et al.* [49] explored safety systems for collision avoidance, contact mitigation, and the inclusion of cognitive ergonomics in the design stages. Their investigations were limited to the time period 2015–2018 for emerging trends and focus and to journal-type documents, which reduced the scope of their study in a fast-moving field.

Guo *et al.* [45] undertook a review on the introduction of Graduation Intelligent Manufacturing System (GiMS) for fixed-position assembly islands (FPAI). A 5-layer APICS roadmap for Assembly 4.0 to achieve flexible and efficient production arrangement in the customer-centred dynamic production environment, in the context of I4.0. Weiss *et al.* [50] investigated the role of cobots in I4.0 considering modern social practice understanding of humans in a factory setting. However, most studies were conducted in controlled settings. As a result, there is a lack of understanding of how cobots could change work overtime. Inkulu *et al.* [51] discussed HRC techniques in I4.0 and identified challenges and opportunities in one-and two-way collaboration. Similarly, to Weiss *et al.* [50], a lack of mutual performance assessment system between human and robot and, filtering unwanted noises and multilingual capable interfacing was observed.

Humayun and Arabia [52] wrote a conceptual paper that provided a detailed overview of enabling technologies, applications, the problems of prior industrial standards supporting industrial technologies of I4.0, and the importance of I5.0. It will help researchers and industry practitioners to better understand the role of I5.0. Johri *et al.* [53] reviewed the work on sustainability of coexistence of humans and machines, an evolution of I5.0 from I4.0. Segura *et al.* [54] worked on the identification of four structural components for human-robot collaborative systems design: interaction levels, work roles, communication interfaces, and safety control modes. Their study identified several deficiencies in human-robot interaction and made suggestions on advanced robotic systems in relation to these issues.

The review by Maddikunta *et al.* [26] focused on I5.0 and aimed to combine human expertise with intelligent machines for efficient manufacturing. They discussed the new concepts, definitions, and research challenges of I5.0. Their potential targeted applications included intelligent healthcare, cloud manufacturing, and supply chain management. The survey-based tutorial on potential applications and supporting technologies in I5.0 was also presented. Cimini *et al.* [63] discussed human-technology integration in manufacturing and logistics, based on four main themes: human-machine integration, human-robot collaboration, worker assistance systems, and work design 4.0. In their work, a lack of real industrial cases for human-machine integration and human-robot collaboration was found and it can be taken to highlight the need for further exploration and analysis of criticalities and negative effects in implementing technologies (operator assistance e.g., platforms, software, AR tools).

Adel A [64] reviewed I5.0 trends emphasizing the collaboration between humans and machines. Their applications include cognitive computing, creativity, and maintenance planning. Human workers were found to need new competency skills and the adoption of advanced technology requires time and effort. Yang *et al.* [69] reviewed HMI in smart manufacturing and predicted future opportunities and challenges. Iyengar *et al.* [70] investigated I5.0 in trauma and orthopaedics, personalised care through human intelligence and technology, patient related clinical outcomes and measures. Alojaiman, B [72] examined technological advancements across practice settings and shifting in HRC and identified three significant issues for I5.0.

Chi *et al.* [75] surveyed the network automation for Industrial Internet of Things (IIoT) in I4.0. They analysed state-of-the-art technologies, standardization approaches and forecasting of next-generation network automation for I5.0. It was found that interoperability challenges in diverse IIoT environments, scalability issues in handling increased device and traffic volume and lack of a comprehensive overview of network automation require further investigation. Various approaches have been taken to apply these findings to industry and products; Sladić *et al.* [55] worked on the importance of collaborative robot applications and their improvement in the Yaskawa factory in Slovenia. Their study featured no mention of any specific outcome variables in the experiment and there is lack of knowledge on robot applications and the need for specialized tooling in certain industries.

Hjorth and Chrysostomou's [62] paper examined the landscape of human-robot collaborative disassembly (HRCD). They reviewed progress in the HRCD field from 2009–2020 and how the circular economy business model (CEBMs) has been adopted. They noted that the links joining sub-components make non-destructive disassembly difficult. This allowed them to conclude that further advancements are needed in HRC technologies and standardization policies to create practical disassembly assistance technologies. Othman and Yang's [66] review focused on classifying and highlighting the current HRI in manufacturing areas and the importance of HRC in improving production lines (targeting productivity, efficiency, material waste reduction, production time reduction).

Chutima P [68] provided an inclusive review of robotic assembly line balancing problem (RALBP) research, demonstrating chronological development in the research area and classifying it based on types of layouts and the 4-M (Man, Machine, Material, and Method) concept. In particular, their focus was on multi-and mixed-model RALBP, with an assembly line with parallel workstations (PWAL), parallel assembly lines (PAL), and hybrid lines (HL) layouts. Constraints related to robots and their impact on task allocation were identified as needing further exploration. Çiğdem, Ş. *et al.* [29] investigated robot trust that hinders acceptance in manufacturing workplaces.

Lu *et al.* [67] investigated human needs and human-machine relationships. They discuss bi-directional empathy, proactive communication, collaborative intelligence- transparency, trustworthy, and quantifiable technologies for a rewarding working environment. Their focus was on placing the wellbeing of industry workers at the centre of manufacturing processes. However, technologies need to be trustworthy and friendly for humans, and philosophical, social, and ethical issues should drive development. Coronado *et al.* [65] reviewed human well-being, quality and the performance aspects and quality measurement in HRI applications. They found that quality models do not provide constructive quality assurance.

Castro *et al.* [59] discussed the concept of HRC, human-robot communication channels, physical interaction in collaboration, idealization of co-working between humans and robots, improvement of task execution quality, safety, and ergonomics. They found that cognition depends on the interaction levels and application domain and accurate models of environment and objects, which can be difficult. Yan and Jia [60] worked on the measurement and improvement approaches for human comfort factors. However, challenges in robot sociability factors remain a major concern. Additionally, the relationships between appearance and comfort requires further research in ergonomic factors, anthropomorphism, robot sociability factors, and robot motion-based factors.

Jahanmahin *et al.* [61] surveyed human behaviour modelling in HRI for manufacturing. For this purpose, all papers related to HRI in additive manufacturing, production systems, human cognition, agent behaviours, multi-robot design, cooperative Markov decision process, cloud robotics, and collaborative robots were included in their review. They were notably divided into two categories; human-centered HRI and robot-centered HRI. The survey by Sheridan, T. B. [18] focused on the challenges of human factors research in HRI. Teaching, trust, and acceptance of robots by hospital patients and elderly people was a concern and needed to be explored further. Ranavolo. *et al.* [56] investigated the use of HRC technologies to reduce work-related musculoskeletal disorders. Their SOPHIA project develops CoBots and Wearbots. However, existing standards do not cover biomechanical risk detection. Lorenzini *et al.* [76] investigated the importance of assessing and improving workers' health conditions, postures, productivity, physiology, biomechanics and investigates solutions for ergonomic collaboration in hybrid environments. The exclusion of macro ergonomics was a noted limitation of their study, their focus being mainly on micro ergonomics.

The above section summarises the different surveys in the HRC domain between the years 2013–2023 focusing on manufacturing applications, I4.0, I5.0, information modelling, HRI interfaces, human factors, and the new emerging AI tools. From this, the reader can see and introspect on the areas in which more research is required by seeing the different coverage (L, M, H) in the respective research aspects.

4. Emerging technologies and HRC manufacturing advancements

This section describes human-robot communication interfaces, the role of AI, ML, ontology, evaluation metrics, and different emerging technologies including AR/VR, CPS, LLM etc., in HRC advancement. It also outlines the advancements in HRC for manufacturing applications, assembly and inspection and the potential benefits that can be achieved through its integration.

4.1. Human-robot communication interfaces

The Human robot interaction (HRI) has attracted significant attention within research communities, focusing on the interactions and communication between humans and robots [59,82]. Robots have proven to be efficient in various fields, but their evolution is slow [59]. Fig. 8 shows the key attributes for an effective human robot interaction; expression attractivity, perception & communication, contextual interaction, autonomy & mobility, and physical interaction. To enable effective interaction between the human and the robot, it is necessary to combine and merge the capabilities and strength of the robot from both the social (human perception of a robot) as well as the industrial perspectives (Fig. 8). In this, I5.0 calls for a functional middle ground which allows the strengths of each party to be leveraged.

Fig. 8 shows that for social robots the expression attractivity and perception communication (shown in the bars) are the primary design focus, but for industrial robots the physical interaction is the priority. I5.0 requires the merging of the strength of both sides for effective interaction [83].

In keeping with this understanding of effective collaboration, United Robotics Group® (URG) developed a new robot, called Amica, with 'human-like' features [83]. The company (URG) recognizes the significance of appearance and experience in human-robot interaction. Their crew robot was designed to establish a compassionate connection with children, while also providing unique interactions with other people. URG enterprise also comes with a third generation of robots termed as CobiotX [83]. The first generation of robots worked independently from people, while the second generation cobots require human training and a controlled environment and are designed to work side-by-side with

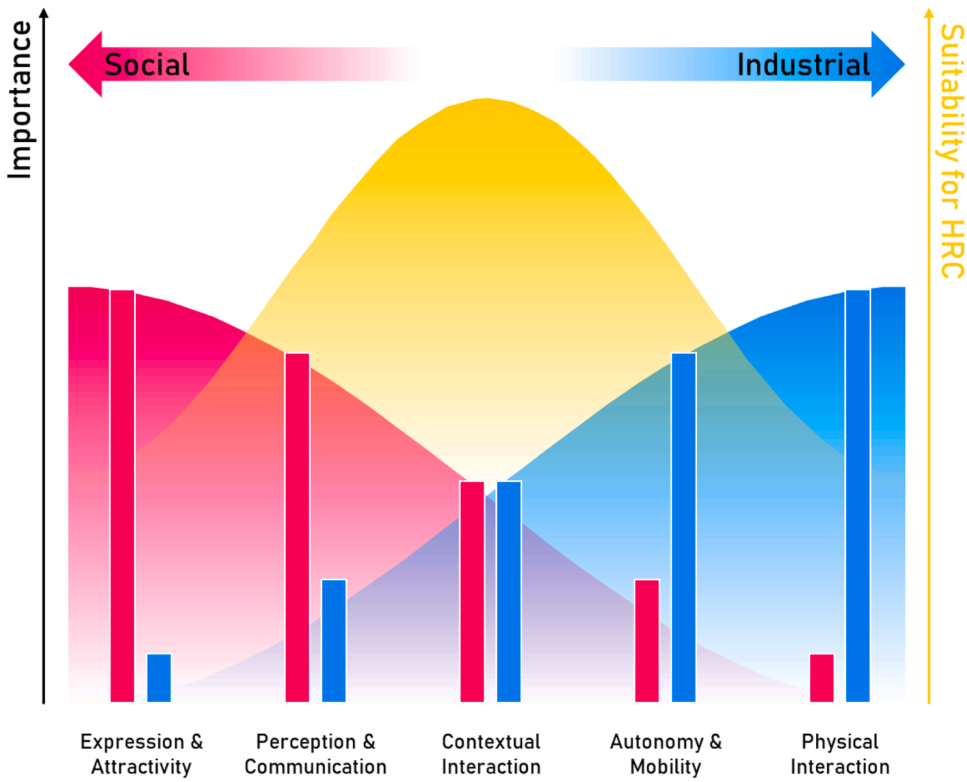

Fig. 8. Key attributes for an effective human-robot interaction [83].

Fig. 9. Mind map of the Human-Robot Collaboration paradigm (Based on Castro *et al.*, 2021 [59]).

people. The third generation CobiotX is designed to work hand-in-hand with people [83]. Here CobiotX stands for [Co-collaboration, bio-life, emotion and sustainability, bot-technology, automation, efficiency, IoT-connection, cognition, perception, X- diversity, versatility, experience] [83]. The importance of HRI is evident in the development of cobots, although the external design must balance creating a human-like experience with the risk of causing fear or discomfort (a risk area commonly known as the "uncanny valley" [84] which states that users may experience discomfort while interacting with human-like artificial characters). Fig. 9 provides a mind map of HRC involving interaction, cognition, and metric paradigms [59].

As evident from the HRC mind map, interaction can be through physicality (object handover, joint manipulation), and verbal and nonverbal communication. The communication interface depicting different methods/modes in HRI is shown in Fig. 10 based on the work of [59], in which gesture and voice control are shown to be predominant in ongoing research.

To achieve successful HRI, a robot needs to possess the capability to perceive, comprehend, and engage with a diverse array of human interaction modes. These scenarios can be explicit, involving verbal communication from humans, or implicit, involving inference from human gestures and expressions. Moreover, an intelligent robot must be able to actively participate in joint actions by planning and proposing feasible plans to humans, as well as reactively following human instructions [162,163]. It is crucial that all these actions are performed in a safe, efficient, and comprehensible manner, while adhering to the social norms relevant to each situation. Achieving such behaviour necessitates interdisciplinary support from fields such as psychology, interaction studies, philosophy, and computer science.

Fig. 11 illustrates a universal procedure for robot interaction in which the sensors of the robot perceive unprocessed data from the surroundings, which is subsequently analysed through methods of extracting features. Techniques from the fields of AI and Computer Vision have been employed to acquire a comprehensive model of the circumstances, thereby empowering the robot to strategize and perform suitable manoeuvres [140,86].

Audio modality signals are used in several applications such as voice assistants, voice-controlled robots, and even some language tutor robots [88]. They play a pivotal role in facilitating the interaction between robots and humans, as they can furnish robots with significant data pertaining to the locations, instructions, and emotional states of the human individuals. Additionally, these signals facilitate the process of speech recognition and synthesis, thereby fostering effective communication between humans and robots [89].

In an effort to strategize actions, the robot needs to be able to undertake tasks involving semantic comprehension by employing features extracted from sensory signals. The subsequent section, 4.4, details to a selection of ML techniques from literature that are relevant to HRC.

4.2. Role of ML in HRC advancements

This section provides perspectives and advancements in the utilization of AI and ML in investigations encompassing the cooperation between humans and robots. With the increasing complexity of manufacturing systems, managing nonlinear and stochastic activities becomes challenging due to uncertainties and interdependencies [71]. AI has facilitated the development of cobots capable of making complex decisions and taking autonomous actions. By incorporating ML algorithms, cobots can optimize processes and improve operational efficiency [90]. AI-powered cobots also contribute to materials engineering

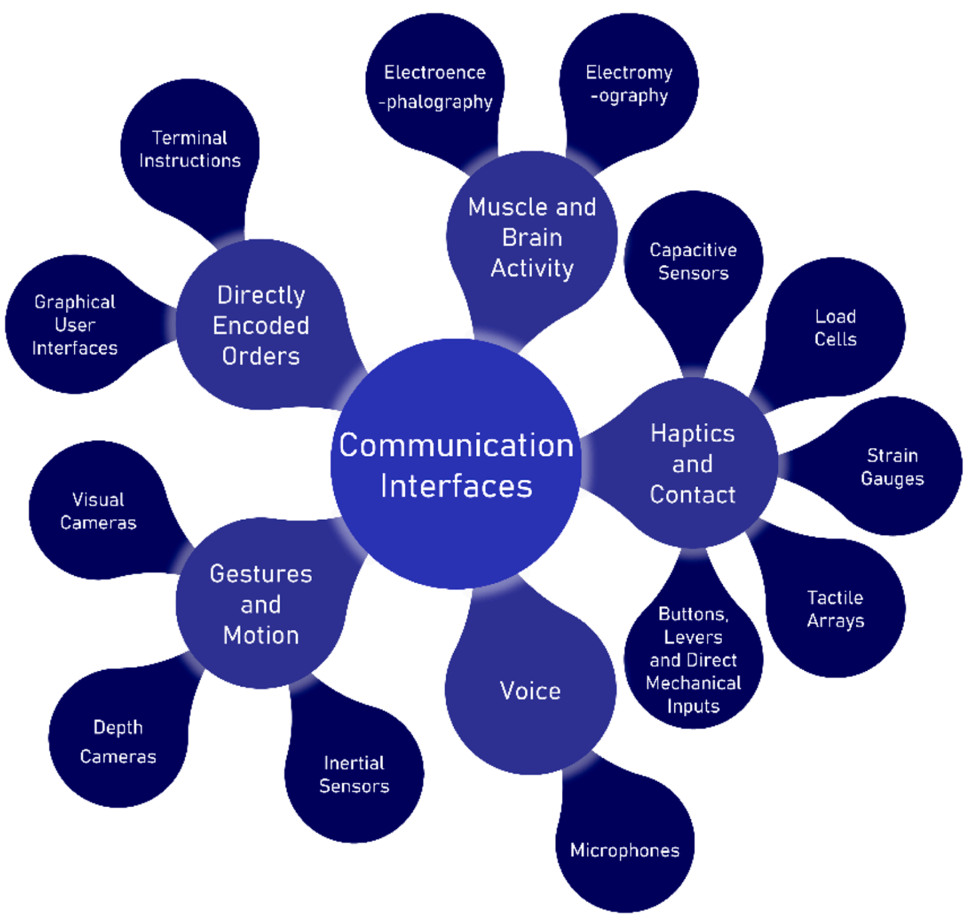

Fig. 10. HRC communication Interfaces (Based on Castro *et al.*, 2021 [59]).

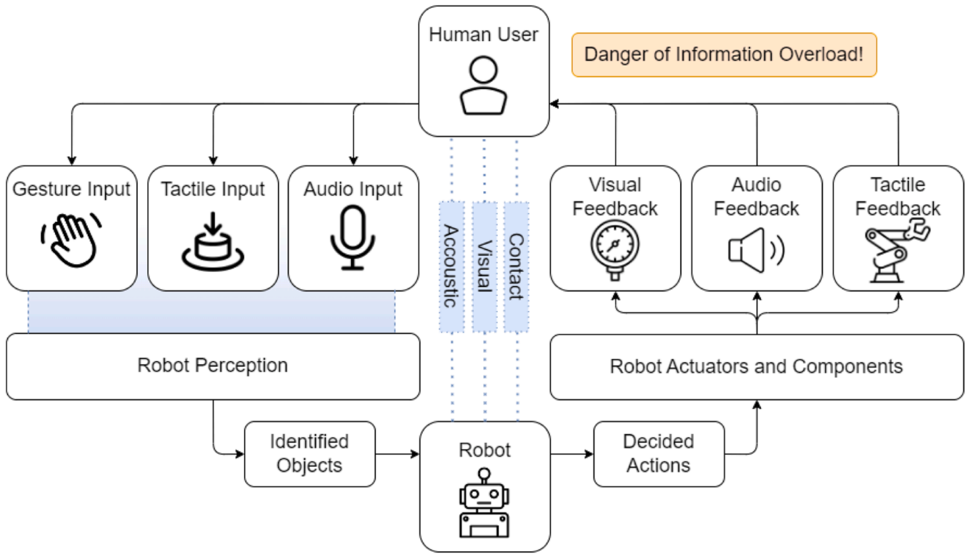

Fig. 11. General Human-Robot interaction process (based on de Lima *et al.*, 2019 [86]).

through advanced process modelling and control techniques [90]. The utilization of AI in manufacturing ecosystems enhances flexibility, efficiency, collaboration, consistency, and sustainability. The combination of advanced technologies like cobots, AR, DT, and AI-powered analytics tools reshapes human-robot interaction and optimizes manufacturing processes [91].

AI holds promise in human-robot cooperation but brings significant challenges in data security, ethics, and interdisciplinary cooperation. It can play a major role in advancing human-robot cooperation by combining human expertise with AI-driven capabilities to achieve efficiency and quality [140]. By leveraging AI, robots can acquire greater independence and enhance their proficiency in assisting with various tasks. This is achieved through the acquisition of skills such as human interaction comprehension and learning, object detection and grasping, as well as improved navigation path management [92]. AI is at the core of collaborative robotics and helps robots with capabilities including speech, object, facial, and emotion recognition. In addition to people and object tracking, AI methods can be applied to fall detection, environment understanding, and control and manipulation of objects [93].

HRI presents a significant challenge within the domain of AI research [93]. Traditional AI methods were not specifically tailored to handle the ever-changing, unpredictable, and partially unknown environments encountered in the physical world. Historically, robots have been limited to executing simple tasks that involve predictable scenarios, such as packaging, welding, and spray painting, thereby achieving commercial success in repetitive industrial processes. However, when it comes to engaging in physical interactions and communicating with humans, robots should be designed to exhibit socially acceptable responses and possess a common sense understanding capable of navigating a wide range of complex situations with complicated semantics. It should be noted that robots designed for human interaction differ greatly from those utilized on assembly lines, as they require a higher level of adaptability beyond mere adherence to a set of instructions for repetitive tasks. Consequently, the field of robotics is now venturing into domains where sensor input plays an increasingly vital role, and the AI must demonstrate robustness in anticipating and managing a diverse range of circumstances.

Semeraro *et al.* [94] compiled a systematic literature review on ML in HRC. Table 3 is based upon their studies and analysis. It details the recent work on ML techniques involving robots and humans.

In most of these ML based HRC studies (Table 3), the robot can identify the specific stage of the sequence that the user is currently engaged in. It can then take actions to support the user in carrying out similar sub-tasks. For example, Munzer *et al.* [109] discussed a robot's role assisting users with assembling tasks, either by understanding the ongoing process or by predicting and setting up the next steps for the user. In a different scenario presented by Vinanzi *et al.* [122], the user constructs a shape using blocks, and the robot completes the construction based on gathered information.

Another area of focus is object handover, where interactions between users and robots involve the exchange of items. The robot must accurately interpret the user's intentions and expectations when transferring objects. Shukla *et al.* [117] highlight the robot's ability to identify and hand over the desired object among a selection. In studies by Nikolaidis *et al.* [112] and Peternel *et al.* [129], the robot plays a supportive role by holding and positioning objects based on user intentions and optimization parameters for tasks like polishing and drilling. Object handling, a common interaction type, involves joint manipulation of objects by the robot and user without releasing them. Roveda *et al.* [114] and Sasagawa *et al.* [116] describe systems where robots provide assistance tailored to user needs in tasks like holding utensils or coordinating food scooping.

A considerable amount of ML research within the HRC domain, as highlighted in Table 3, demonstrates the improvements in system performance when compared to a hypothetical baseline scenario. The baseline comparison can take various forms, such as contrasting the accuracy of a proposed ML system with that of a supervised classifier [102,122]. Zhou *et al.* [128] took a different approach and conducted a series of experiments aimed at exploring diverse system configurations to pinpoint the most effective setup that yields optimal performance outcomes in enhancing the efficacy of ML algorithms for HRC applications. Here, the robot predicts the human's intention and hands over the related tool to its human counterpart during assembling of a chair.

4.3. Effect of state-of-the-art emerging technologies on HRC

In industry, manufacturers are placing emphasis on restructuring work environments to become more intelligent and adaptable to evolving market demands and tailored products. Thus, the demand for flexible solutions is on the rise to address these challenges. The utilization of HRC systems in smart manufacturing settings holds the potential to increase productivity and efficiency. Within smart manufacturing systems, various emerging technologies are in place to enhance the work environment and processes. These technologies play a key role in facilitating the integration of the HRC system in smart manufacturing, leading to a significant enhancement in system efficiency and

Table 3
Role of ML techniques in HRC.

Authors	ML technique	Interaction task	Cognitive ability	Robot role	Human role	Results
[95]	CNN (B)	Object handling	Position of object of interest (4)	The robot actuates itself changing orientation of flexible tip	The human positions the tool	R1
[96]	Interactive RL (A)	Collaborative assembly	Decision making (6)	The robot observes the scene, understands the assembly process, and chooses action to perform	The user has their own part in the process, but can also actively alter the decisional process of the robot	R2
[97]	SARSOP (A)	Object handling	Human trust (2)	The robot clears objects from tables	The human either stays put or prevents the robot from executing an action, if not trusting it	R3
[98]	ANN (B)	Collaborative manufacturing	Human motion (3)	The robot holds the other end of the saw and tracks its movement by recognizing parameters	The human holds one end of the saw and saws different objects in different ways	R4
[99]	GMM (C)	Object handling	Position of object of interest (4)	The robot detects its own end effector and adjusts it with its distal DoFs	The human positions the end effector of the robot with a certain pose and holds the robot in place	R5
[100]	RL (A)+ Bayes (B)	Collaborative assembly	Decision making (6)	The robot understands the intention and goes to reach the same object jointly with the human; if it is not confident about the action to perform, it can request help to the human	The human gazes at an object and goes to fetch it	R3
[101]	Q-learning (A)	Object handling	Decision making (6)	The robot holds the other end of the plank and moves jointly with the human to prevent the ball from falling	The human holds one end of a plank with a ball on top of it and moves it	R5
[102]	VAE (C)+ LSTM (B)+ DQN (A)	Collaborative assembly	Decision making (6)	The robot understands the actions performed by the human and plans its choices to assist in the assembly	The human packages an object	R4
[103]	ANN (B)	Object handling	Control variables (5)	The robot adapts its movements to the trajectory imposed by the human	The human grasps a tool held by the robot and moves it to a certain position	R1
[104y, 105]	ANN (B)	Object handling	Ground reaction force + centre of pressure (1)	The robot grabs the object by the other end and helps the human lifting	The human lifts an object by one end	R5
[105]	LSTM (B)+ Q-learning (A)	Object handling	Human intention (2), control variables (5)	The robot detects the intention of the human and follows the trajectory forced by the dragging of the object	The human drags the object held by the robot	R5
[106]	GMM (C)	Collaborative assembly	Human motion (3)	The robot has to touch different pads than the human, avoiding undesired collisions	The human touches pads of certain colour	R3
[107]	GMM (C)	Object handover	Human motion (3)	The robot, from the opposite end of the table, recognizes what type of object is being passed, and receives it accordingly	The human passes an object to the robot, from one end of the table	R4
[108]	Interaction Probabilistic Movement Primitives (C)	Object handover	Human motion (3)	The robot on human's adjacent side picks an object from human's opposite end of the table and hands the object to the human	The human is located at an end of a table and holds its hand to receive an object	R1
[109]	Relational Action Process (A)	Collaborative assembly	Human intention (3), robot decisions (6)	The robot classifies the user and its own actions and assists accordingly	The human assembles a box	R2
[110]	RNN (B)	Collaborative assembly	Goal target (7)	The robot recognizes the sequence and replicates it; the last part of the sequence must be done collaboratively	The human hits some objects with a known sequence	R3
[111]	VAE (C)+ LSTM (B)	Object handover	Goal image (7)	The robot looks at the human hand, understands the desired object and hands it over the human	The human needs to move objects from one place to another	R2
[112]	Inverse RL (A)	Collaborative manufacturing	Human type of worker (2)	The robot recognizes the type of user and adjusts itself according to the information	The human has to polish two sides of an object held by the robot	R3
[113]	Gaussian Process Regression (B)	Collaborative manufacturing	Human muscular activity (1)	The robot orients the surfaces to maximize certain parameters of interest	The human has to polish or drill surfaces held by the robot	R5
[114]	ANN (B)	Object handling	Robot level of assistance (6)	The robot assists the lifting of an object, recognizing the type of assistance required	The human has to lift an object	R5
[115]	Model-based RL (A)+ MLP (B)	Object handling	Control variables (5)	The robot assists the lifting of an object	The human has to lift an object	R3
[116]	LSTM (B)	Object handling	Control variables (5)	The robot holds a spoon and helps the human scooping the same piece of food	The human holds a fork and uses it to collect food	R3

(continued on next page)

Table 3 (*continued*)

Authors	ML technique	Interaction task	Cognitive ability	Robot role	Human role	Results
[117]	Proactive Incremental Learning (B)	Object handover	Decision making (6)	The robot recognizes the command, grabs the required object and hands it over the human	The human gestures to the robot for the action and gazes at the object of interest	R4
[118]	RL (A)	Collaborative assembly	Decision making (6)	The robot moves other pieces according to human's actions following a shared objective, giving reasons for the actions performed	The human moves pieces on a surface according to certain rules	R3
[119]	Interactive RL (A)	Collaborative assembly	Decision making (6)	The robot jointly moves other pieces at the same time	The human has to move blocks from a place to another	R3
[120]	RL (A)	Collaborative assembly	Decision making (6)	The robot has to act concurrently with the human in the preparation; it communicates the steps it is about to perform to the human	The human has to follow different steps to prepare a meal	R4
[121]	kNN (B)	Object handling	Human hand pose (3)	The robot, by looking at the human hand pose, has to provide the required rotation	The human has to support an object, while applying a rotation to it	R5
[122]	Clustering (C)+ Bayes (B)	Collaborative assembly	Human intention (2)	The robot recognizes human intention and grabs the remaining needed blocks	The human has to align 4 blocks, with a rule unknown to the robot	R4
[123]	Extreme learning machine (B)	Object handover	Human intention (2)	The robot understands the intent of the human and acts accordingly	The human is handing over an object to the robot	R4
[124]	DNS (B)	Object handover	Decision making (6)	The robot looks at the human, understands the step of the process it is currently at and passes the pipe needed by the human	The human is assembling a system of pipes	R4
[125]	Q-learning (A)	Object handling	Control variables (5)	The robot follows the trajectory forced by the human on the object; if they go to the third point, it plans another trajectory to reach the second point	The human moves an object held by the robot from a point to another repeatedly; in case of variation, it moves it to a third point	R3
[126]	LSTM (B)	Collaborative assembly	Human intention (2)	The robot has to predict the intention of the human and assist in it accordingly	The human is assembling different pieces together	R1
[127]	RNN (B)	Object handover	Human pose (3)	The robot looks at the human, predicts its next pose and, according to that, moves pre-emptively to pick up a screwdriver and pass it to the human	The human is working on the assembly of an object	R3
[128]	DNS (C)	Object handover	Human intention (2)	The robot, positioned at the side of the human, predicts the human's intention and hands over the related tool	The human is assembling a chair	R4

For the "ML method" column, the legend is: ANN = Artificial Neural Network, CNN = Convolutional Neural Network, Fuzzy = Fuzzy systems, DQN = Deep Q Network, GMM = Gaussian Mixture Model, HMM = Hidden Markov Model, MLP = Multi-Layer Perceptron, DNS = Dynamic Neural System, RL = Reinforcement Learning, RNN = Recurrent Neural Network, LSTM = Long Short-Term Memory, VAE = Variational Autoencoder. Besides, for the same column, the numbers refer to which category they belong: A = Reinforcement learning, B = Supervised learning, C = Unsupervised learning. For the "Cognitive ability" column, the legend is: 1 = Human effort, 2 = Human intention, 3 = Human motion, 4 = Object of interest, 5 = Robot actuation, 6 = Robot decision making, 7 = Task recognition. For the "Result/Focus" column, the legend is: R1 = Accuracy of movement, R2 = Robustness, R3 = Proof of concept, R4 = High-level performance increase, R5 = Reduction of human workload.

Table 4
Utilization of enabling technologies on I5.0 applications.

	Advanced Technologies						
I5.0 Applications	Cobots	AI	LLMs	IoT	Digital twins	6G	Big data
Manufacturing	H	H	L	H	H	H	H
Human–CPS	H	H	L	H	H	H	H
Education	L	M	L	M	M	M	M
Intelligent healthcare	L	H	L	M	M	H	M
Supply chain management	L	H	L	H	L	H	H
Disaster management	M	H	L	H	M	H	H

L	Low Utilization	M	Medium Utilization	H	High Utilization

productivity.

I5.0 is centred around the utilization of these emerging state-of-the-art technologies such as AI, IoT, DTs, AR, VR, Cobots, 6G, cloud computing, big data and Large Language Models (LLMs), whilst also better harnessing the power of human ingenuity and intelligence [20, 153]. Table 4 shows the utilization of enabling technologies on different I5.0 applications: manufacturing, human-CPS, education, healthcare, supply chain management, and disaster management [20].

In I5.0 manufacturing applications, these technologies all have high utilization (H) with the noted exception of LLMs, which are an emerging field of AI that is gaining significant attention across industry and wider society [131]. The next section will discuss the role of LLMs in HRC.

4.3.1. *Role of generative AI technologies like LLMs in HRC*

Various control strategies have been implemented to enhance and facilitate the interaction (gestures and behaviours) between humans and robots by utilization of AI [132], deep learning and reinforcement learning methods [133]. Nevertheless, most existing practices still lack resilience, particularly in relation to the unpredictability of human behaviours. The recent progress in LLMs, exemplified by ChatGPT [131], presents a new prospect for HRC. However, it is imperative to address the growing concerns and challenges that arise from the utilization of LLMs [134].

LLMs are a frequently misunderstood area and are often anthropomorphised or attributed undue abilities due to their perceived depth of knowledge [135–138]. In practice, they are perhaps best considered to be large data structures, optimised to mirror on vast quantities of data. They most commonly take a form akin to large tree models or Markov chains which achieve their complexity and accuracy by brute force of data more than any special virtue of their design, much less their name. This need for scale has economic impacts, making the training of specific LLMs unworkable in most circumstances and the adaption of existing models a more appealing approach to development in many circumstances [139].

For LLMs, a critical limiting factor to their use is that they are not transparent. This makes their outputs difficult to explain or justify and leads to liability limitations and valid safety concerns [140]. The effectiveness of human interactions with LLMs is a hotly debated topic [136,138,141], and steps can be taken to improve user understanding and, subsequently, outcomes [138], but these steps do increase the burdens put on the human users. Humans should always have an avenue to verify or prevent the output of an LLM at the point of implementation [142,143].

Despite this, with the large data sets accessed by these models, LLMs often have a higher capacity to adapt to unexpected situations when compared to lighter ML approaches, and modern versions can readily handle a good section of the range of human requests. For this reason, they are a particularly popular technology for roles involving novice human interactions, which lends itself well to many HRC uses and I5.0 [144–147].

Research is ongoing into the utilisation of LLMs in HRC. Ye *et al.* [144] have explored the impact of ChatGPT on trust in a HRC assembly operation. Their research constructs a designated system for controlling a robot named RoboGPT, utilizing ChatGPT. Fig. 12 details an experiment involving human subjects which demonstrates the integration of LLM (ChatGPT) into robots, resulting in an enhancement of human trust towards robots in collaborative endeavours [144].

Janamla *et al.* [145] used ChatGPT to examine how humanoid robots (robot resembling the human body) might be used in the medical industry, particularly in light of the COVID-19 pandemic and in the future for improving healthcare and patient outcomes [142]. Ooi *et al.* [146] studied and provided insights on the potential of generative AI in specific industries, for example, marketing, healthcare, education, manufacturing, and sustainable IT management. Although they found there are benefits to using LLMs in HRC, Luo *et al.* [147] found ChatGPT could be limited by hallucinations/unreal and limited understanding. To overcome these limitations, they proposed a method called Reasoning on Graphs (RoG) to synergise LLMs with Knowledge Graphs (KGs) and enable interpretable reasoning. This eased access algorithmic access to up-to-date knowledge and reason using reliable plans on graphs. RoG enhances the reasoning ability of LLMs by extracting knowledge from KGs during training and facilitates smooth integration with any LLMs during inference [147].

Wang *et al.* [17] explored the capabilities of ChatGPT in understanding the cutting-edge fields of I5.0 by inputting prompt questions on I5.0. It has demonstrated effectiveness in providing comprehensive information and knowledge. Their study found that the responses may not always be clear and accurate, and it may require explicit and specific information, rather than being able to understand implied cues. The research of Rane N. L. [148] examined the changing role of ChatGPT and similar LLMs and Generative AI within the contexts of I4.0 and I5.0. Their work analysed the ethical issues associated with LLM applications

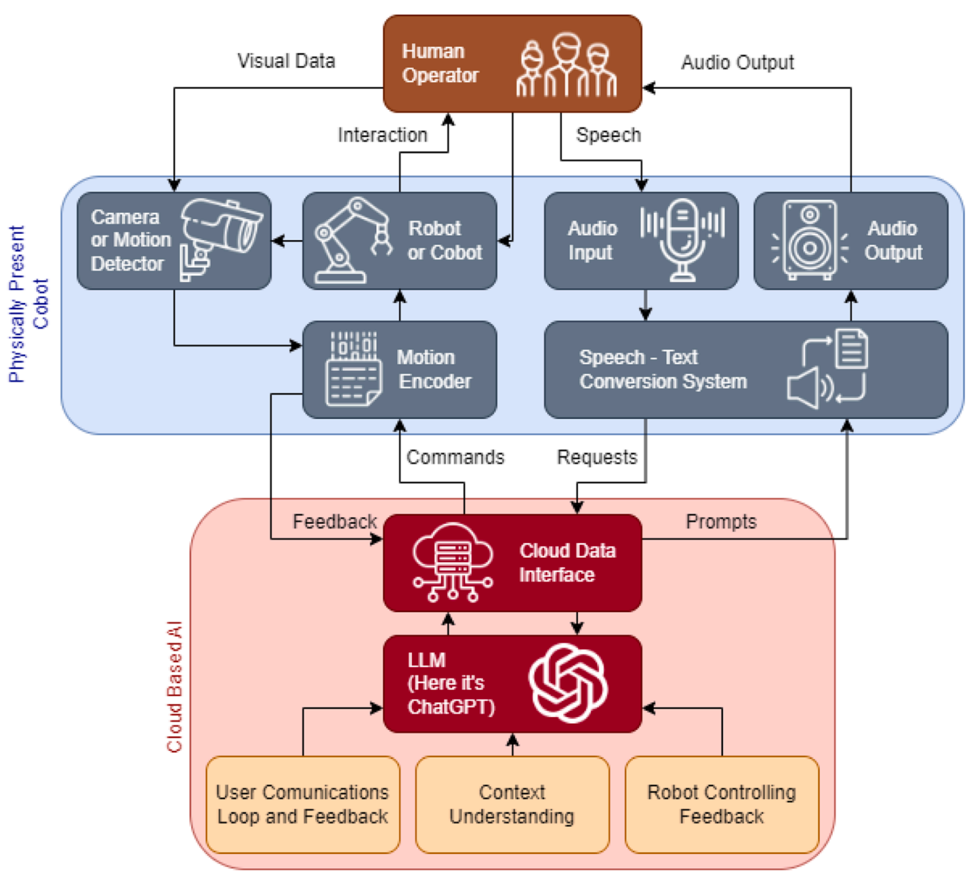

Fig. 12. Use of ChatGPT in workflow of HRC (based on Ye *et al.*, 2023 [144]).

and emphasized the need for ethical frameworks to guide their application. Wang *et al.* [149] conducted a study on methodical assessment of ChatGPT to reveal its strengths and weaknesses within the context of manufacturing proposing a three-layer model (knowledge, reasoning, and collaboration) for its effective use. Additionally, the authors also proposed a roadmap for technological advancement to effectively incorporate ChatGPT into the manufacturing sector [149]. Research in the emerging LLMs, i.e., ChatGPT, Generative AI etc. in HRC lays the groundwork for the development of reliable HRC systems in the future.

The above section summarises the use of generative AI technologies like LLM's in HRC. Existing methods employing AI, deep learning and reinforcement learning, which aims to improve HRI, often struggle with the unpredictability of human behaviour. The advancement in LLM's like ChatGPT, offers new possibilities for HRI in similar situations. LLM's, though powerful in handling large data sets, lack transparency and there are considerable concerns over utilization making their outputs difficult to fully explain. Despite this, LLM's are popular for roles involving novice human interactions in HRC and I5.0. Researchers are exploring the impact of LLM's in various industries, such as healthcare and manufacturing to enhance collaboration and decision-making processes. Different studies, as highlighted in this section, have evaluated the capabilities and limitations of LLM's in HRI's, suggesting methods to improve their effectiveness and trustworthiness in collaborative environments.

4.3.2. Role of digital and virtual technologies in HRC

In the domain of I5.0, Digital Twins (DTs) are of significance as they facilitate a two-way data exchange between the physical system and its virtual counterpart [150]. Robot Digital Twins (RDTs), which are digital representations of robotic systems, are commonly utilized for the simulation, testing, and improvement of industrial processes [151]. In the pursuit of human-centricity, Human Digital Twins (HDTs) - digital representations of individuals and their interactive environment - have emerged as crucial elements of I5.0 [150]. These HDTs are typically developed to amplify human capabilities, productivity, and overall welfare [152]. The merging of RDT and HDT can lead to the development of comprehensive systems that bridge the gap between humans and technology by leveraging the strengths of both humans and robots, thereby enhancing human interaction and well-being. Nevertheless, the creation of precise digital twins necessitates expertise from multiple fields, including engineering for physical modelling, computer science for software development, data science for analysis, and domain-specific professionals [152]. Moreover, the system architectures of HDT may require the integration of numerous components in a scalable manner, encompassing smart devices, collaborative robots, Augmented Reality (AR), Mixed Reality (MR), Virtual Reality (VR) devices, and Human-Machine Interfaces (HMIs) [150]. A generic system architecture showing workflow of HRC involving Digital Twins and Human-computer Interfaces (AR/VR) and other systems is shown in Fig. 13. Here the flow (from source to sink) of data, information, and knowledge models from and within the different computational & physical systems in HRC are depicted. The physical systems include Robots/Human, Sensors, Human Computer Interfaces (AR, VR, etc.). Computational systems include Digital Twins (HDT, RDT), Cloud, Robot Control and other intelligent tools for real time monitoring, optimisation and response analysis. Each of these systems has its own importance in the workflow of HRC.

As elucidated in Inkulu *et al.* [51], the utilization of immersive devices and advanced visual sensors enables a bidirectional interaction between humans and their surroundings. This interaction helps in mitigating potential risks, while simultaneously boosting operational efficiency and optimizing resource utilization [153,154]. Fostering interdisciplinary collaboration is a critical element in ensuring the accuracy and relevance of these digital twins [155].

A significant number of emerging technologies have been identified in the HRC research domain [54]. Table 5 shows a classification of these assistive technologies, which can be categorized into four main groups: VR/AR assistance, adaptation to human fatigue/workload, in-process robot control and teaching, and flexible/intelligent task allocation.

Various approaches within these groups have been emphasized, including the use of DTs for rapid exchange of product lifecycle information [158], the development of mobile robots equipped with body gestures, and eye tracking recognition systems for human-friendly

Table 5
Emerging technologies in HRC.

Virtual/ augmented reality assistance	Adaptation to human fatigue/ workload	In-process robot control and teaching	Flexible/ intelligent task allocation
[156–159]	[129,160–164]	[118,158,236, 237]	[167,169–173]

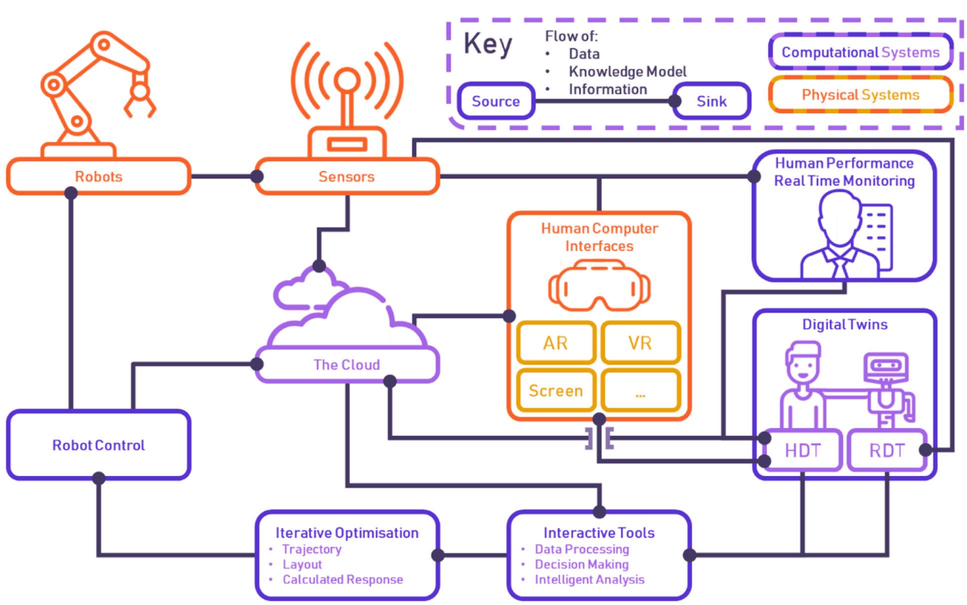

Fig. 13. Generic architecture showing HRC workflow of different systems.

interaction [169], and the teach-by-demonstration framework for smartphone assembly proposed by Haage *et al.* [168]. Although few assistive technologies are currently utilized in industrial shop floors, solutions based on VR and AR have been found to be suitable for this environment. For instance, HoloLens, the AR headset from Microsoft, is employed by Hietanen *et al.* [156] for visualizing safety zones in an engine assembly operation. Similarly, Vosniakos *et al.* [159] utilize Facebook's VR headset Oculus Rift for screening robot motion paths in a shell handling task, demonstrating that certified AR/VR devices can provide robust and reliable virtualisation solutions for current manufacturing safety and training needs.

Dianatfar *et al.* [174] provided an overview of the current VR and AR solutions applicable to HRI and Collaboration scenarios. Their emphasis lay in the approach to its implementation and ongoing challenges. The progression in VR and AR technologies has the potential to be leveraged in real-world and industrial settings, offering users a more immersive experience to interpret instructions and environmental factors. Furthermore, their case studies predominantly concentrated on enhancing operator awareness and support. Subsequent research directions may involve prioritizing user safety considerations and exploring interactions with heavier robots in diverse manufacturing tasks.

Dario *et al.* [175] validated the significant advancements achieved in the field of smart factories, highlighting the crucial role played by automation and HRI. The progress made underscores the increasing importance of integrating advanced technologies to optimize processes and enhance productivity in modern manufacturing environments.

Lou *et al.* [176] provided a comprehensive review of industrial human-cyber-physical system (HCPS) from a human-centric standpoint. They utilized a cohesive framework that addresses the integration of cognitive-to-technology and human-to-human interactions in HCPS. Specifically, it emphasizes the paradigms of human-in-the-loop, human-on-the-loop, and human-in-the-society, investigating their mechanisms and impact on design, production, and service to enhance the scope of research in intelligent manufacturing for I5.0.

Zou *et al.* [177] have optimized the order picking through HRC to improve the operational efficiency. An adaptive large-neighborhood-based tabu search algorithm was developed to offer a precise efficient solution. Experimental findings demonstrated the significant advantages of this algorithm suggesting using this model in order picking optimization for smart warehouses facilitated by IoT-enabled robot assistance.

Apostolopoulos *et al.* [178] introduced an innovative method for training operators utilizing AR technology. The method included a guide mode that allows users to become acquainted with Information and Communication Technologies (ICT) data flows in addition to seamless HRI in cooperative settings. Specifically, user-friendly instructions combined with ML-driven physical object recognition are employed to facilitate faster learning progress and offer practical training to operators. An analysis using an automotive industry case study is also conducted to assess the effectiveness of the training approach in a HRC assembly scenario.

Pauliková *et al.* [179] aimed to uphold health and safety standards within the workplace and ensure adherence to quality criteria during the manufacturing process. Their study sought to offer insights into potential negative consequences of HRI, to recommend proactive measures for prevention and rectification.

Mandischer *et al.* [180] proposed a system for integrating individuals with disabilities with collaborative robots that examines a person's in-the-moment abilities. The approach was grounded in an ontology enabling the matching of individual abilities with task requirements. Through this approach, inclusive work environments could be adapted independently to an individual's capabilities, eliminating the need for personalized adjustments.

Andronas *et al.* [181] illustrated the development of a symbiotic workstation featuring a human-high payload robot to enhance ergonomics and performance in industrial settings. They delved into the essential technologies facilitating seamless collaboration, such as 'a multi-modal human-robot interaction pipeline,' 'a gesture-based manual guidance module that is contactless,' 'a safety monitoring system and logic that operates without physical barriers,' and 'an augmented reality-based training application designed to involve the operator'. Through a case study in the automotive sector, the effectiveness and efficiency of the complete hybrid system are validated, showcasing enhancements in operator ergonomics and well-being. The results of this research demonstrated that high-payload robots can assist operators through intuitive interaction methods, thereby enabling businesses to depend on collaborative systems to enhance performance metrics and job flexibility.

Mielke *et al.* [182] analysed data from human-human dyad experiments to determine motion intent for human-robot co-manipulation, showing non-negligible interaction forces and distinct torque triggers at the start of lateral movement. Various metrics were used to evaluate dyad performance. A deep neural network was subsequently developed to predict human intent based on past motion data.

Nicola *et al.* [183] created a data-driven model to estimate material deformation from a depth image using a Convolutional Neural Network (CNN). The deformation state was defined as roto-translation from robot pose to human grasping position. It discussed the dataset acquisition, preprocessing, and model training. A comparison with a camera skeletal tracker method showed better performance and how the known drawbacks could be avoided. The model's generalization ability was then validated on three materials, and the performance studied based on different architectures and dataset dimensions for faster dataset acquisition.

The above section summarises the importance and effect of emerging technologies such as Digital Twins, AR/VR, and CPS on HRC. With a focus on HRC applications, it is suggested that HRC represents the future direction as an alternative to traditional robotic and automation frameworks. HRC systems empower humans to interact more efficiently and effectively with robots through user-friendly interfaces. Traditional systems necessitate substantial installation efforts and the expertise of skilled individuals for programming and management. Furthermore, older machinery must be modernized to enable collaboration with HRC units in the manufacturing process and it could be done by utilizing some of these emerging technologies.

4.3.3. Enabling technologies assisting I5.0 goals

Fig. 14 provides a view of how I5.0 represents a value-driven (in terms of economy, ecology, society) initiative that catalyzes the technological advancements (I4.0) through enabling technologies such as HRC, DTs, AI, Bio-inspired technologies etc. with specific interrelated goals of human-centricity, sustainability, and resilience.

I4.0 places considerable emphasis on digitalization and AI technologies, neglecting the core principles of social equity and sustainability [184]. The emergence of I5.0 in manufacturing is expanding rapidly, with a focus on human-centric principles and collaboration [25]. This paradigm shift prioritizes human needs within the production process, transitioning from a technology-centric model to one that views workers as valuable investments, thereby fostering an adaptive technological framework that serves societal interests.

Authors such as Maddikunta *et al.* [26] argue that I5.0 can reintegrate human labor into factories and create more specialized roles. This involves moving from limited human-machine interactions in I4.0 to more collaborative, adaptable, and personalized settings in I5.0 [65]. According to Nahavandi *et al.* [23], a key distinction between I4.0 and I5.0 lies in the use of robots, particularly in I5.0 where robots are envisioned as 'cobots' working alongside human operators. Adel [64] also supports this view, describing I5.0 as a new paradigm centered on human-machine collaboration. Similarly, Akundi *et al.* [185] point out that I5.0 is characterized by the emergence of human-robot co-working environments and the development of a smart society. Further studies

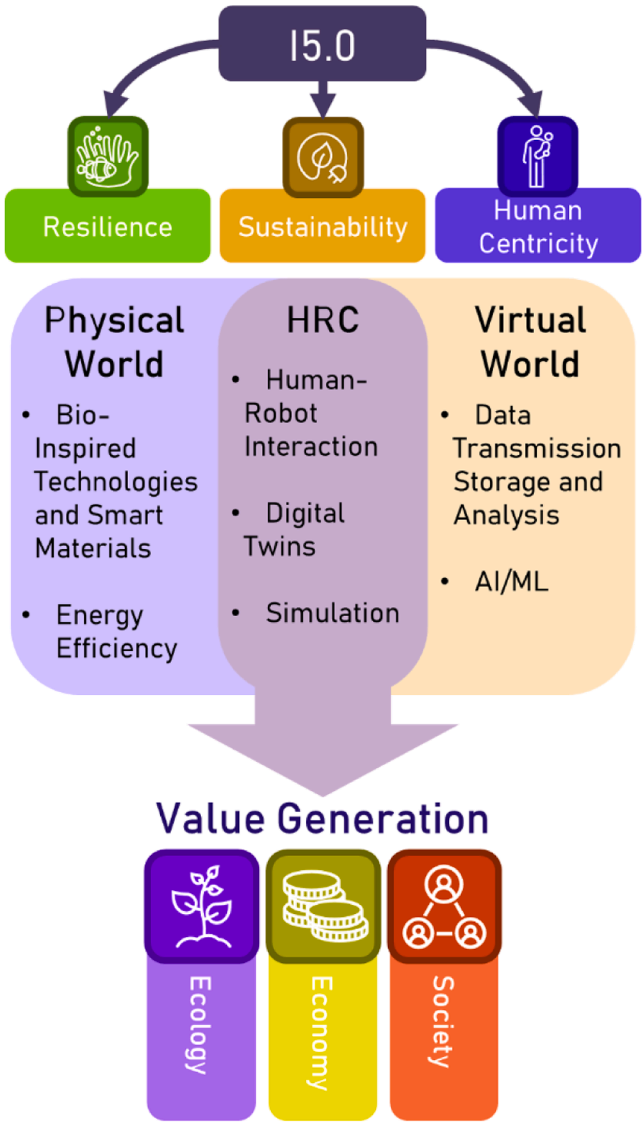

Fig. 14. Technological enablers and Industry 5.0 goals (reproduced based on Müller, Julian, 2020 [189]).

have been carried out by various researchers to emphasize the concept of HRC within the framework of I5.0 [25,186–188].

According to Muller [189], additional concepts and technologies linked to I5.0 include bioinspired technologies, energy-efficient technologies, DTs, cybersecurity, and AI. While the latter three concepts are also fundamental in I4.0, they do not emphasize the unique characteristics of I5.0 i.e., human-robot coworking environment. When it comes to bioinspired technologies and energy efficiency, there is a limited amount of discussion on these subjects in the existing literature on I5.0 [190]. Hence, it can be argued that HRC is the key technology defining I5.0 and setting it apart from I4.0, a point also supported by various researchers (e.g., [23,26,185]).

Section 4.3.3 summarises the transitional shift from digital technological advancements (I4.0) to the human centric technological transformation (I5.0) that aims to better serve societal interests. The rise of I5.0 is transforming manufacturing by prioritizing human-centric values and fostering collaboration, unlike I4.0′s focus on digitalization and AI at the expense of social equity. This new paradigm aims to reintegrate human labor, evolving from mere human-machine interactions to dynamic partnerships where robots act as collaborative ’cobots.’ I5.0 not only emphasizes human-robot co-working environments but also introduces innovative concepts like bioinspired and energy-efficient technologies. Ultimately, HRC emerges as the defining feature that distinguishes I5.0 from its predecessor, I4.0.

The key outcomes from Section 4.3 (the effect of state-of-art emerging technologies on HRC) are as follows.

- The application of LLM's offers enhanced interaction between humans and robots, yet it is crucial to tackle the concerns associated with their use & lack of transparency, as various studies propose strategies to boost their efficacy and reliability in collaborative settings.
- Digital Twins play a crucial role by enabling data exchange between physical systems and their virtual counterparts in HRC systems leading to improved interaction and well-being. This improved interaction helps in mitigating potential risks, while simultaneously boosting operational efficiency and optimizing resource utilization.
- Various approaches have emphasized the use of DTs for rapid exchange of product lifecycle information, the development of mobile robots equipped with body gestures, eye tracking recognition systems for human-friendly interaction, and the teach-by-demonstration framework for smartphone assembly. Fostering interdisciplinary collaboration is a critical element in ensuring the accuracy and relevance of these DTs.
- VR, AR and HCPS technologies have shown potential in industrial shop floors for assistive technologies, such as visualizing safety zones and screening robot motion paths, improving operational efficiency, ergonomics, and job flexibility.
- Researchers have also focused on upholding health and safety standards, integrating individuals with disabilities, and developing symbiotic workstations with human-high payload robots utilizing these emerging technologies. Future research should prioritize user safety and explore heavier robot interactions in diverse manufacturing tasks.
- I5.0 emphasizes human-centric values and collaboration environments, reintegrating human labor and introducing innovative concepts like bioinspired and energy-efficient technologies. While I4.0 places greater emphasis on enabling technologies including digitalization and AI technologies, whilst having less focus on social equity and sustainability.

4.4. Information modelling and knowledge use in HRC

In manufacturing, there are ongoing research challenges focused on the development of control systems that can effectively predict changes in production requirements and objectives [191]. The fundamental actions of a robot are hard-coded and less flexible in terms of its functionality. Besides the lack of functionality, the robot has very limited understanding of its environment [192]. The increased levels of flexibility and adaptability in robots are essential in addressing the demands of I4.0 and I5.0 [193] where data collection and analysis become important.

As the complexity, variability, and richness of data and knowledge increases, there is a need for structured methods to effectively manage it for decision-making purposes. Data can be obtained from robots, sensors, ML algorithm outputs, etc., which when processed and interpreted provides new information on processes and scenarios. Additionally, knowledge is gained on aspects such as the behaviour of actors/individuals, occurring processes, and the status of objects and the environment. There is a need for systems that can provide all this information in a standardized format and describe the complex relationships between both physical, virtual, and abstract entities (from products, machines, and documents to human behavior, preferences and planning).

Information modelling techniques consisting of knowledge and data maps are commonly employed to facilitate data management [194]. A common approach to manage knowledge within a domain is an ontology. This serves as a means of formally organizing this knowledge within a system and offers a shared vocabulary for diverse systems, processes, and actors [195]. It allows for the representation of hierarchical relationships between various concepts or objects and the storage of any possible relationships among different entities within the entire system. This, in turn, enhances information sharing across different components of distinct systems [196].

By employing an information sharing approach through an ontology, both humans and robots can better understand the different information points and gain a better comprehension of each other's abilities and limitations, leading to enhanced collaboration efficiency and effectiveness [85]. Additionally, the ontology functions as a knowledge repository that remains accessible even when participants are not fluent in the same language, while also being intelligible to all elements within the system [55]. In comparison to database approaches, ontologies have been shown to outperform them as data volume increases [57], in addition to preserving the meaning of the information, such as the types of 'things' and how they are related [197].

The conventional way of representing an ontology is through adopting the Unified Modelling Language (UML) and Web Ontology Language (OWL) formats. OWL serves as a standard language for encoding ontologies on the semantic web, utilizing the .owl file format [198]. This format is built upon the Resource Description Framework (RDF), which is a standardized means of encoding metadata and structured data on the web. The OWL files are composed of a collection of RDF triples [199], which express statements about entities and their relationships within the ontology. Each triple is comprised of a subject, predicate, and object, representing an entity, a relationship, and another entity, respectively, as illustrated in Fig. 15.

The retrieval of information from ontologies can be facilitated through the utilization of a query language such as the SPARQL Protocol and RDF Query Language (SPARQL), which is based on the RDF format [199]. Moreover, the updating and retrieval of ontological models can be accomplished using SPARQL [198]. An alternative approach involves the utilization of rule-based languages, such as the Semantic Web Rule Language (SWRL), which can be effectively employed within ontologies. By employing rules and RDF triples, semantic reasoning engines have the capability to deduce implicit knowledge and ascertain the consistency of a model [200,201]. Querying and retrieving knowledge can assist in planning strategies, where information such as object location or current agent behaviour and performance can be obtained and used to determine the next task execution [56,85].

General ontologies have been developed aiming to describe and organise knowledge and concepts in various fields, including linguistics, cognitive science and AI [202]. These include the Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE) [203], a lightweight version DOLCE Ultra Lite (DUL) [204], and the Suggested Upper Merged Ontology (SUMO) [205]. These more general high-level ontologies can serve as foundational elements for numerous ontologies within the domains for manufacturing systems and human robot interactions. For instance, DolceEng extends DOLCE to introduce concepts such as artifacts, roles, activities, capabilities, and capacities in order to represent entities in the manufacturing domain [206].

The Manufacturing Process (MPRO) ontology builds upon aspects of the SUMO ontology and focuses on classes and properties specific to manufacturing processes. These processes are further divided into types, such as assembly processes, which can be further categorized into permanent joining and mechanical fastening, among others [207]. The Semantic Sensor Network (SSN) and Sensor, Observation, Sample, and Actuator (SOSA) ontology is extensively employed for expressing sensors and sensor networks in a machine-readable format [208].

General core ontologies for robotics and automation have been developed, such as the Core Ontology for Robotics and Automation (CORA) ontology, which is based on SUMO [209]. Collaborative CORA (CCORA) extends the CORA ontology by incorporating concepts related to human-robot collaboration. The Ontology for Collaborative Robotics and Adaption (OCRA) is developed to formally represent collaboration and plan adaption [210]. OCRA primarily addresses uncertainty and safety constraints arising from the deployment of collaborative robots in industrial tasks within a limited area. The Sharework Ontology for Human robot collaboration (SOHO), developed by Umbrico *et al.* [211], represents human-robot collaboration within collaborative workcells, where robots and operators collaborate at various cognitive and physical levels with seamless communication. Concepts are introduced to define human intention, commitment, and coordination. KnowRob, a knowledge processing system for robots is based on OpenCyc upper ontology [212] and enables reasoning and complex task performance. It bridges the gap between vague task descriptions and the detailed information required for execution [212].

4.4.1. Industry 4.0 ontologies

The ontologies briefly mentioned in the previous section can be reused and represent many of the technologies involved in I4.0, such as sensors and robotics. Sapel *et al.* [213] thoroughly review and classify 65 manufacturing ontologies focusing on the benefits for knowledge management in I4.0. The Ontology for Industry 4.0 (O4I4) is specifically designed to encompass the domain concepts of I4.0, while also incorporating elements from existing ontologies such as CORA [209], ROA

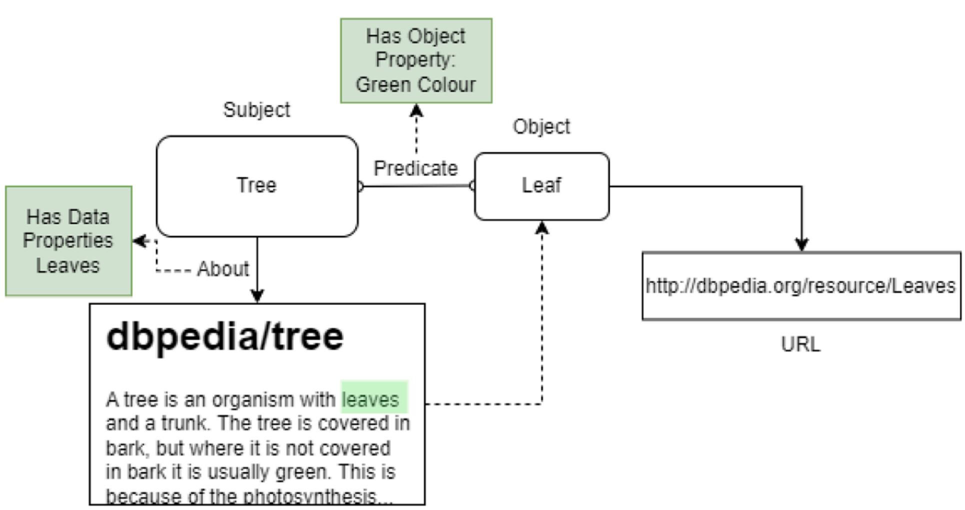

Fig. 15. Resource Description Framework (RDF) triple of a simple sentence "Tree has Leaves". Tree is linked with "about" data property to its universal definition on dbpedia.com (based on Zangeneh *et al.*, 2020 [199]).

[214], and ORArch [215] for the robotic facet of smart manufacturing.

The successful implementation of I4.0 relies heavily on the use of robotic agents that can evolve and carry out essential operations within a smart manufacturing environment [216]. These robotic agents are required to communicate with various stakeholders, including human operators, customers, and distributed partners. To ensure smooth and efficient development of I4.0, it is crucial to establish standardized knowledge representation. This need for standardization has prompted the incorporation of the IEEE 1872–2015 Standard Ontologies for Robotics and Automation [215], which provides a foundation for ontological standardization efforts in the I4.0 context. This foundation can be expanded upon by introducing specific ontological concepts relevant to I4.0. Additionally, researchers have proposed two ontological frameworks to address the broader domain of smart manufacturing and I4.0 [217]. These frameworks, proposed by Cheng *et al.* [218] and Engel *et al.* [219], contribute to the ongoing efforts towards establishing ontological standardization in I4.0.

Overall, the ontology proves to be a valuable tool in enhancing the safety, efficiency, and effectiveness of human-robot collaboration within the context of I4.0 [200]. As the field of HRC continues to advance, the way information (between the human and robot) is managed and used within an ontology is expected to play an increasingly significant role in I4.0 and I5.0 [220].

4.4.2. *The effect of ontologies on HRC*

Ontologies can play a significant role in enhancing the flexibility of control solutions improving the collaboration between humans and robots by mapping and structuring the different information related to working environments and to human intentions. These can be utilized for future improvements, including path planning and predictions of human movement. [221]. It facilitates the efficient coordination of human and robotic agents by offering a structured representation of: (i) production goals, tasks, and operational restrictions; (ii) abilities and skills of workers and robots; (iii) recognized performances, preferences, and physical/behavioral characteristics of workers that could impact interactions with the robot and the resultant collaborative activities [221]. In the context of HRC, ontologies are crucial in facilitating effective communication between humans and robots by establishing a shared understanding of the environment, tasks, goals, limitations, capacities, constraints, and interactions [200]. They can enable robots to better comprehend human behaviours and intentions, even in unpredictable or uncontrollable situations. Using diverse knowledge representations and abstract reasoning, ontologies contribute to adaptable control solutions in collaborative scenarios. These ontologies are constantly updated and improved as the field of HRC progresses [192]. Fig. 16 shows the role of an ontology in HRI and how the information flows and data transfers through a set of channels in the HRC system. For a specific HRC task, the generated data through interactions transfers to the knowledge graph (a graph structure representing knowledge in organised manner). Then a database is created through RDF triples which populates the different classes in the static ontology (set of relationship between different entities). This processed data is then dynamically updated adding new information and instances and linking the real-world concepts in the static one, representing a dynamic

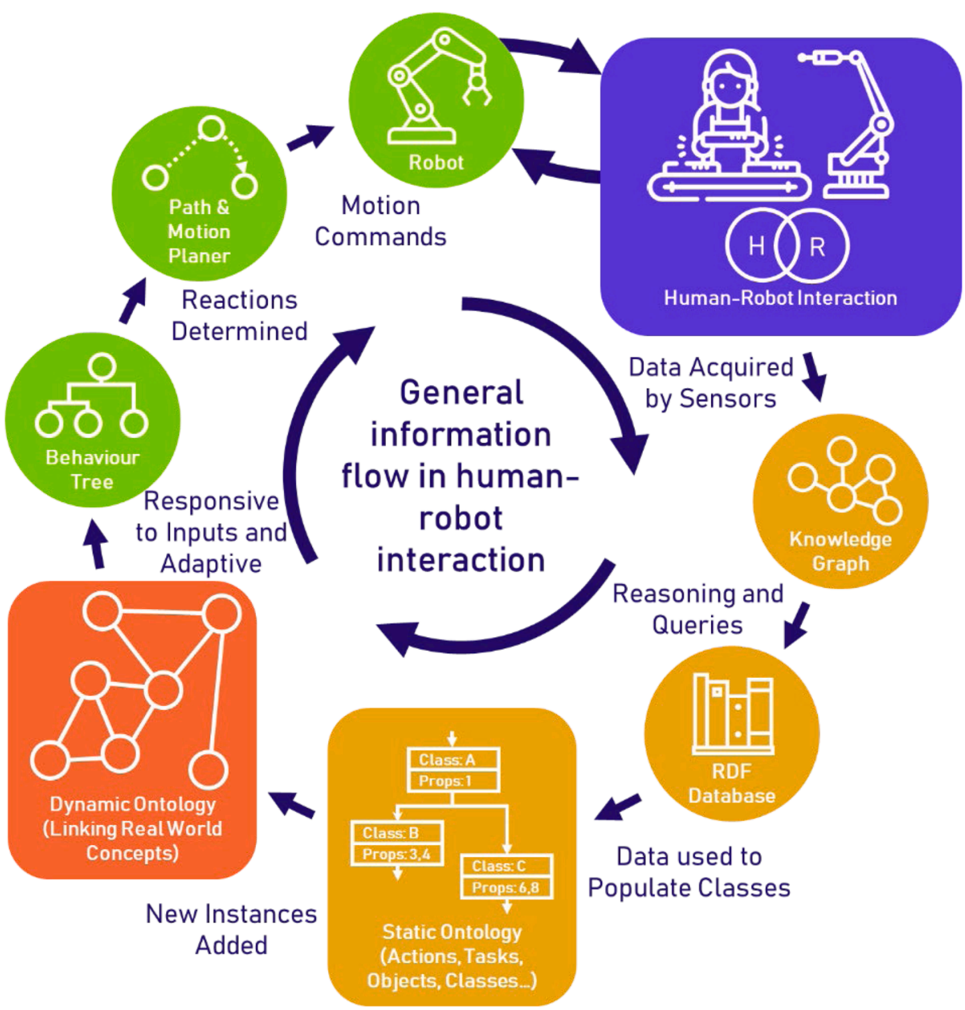

Fig. 16. General Information flow and effect of ontology in HRI.

ontology. The adaptive responses are collected and fed to the behaviour tree (a set of procedures) to make the decision for the task execution. Finally, a collaboration task is performed through the robot action after passing the motion command through the task planner. This cycle repeats for every task and the feedback is collected through exchange of data & information between robot and human and interaction history is updated and stored.

In the domain of manufacturing, ontologies have primarily concentrated on manufacturing systems rather than on specific production facets such as modeling procedures, the capabilities of operational entities, and the potential interactions associated with production goals, as evidenced by references [222,223]. The depiction of CPSs like HRC Systems necessitates the modeling of the dynamics of the participating agents from both a local (i.e., the standpoint of an individual agent) and global perspective (i.e., the standpoint of production) [224]. Within this framework, ontologies have been predominantly utilized to enhance the adaptability in modeling and strategizing for mechatronic devices [225] and resources in collaborative settings [226]. Ontology-based HRC systems are becoming the thrust for several potential future research endeavors [58].

- The researchers are primarily concentrating on enhancing ontologies within knowledge representation, while advancements in the mechanism aspect are lacking.
- There is a necessity for further exploration towards the standardization and effective implementation of ontology-based knowledge representation systems.
- In addition to ontologies, future studies should also target the enhancement of efficient queries and reasoning mechanisms that can be employed across numerous distributed ontologies with limited resources.
- Future research could significantly benefit robot autonomy if potential impacts of ontology-based HRC systems integrated with context awareness are considered carefully.
- Ongoing research should persist in more practical scenarios for the cultivation of culturally competent ontology-based HRC systems, empowering robots to execute various intricate tasks in dynamic environments by recognizing culture-specific needs and preferences.

The key outcomes from Section 4.4 (Information modelling and knowledge use in HRC) are as follows.

- Information modeling techniques help to manage and analyse data (generated by robots, sensor etc.) effectively for decision-making through ontologies. An ontology enhances collaboration efficiency and effectiveness by providing a shared knowledge repository for both humans and robots, ensuring understanding of each other's abilities and limitations.
- Ontologies improves control solutions, adaptability, and HRC by mapping information and facilitating bi-directional communication. Current research focuses on refining knowledge representation and standardized implementations, while future research should enhance ontologies and mechanism advancements for better HRC systems.
- General ontologies like DOLCE and SUMO form foundations for manufacturing processes and robotics. Core robotics ontologies like CORA and OCRA address collaboration, plan adaptation, safety constraints, and HRC in collaborative workcells.
- Ontologies in manufacturing focus on manufacturing systems rather than specific production aspects. They enhance adaptability in modeling and strategizing for mechatronic devices and collaborative resources. Ontology-based HRC systems are becoming the focus of future research, as they help visualize the dynamics of agents from a variety of internal and external stakeholders.

It is anticipated that, under the umbrella of AI, semantic web technology, and other associated concepts or visions, the progression of this field towards real-world robotic applications will continue.

4.5. HRC manufacturing advancements

This outlines the advancements in HRC for manufacturing applications, assembly, and inspection. Assembly operations involve a variety of tasks such as manual setting, screwing, mounting, fixing, and material handling. HRC assembly examples along with the control systems and collaborative methods used have been presented in Table 6. Table 7 presents the case studies and the types of technology used in HRC inspection.

4.5.1. HRC for assembly

The utilization of HRC in assembly operation varies from other manufacturing processes due to the high level of flexibility it demands. This stems from the need for frequent changes in the assembly layout to achieve mass customization. Advanced manufacturing processes have empowered designers to create intricate shapes and alterations in part geometry that considerably impact the assembly sequence. Consequently, a novel assembly layout is often essential, which poses a daunting task for industrial engineers [38,227]. To adapt to these alterations, the assembly layout must be reconfigurable, and the resources should be capable of collaborating to share assembly operations. Several authors [1,228–230] have suggested cooperation-based assembly layout design through distinct modes and working towards safety and collision-free tasks. However, issues of safety and collision-free interaction need to be addressed [51]. It is believed that HRC can be applied to low speed and low payload robots in small and medium-scale industries [51]. However, the potential consequence of collisions is significant for a large payload robot [230]. Therefore, there is a need to design a safe HRC system appropriate to the variety of assembly operations [231].

According to Papanastasiou *et al.* [229], the most effective technique for facilitating collaboration between high payload robots and humans is two-way communication utilizing speed separation monitoring with augmented reality (AR). They successfully demonstrated a 35% reduction in assembly time using this technology. The use of AR technology decreases cognitive burden during assembly operations and facilitates the use of human intelligence and perception to manage the assembly of heavy parts, such as refrigerator cabinets [229]. Makris *et al.* [232] successfully implemented this technique in seamless HRC within an automotive axle assembly case study. Rajnathsing and Li [92] employed object detection, speech recognition, and neural networks to identify normal production cell operations. Robots with the assistance of AI and machine vision technologies were used in disassembly and recycling operations for identifying and removing e-waste from the hybrid battery systems of an Audi Q5 [233].

Various researchers [234–236] have developed virtual teaching for unskilled workers to collaborate with robots effectively. They have proposed an advanced gesture recognition system with an RGB-D camera, analysed various gestures, and implemented an optimal assembly sequence for flange assemblies considering resource allocation for humans and robots. Mura and Dini [237] employed a genetic algorithm to reduce costs by replacing human workers with collaborative robots in the assembly line balancing problem. Meanwhile, Liau and Ryu [238] focused on the ergonomic issues of repetitive heavy component handling and suggested the use of genetic algorithms to improve operation cycle time. They enhance agent capability through human and robot collaboration with alternate generation, thereby optimizing manufacturing processes and improving assembly line efficiency.

Guo *et al.* [45] suggested the application of fixed position assembly islands as a solution for I4.0 challenges. The author's presented a five-layered network, including an assembly layer, perception layer, interaction layer, cognition layer, and service layer. This enabled optimization of factory layout and equipment selection, real-time tracking and communication, and autonomous operation of assembly islands.

Table 6
Human-robot collaboration for manufacturing assembly.

Ref	Year	Robot/Cobot Used	Control System	Collaboration Methods	Objective	Application	Factors Optimised in Assembly (Cost, Time, Ergonomic, Others)
[241]	2013	ABB FRIDA (YuMi)	Vision	SSM	Safety	Assembly	Safety distance
[242]	2013	ABB FRIDA (YuMi)	Vision	SSM	Safety	Assembly	Safety distance
[243]	2013	Industrial robot	Position	SSM	Safety	Assembly/Quality Control	Safety distance
[244]	2014	Universal Robots UR10	Vision	PFL	Productivity	Assembly	Time
[245]	2015	Universal Robots UR5	Impedance	-	Productivity	Machine Tending	Time
[246]	2015	Industrial robot	Position		HRI	Human Assistant	-
[247]	2015	Kawada HIRO	Vision	PFL	HRI	Assembly	-
[248]	2016	Kinova MICO 2-finger	Vision	-	HRI	Assembly	-
[249]	2016	Rethink Baxter	Vision	-	Productivity	Assembly	Time
[250]	2016	WAM robot/ KUKA LWR iiwa	Impedance/ admittance	MG	HRI	Assembly	-
[251]	2016	ABB FRIDA (YuMi)	Vision	SSM	Safety	Assembly	Safety distance
[252]	2016	KUKA LWR4+	Admittance	SSM	Safety	Assembly	Safety distance
[253]	2016	Rethink Baxter	Vision and audio recognition	PFL	HRI	Assembly	-
[254]	2016	Industrial robot	AR system	MG	Safety	Human Assistant	Safety distance
[255]	2017	KUKA LBR iiwa	Impedance/ Admittance	MG/ PFL	HRI	Assembly	-
[256]	2017	ABB YuMi	Admittance	PFL	Productivity	Assembly	Time
[257]	2017	KUKA LBR iiwa	Vision	MG	Productivity	Assembly	Time
[258]	2017	Rethink Baxter	Human tracking system	PFL	HRI	Assembly	-
[259]	2017	Rethink Baxter	Vision	PFL	HRI	Assembly	-
[260]	2017	KUKA LWR4+	Admittance	-	HRI	Screwing	-
[168]	2017	ABB YuMi	Vision	-	HRI	Assembly	-
[261]	2017	Universal Robots UR3	Impedance and audio recognition	MG/ PFL	HRI	Assembly	-
[262]	2017	KUKA LBR iiwa	Admittance	MG/ SSM	Safety	Assembly	Safety distance
[263]	2018	Industrial robot	Gesture recognition	MG/ PFL	Productivity	Assembly	Time
[264]	2018	KUKA LBR iiwa	Vision	SSM	HRI	Assembly	-
[265]	2018	Rethink Baxter	Vision	PFL	Productivity	Assembly	Time
[266]	2018	ABB YuMi	Vision	PFL	Productivity	Assembly	Time
[267]	2018	ABB YuMi	Sensitive skin	SSM	Safety	Test of Collision	Safety distance
[268]	2018	Universal Robots UR10	Vision	SSM	Productivity	Human Assistant	Time
[269]	2018	Industrial robot	Admittance	MG/SSM	Productivity	Assembly	Time
[270]	2018	KUKA LBR iiwa 14 R820	Vision / Admittance	MG/SSM	Safety	Assembly	Safety distance
[271]	2018	Industrial robot	Admittance	MG	Safety	Assembly	Safety distance
[272]	2018	Industrial robot	AR system		Safety	Assembly	Safety distance
[273]	2018	Rethink Baxter	Vision and audio recognition	PFL	Productivity	Assembly	Time
[236]	2019	Universal Robots UR3	Haptic, HRIS	PFL	Optimal assembly sequence	-	Time &Cost
[274]	2020	-	Quick Assessment algorithm, simulations		I4.0, Productivity	Wire harnesses Assembly	Ergonomic, Cycle time
[238]	2020	1H:2R	task allocation model (1H +2 R)	GR	Multi-robot HRC	Two plates mold assembly	Time Ergonomics
[275]	2021	ABB robot	Haptic, voice, hand gesture	MG	HRC adaptability and flexibility	Assembly of engine cylinder	Time & cost
[276]	2021	-	Simulation GUI Workcell	-	Scheduling	Panel assembly	Ergonomics, time and safety distance
[277]	2022	-	MILP, CP, and BD approaches	-	Productivity	Balance shaft assembly	Cycle time & Ergonomics
[239]	2023	KUKA Systems	-	-	Safe & Efficient scheduling HRT	Aircraft assembly	Time & Safety distance

[For the "Collaboration method" column, the legend is: SSM – Speed Separation Monitoring; PFL – Power and Force Limiting; MG – Manual Guidance; GR- Gesture Recognition]

Table 7
HRC for inspection.

Ref.	Task/Case Study	Human-robot collaboration technology					HRCo
		SSM	PFL	GR	VC	MG	
[285]	Rainwater testing of a car						✓
[294]	Front wind screen of car					✓	✓
[284]	Train axle inspection						✓
[295]	Painting				✓		
[296]	Visual screening of end-offline vehicles					✓	
[166]	Visual screening of polished metallic parts					✓	

Notes: SSM – Speed Separation Monitoring; PFL – Power and Force Limiting; GR – Gesture Recognition; VC – Voice Controlled; MG – Manual Guidance; HRCo – Human–Robot Co-operation.

They continued their work on efficiently scheduling collaboration between human-robot teams, developing towards synchronized production-logistics tasks in the context of aircraft assembly [239].

Table 6 provides the cited research literature (from the years 2013–2023) on HRC systems for manufacturing assembly case studies and the technology used for HRC. This table summarizes the different cobot/robot uses, control systems, collaboration methods, objectives, and optimisation factors (cost, time, ergonomics) in HRC assembly applications [51,87,240].

The utilization of HRC techniques and other computational and emerging AI tools has the potential to optimize assembly line balancing, improve ergonomic conditions, and enhance overall efficiency of the assembly line [20,237,239,278].

HRC has gained significant attention in material handling due to its ability to enhance operations, improve resource utilization, and adapt to production demands through the use of cobots, which offers a high level of flexibility and real-time guidance from human collaborators [54,165,279,280]. The study conducted by Matheson *et al.* [281] emphasized the emergence of cobots and their potential benefits, particularly in efficiently implementing cost-effective solutions, and discussed layout changes in material handling applications.

Examining up-to-date case studies is imperative to improve understanding of the tangible consequences of human-robot cooperation in the domain of material handling. The implementation of HRC in material handling presents both opportunities and challenges. Ensuring the safety of human operators working with robots is crucial, requiring the development of advanced safety systems and protocols. Additionally, designing intuitive communication interfaces and interaction modes is a critical challenge that impacts collaboration effectiveness. The identified array of ongoing research [280,281] generally aims to address these challenges and establish human-centered conceptual models for future material handling applications.

4.5.2. *HRC for inspection*

Inspection plays a crucial role in manufacturing through evaluating the quality of the end product during and after fabrication. This application of HRC has been explored in various contexts, such as inspection for airplanes, railway axles, and moisture detection [282,283]. Charalambous and Stouts [284] found that snake-like robots can effectively navigate and analyse shaded areas in railway inspection, providing better visualization and coordination with humans to identify and analyse cracks.

Muller *et al.* [285] introduced a new methodology for inspection aimed at improving worker safety and reducing labour costs in production. Their approach involves using an automated moisture detection system that collaborates with human workers to inspect moisture inside cars after a rain test, thereby reducing the amount of physical labour required. A virtual model was also developed to assess the HRC applicability in real-time manufacturing environments [285].

Zhao *et al.* [286] developed a HRC method for uncertain surface scanning to achieve maximum freedom in controlling the robot's position and pose without the need for extra sensors leading to uncertainty in determining the surface's exact position. To do so, they assumed that the surface is ideally uniform with the same properties. Bakopoulou *et al.* [287] examined the use of collaborative robots to automate the inspection process for large parts, with a case study in the steel production sector, allowing experts to focus on reviewing and interpreting results. Their system has been partially developed and is currently not able to inspect metal components with more complex shapes. Additionally, it is anticipated that more work is required on its safety aspects.

Caterino *et al.* [288] used the LABOR approach (Lean robotized AssemBly and cOntrol of composite aeRostructures) for inspection of composite fuselage panels, adopting a HRC approach and a distributed software architecture. The existing solutions lacked robustness when applied to industrial applications, as they tend to generate a significant number of false positives during the human tracking phase. Consequently, unnecessary halts in robot movement occur resulting in a decline in production rate.

In most manufacturing environments and scenarios, it is often imperative that the robot's pre-programmed path remains unaltered, as any modifications may lead to violations of certain constraints (design constraints, safety concern, workflow) and may hamper productivity and quality. Karami *et al.* [289] extended the flexible human–robot cooperation (FLEXHRC) framework to allow a human operator to interact with multiple robots simultaneously for a joint task, specifically focusing on inspecting product defects. This is in contrast to the research conducted by Oh *et al.* [290] and Cho *et al.* [291] which involved robots conducting visual examinations to verify the quality of products. It is probable that a combination of auditory, tactile, and visual perception will be necessary to validate the aforementioned quality [292,293]. This integration of sensory modalities remains a topic that requires further investigation. Wang *et al.* [130] reviewed work on the development of intelligent HRC welding systems and the related quality inspection and assessment. They suggest that the machines "intelligence" can be used in quality inspection through the identification of weld features or defects, categorization of the state of the weld, determination of necessary actions to be taken, and enhancement of process robustness. Table 7 lists the recent literature on HRC-based inspection, showing the tasks and the technology used.

4.6. *Evaluation metrics and tools for HRC*

Evaluation methodologies and tools for HRC in manufacturing are essential in determining the efficiency and effectiveness of collaborative efforts between humans and robots on the factory floor. The development of a "collaboration scale" supports the assessment of HRC across different disciplines and helps to bridge the gap between engineering and social sciences [297]. There are several tools that can be used to evaluate HRC systems [59]. These tools can be used to collect data on the performance of the system, and to analyse data to identify areas for improvement. Some of the common tools that are used to evaluate HRC systems include [59]:

- Simulation tools: These can be used to create virtual models of HRC systems. These models can be used to test the safety, productivity, and quality of a system before it is implemented in a real-world environment.
- Data collection tools: These can be used to collect data on the performance of a HRC system. This data can be used to track the performance of the system over time, and to identify areas for improvement.
- Analysis tools: These can be used to analyse the data that is collected from a HRC system. This analysis can be used to identify areas for improvement, and to make recommendations for how to improve the performance of the system.

Evaluation metrics and tools for HRC in manufacturing applications are important for ensuring the key metrics i.e., safety, productivity, and quality [79]. These metrics can be used to measure the specific needs of a particular application, such as the efficiency, team fluency, ergonomics, ease of use, or the environmental impact [79]. Table 8 shows the metrics and measures for assessing HRC methods in industrial scenarios. The different tools and activities used with corresponding metrics has also been indicated.

Furthermore, a comprehensive framework has been proposed for evaluating human-machine interfaces (HMI) and HRI in collaborative manufacturing applications [14]. This framework offers both objective quantitative metrics and subjective qualitative measures to guide the development and assessment of interfaces and interactions in HRC scenarios, as shown in Table 9. The metrics aim to promote operator situation awareness, effective process and system diagnostics reporting, and faster responses to equipment or application errors, thereby enhancing the overall collaboration experience. This approach empowers manufacturers to design more intuitive and efficient human-robot interfaces, enabling seamless communication and interaction between human operators and robotic systems [14].

The evaluation of HRC systems is an important part of ensuring the safety, productivity, and quality of the collaboration. Evaluation metrics and tools play a vital role in assessing the success of HRC in manufacturing applications. By providing a structured and systematic approach to analysing various aspects of collaboration, these tools contribute to the ongoing development of effective and efficient HRC systems, fostering innovation and improvements in manufacturing processes.

5. Challenges and future perspectives in HRC

The rate of implementation of HRC in the manufacturing sector has fallen short of initial expectations, partly, in response to apprehensions about the safety of physical interactions [26]. As per the information provided by the IFR [329], collaborative robots have experienced an average installation growth rate of just 6% over the past five years. This places cobots within the phase of enlightenment on the Gartner Hype Cycle [330]. Through analysis of different past surveys, responses, and feedback [331], cobots can be categorized into four key stages on the Gartner Hype Cycle, as illustrated in Fig. 17.

It is crucial to perceive humans and cobots as interconnected participants within a sociotechnical framework, rather than as distinct entities. This necessitates a purposeful approach to HRC design. Further examination is necessary to ascertain which elements of workflows can be efficiently automated, the level of collaboration in terms of complexity and profundity, and the impact on individuals' cognitive workloads. This will notably impact the requisite skills and training and perspectives on work quality of involved humans [332]. Moreover, the potential dispersion of responsibility that might arise from the utilization of cobots and other networked systems in the context of I5.0 [143] must be considered. The attribution of agency and the related role expectations of cobots may reduce human agency by modifying the role structure within the sociotechnical system [333]. Consequently, it can become more difficult for humans to take autonomous action, assume responsibility, and retain control over the process and outcome [142, 332]. Despite the recent development of advanced methods and mechanisms, this has caused most approaches to HRC implementation to be confined to laboratory environments at the time of writing.

Table 8
Relevant metrics for assessing HRC methods in industrial scenarios [79].

Metrics	Measures	Tools/Activity
Productivity	Efficiency	Cooperative speed up [298]
		Relative Helpfulness [299]
		Robot Error Rate [300]
	Teaming Fluency	Human/Robot Idle time [300]
		Concurrent Activity [300]
		Robot participation rate [298]
Quality	Phys. Ergonomics	Strain Index (SI) [301]
		Rapid Entire Body Assessment (REBA) [302]
		Rapid Upper Limb Assessment (RULA) [303]
	Cog. Ergonomics	NASA-Task load index (TLX) [304]
		The System Usability Scale (SUS) [305]
		Team Fluency [300]
Safety	Physical Safety	Separation Distance [306]
		Contact Force/ Pressure
	Psychological Safety	Custom Questionnaires [305,307,304,308]
		Anxiety by Physiological Signals [309]
		Posture [310]

Table 9
Shows the distinct metrics and descriptor for HRC [59].

Metrics	Metrics Descriptor	References
Objective Metrics	Success rate	[311,107,312,313]
	Interaction force	[314,315,316,317,318]
	Timing (idle & total)	[311,312,324,300,320,321,322]
	Joint effort	[313]
Subjective Metrics	Fluency	[311,319,322,300,320,324,323,325]
	Satisfaction	[313,318,326,324]
	Comfort	[311,313,320,327,328,324,325]
	Usage of interface	[319,313,318,326,323,324]
	Trust in the robot	[322,300,324]
	Human like motion	[328]

5.1. HRC handling: safety and trust

The field of HRC must recognise the necessity of safeguarding workers against accidents and injuries. To this end, there has been a strong focus on creating dependable and secure operational environments and systems. This has had a particular emphasis on following safety guidelines outlined in ISO standards specific to industrial settings, personal use, and collaborative robots [334]. In addition, industry is actively working on developing new control systems and motion/collision detection to promote collaboration while maintaining operational speed and ensuring separation from robots [32,329,335,336]. Noteworthy reviews by Gualtieri *et al.* [49] and Proia *et al.* [337] have discussed AI applications that aim to control safety and ergonomic performance at the interface between robots and human operators. Moreover, examples of more specialized research efforts have included the comprehensive examination of robotic control systems by Ibrahim *et al.* [338], as well as the investigations into robotic self-awareness, kinematic coordination for collision detection, and kinaesthetic flexibility by Jantsch *et al.* [339], Han *et al.* [340], and Xiao *et al.* [341], respectively.

Factors that are commonly acknowledged to have a significant impact on an operator's performance in HRC include stress, workload, and trust [334]. The mental stress experienced by individuals working with robots can be heightened by various physical characteristics of the robot, such as its size, shape, and movements, particularly when it can move swiftly and unexpectedly [342]. While the introduction of collaborative robots may reduce physical workload, it can lead to a notable increase in mental workload. This increase can be attributed to difficulties in interpreting the intentions of the robot, especially in situations where its level of autonomy is high or when the operator is required to supervise tasks involving the robot, which can impose a considerable cognitive burden [334]. Moreover, according to Gervasi *et al.* [297] trust is identified as a critical factor in achieving optimal performance in HRC. Insufficient trust may lead operators to underutilize the robot, resulting in reduced performance or non-use. The design of a collaborative robot can also influence trust. For example, a robot that is excessively large may deter humans from engaging in collaboration, whereas a smaller robot or one that incorporates social cues may enhance the operator's comfort. To address this, it is suggested by Kim

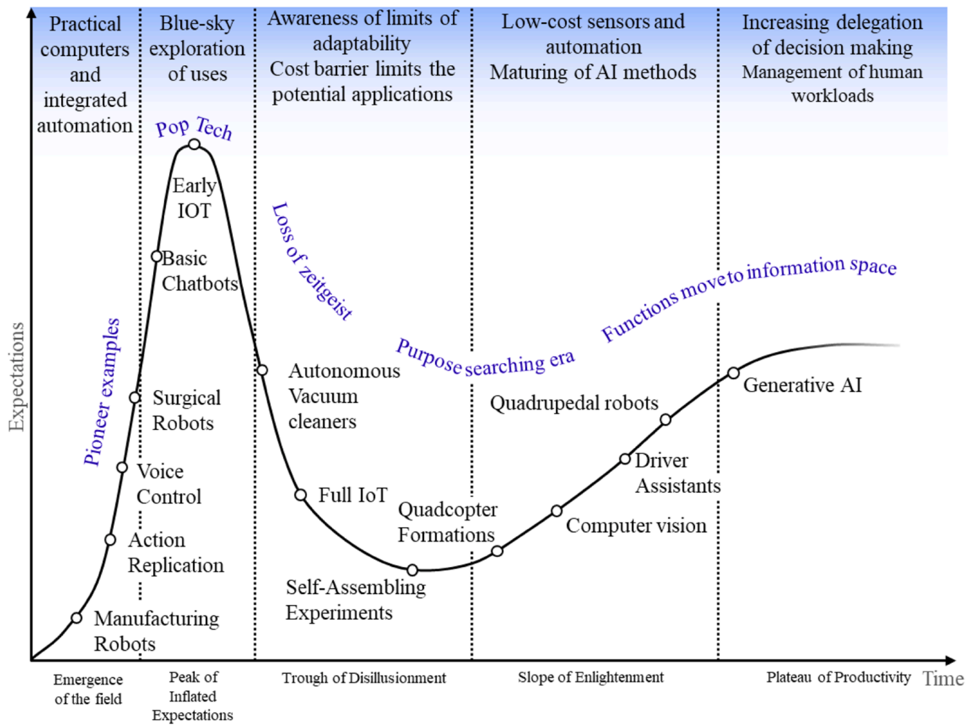

Fig. 17. Bridging the Hype Cycle of Cobots. Adapted from Gartner Hype Cycle [330].

[343] that employees who lack trust in robots should not be obliged to work in HRC environments. Instead, organizations should offer guidance to employees on effectively interacting with and managing robots, as well as educating them on their roles, rights, and responsibilities within the context of HRC.

5.2. Handling difficult materials within HRC

A major challenge facing HRC is the control, handling and manipulation of difficult materials such as non-rigid, flexible and, in some cases, multi-materials that components and products are increasingly consisting of. Numerous control methods have been proposed for the safe and effective handling of non-rigid/flexible materials in HRC domain [344–346]. Considerable progress has been made [347], but more research needs to be done for efficient handling of these materials in a collaborative way. HRC manipulation control strategies for non-rigid materials based on the category of object such as linear objects (like ropes, wires, cables, and flexible beams), flat objects (like metal and plastic sheets, as well as all fabric-like materials) and handling of 2D/3D objects are discussed here.

Research on collaborative tasks involving linear non-rigid objects, like knotting ropes and cables has been conducted by various authors [344,348–350]. Wakamatsu *et al.* [344] explored knotting and unknotting ropes using a topological description. They proposed manipulation operations to transition the object's state and devised a high-level plan for achieving desired states. Saha and Isto [348] expanded on this work by considering crossings with rigid objects and introduced sliding supports for knot manipulation. Additionally, Bell Matthew P [349] devised a sensing-free system using static fixtures and tracks for handling stiff linear objects like steel wire. Moll and Kavraki [351] developed a path planning algorithm for shaping flexible wires with robotic grippers to reduce strain during manipulation. Tavasoli *et al.* [352] investigated cooperative handling of a flexible beam by two planar robots, decoupling the system into "slow" and "fast" subsystems to suppress vibrations. Overall, recent studies on knotting and cable routing emphasize the complexity of operations with arbitrary initial states [344], limited sensing, and interactions with other objects [348], indicating a shift towards more intricate manipulation tasks involving linear non-rigid objects [350,351].

The deformation of planar objects, such as fabrics, leather, and sheet metal, which are typically considered to have minimal stretchability is usually perpendicular to their resting plane. An example of this research is the automation of folding laundry, where strategies like minimizing grasp points and utilizing gravity are employed [349]. Various studies have used vision-based techniques to detect and grasp corners of items like towels, using methods like Hidden Markov Models for cloth behavior recognition [353,354]. For manipulating flexible sheets, Dang *et al.* [355] introduced a method involving an array of micro actuators to control the shape of a flexible surface using potential field-based control. Patil and Alterovitz [346] focused on automated tissue retraction by surgical robots, employing a sampling-based planner to minimize deformation energy, stress, and control effort. Inahara *et al.* [356] experimented with non-prehensile manipulation of thin wheat dough by manipulating a vibrating plate's acceleration. Afterwards it was improved in Higashimori *et al.* [357] by allowing the object to "jump" from the plate during shaping. Bai *et al.* [358] developed an algorithm for animating anthropomorphic hands manipulating cloth by computing necessary joint torques.

Another area of interest in manipulating non-rigid objects involves actively shaping the 2D projection of an object. This encompasses tasks like controlling an object's contour in an image or moving internal points to specific targets. Gopalakrishnan and Goldberg [359] studied grasping an object with two frictionless contacts and introduced the concept of "deform closure," similar to holding a rigid object with contact points in concavities. Yoshimoto *et al.* [360] utilized force control with visual feedback to manipulate objects based on their elastic properties, allowing for shorter manipulation times compared to position-based control. Recent studies reveal a common trend in utilizing multiple manipulators for handling large objects and employing force control to induce desired plastic deformation in a shorter duration, showcasing the advantages of 2D control as a computational simplification for 3D object manipulation [360–362].

Current research on controlling 3D non-rigid objects is nascent, primarily focusing on fundamental shaping tasks and real-time in-hand manipulation strategies utilizing feedback from single sensors without extensive object modelling [345,363]. This results in reactive control approaches that necessitate continuous adjustments based on immediate feedback, highlighting the early stages of development in the field of 3D non-rigid object manipulation. Future research is expected to expand on current trends in robotic manipulation of non-rigid objects, particularly in optimizing solutions for planar and 3D objects like laundry folding. As advancements in ML and computing power continue, robotics will likely see more applications in controlling non-rigid objects, potentially leading to robotic replacements for certain human tasks.

5.3. HRC ethical considerations

Being truthful, diligent, and supportive are some of the facets of ethical conduct expected from human employees. Current robots are non-sentient, mechanistic systems that do not comprehend the idea of 'the self'. They have no ambition, are not lazy, and are incapable of deceit and so will undoubtedly impact the way current work ethic standards are perceived [364]. Humans will find it challenging to rival robots in terms of productivity and this will impact on ethical standards. The evolution of work ethics in a human-robot collaborative setting is difficult to foresee. Moreover, it is highly probable that a set of ethical guidelines need to be established to clearly define the boundaries of interactions between individuals and robots in various societal contexts. These standards are essential in ensuring that the integration of robots into human environments is conducted in a manner that upholds moral principles and respects the rights and dignity of the human. It is crucial for organizations to remain cautious about unethical practices involving robots, such as programming them with malicious intent, cyber security to prevent hacking, infiltrating other robots, sharing unnecessary sensitive information with robots, and promoting 'social loafing' (individuals tend to exert less effort when working in a group than they would if working alone) among employees by transferring their duties to robots [343]. Organizations must guarantee that the data produced and gathered by robots is ethically stored and utilized, with strict protocols in place to safeguard privacy [343,365]. One research study suggests that humans have the capacity to demonstrate feelings of regret and sorrow even when observing scenarios in which one robot is being mistreated by another robot, as evidenced by reference [366]. Moving forward, it becomes imperative to conduct thorough examinations to evaluate and determine the moral and ethical position of robots within various professional settings. This evaluation is crucial to ensure that robots are treated fairly and ethically in their interactions with humans and other machines in workplace environments and derive new policies.

The development of robots for diverse societal roles poses numerous ethical considerations necessitating key guidelines to consolidate ethical best practice in robotics and HRI [367]. Veruggio G [368] addresses general ethical issues related to human-machine relationships and proposes an ethical framework based on the "PAPA" code of ethics from Computer and Information Ethics. Riek and Howard [369] introduce "Specific Principles of Human Dignity Considerations" listing 15 principles crucial in the design of robots or assistance technology, encompassing aspects like privacy, emotional needs, physical and psychological capabilities of users, predictability of the robot, trust, as well as legal and regulatory matters. Misselhorn *et al.* [370] present an ethical framework for robot use in care contexts, while Vandemeulebroucke et al. [371] and Mansouri et al. [372] offer reviews on ethical frameworks for robots in elderly care, and Huber et al. [373] suggests the "Triple-A Model" to integrate ethics in social companion robot design.

The literature analysed provides an extensive array of research on ethical frameworks [367,369,371] to support the integration of robots into society, emphasizing the importance of conceptualizing specific use cases considering diverse user needs and implications before deploying robot technology. User group-specific ethical frameworks such as those described in this section need to be consulted when deploying robots within different production and manufacturing scenarios. Research in this area will continue to grow and evolve as HRC becomes more embedded in industry.

5.4. HRC impacting socio-economic factors

Socio-economic impacts of HRC in the workplace and within wider facets of society has received little comprehensive attention [374]. Current efforts are being devoted to investigating factors related to robots that could impact human labour. However, research gaps remain to be addressed, particularly within real-world contexts such as how to increase productivity with making tasks easier to complete and creating new jobs and tasks for the workers [375]. A limited number of authors have incorporated environmentally friendly principles when evaluating collaborative systems. From an environmental perspective, the implementation of collaborative systems aligned with a human-centered approach could have a significant influence on the effectiveness, enhanced management of production processes, and optimal utilization of resources [376,377]. Consequently, HRI could yield beneficial environmental outcomes by promoting efficient resource utilization leading to reduced energy consumption and lower greenhouse gas emissions. Nevertheless, existing literature predominantly concentrates on energy usage within HRI [378]. In keeping with this, Ojstersek and Buchmeister [379] have designed a simulation model to assess the effects of implementing collaborative workstations on sustainability by amalgamating economic and environmental aspects.

Recent research, as highlighted in Table 10, has demonstrated that the integration of collaborative robotics can yield numerous economic advantages for various industries. Several models have been put forth for the economic evaluation of collaborative systems, with the utilization of cobots proving to be more financially beneficial than manual approaches alone [380].

Gualtieri *et al.* [387] have examined potential assembly scenarios in a human-centric collaborative environment by considering cycle time and payback period. A cost model for comparing manual and cobot-based picking systems, factoring in labour costs, equipment expenses, and errors associated with manual picking to determine system productivity was devised by Fager *et al.* [386]. Additionally, some authors [389,390] have proposed mathematical models to estimate time savings from robot integration in assembly lines or to contrast production time and costs between collaborative and traditional robotic assembly lines.

Within qualitative inquiries, Pinzone *et al.* [391] have pinpointed four social motivators for HRI: safety management, ergonomics (both physical and psychological), learning and training, and work-life balance, which pertain to integrating workers into the workplace. Berx *et al.* [392] have recommended considering organizational aspects for HRI implementation and have categorized three human factors-related dimensions: (1) psychosocial aspects encompassing trust, technology acceptance, human errors, and work-related stress; (2) cognitive ergonomics connected to cognitive workload and perception loss in the work environment; and (3) physical ergonomics associated with physical workload and risk of Musculoskeletal Disorders (MSDs).

Although it is evident that considering physical, mental, and

Table 10
HRC manufacturing impacting Socio-Economic Factors [381].

Reference	Application/ System	Methodology	Factor	Sub-Category Factor	Industrial Application
Rinaldi M *et al.*, 2023 [381]	Assembly cell	Case study + Multi-criteria decision-making	Economic, Environmental, Social	Productivity, Efficiency, Economics, Financial, Energy consumption, Safety, Physical Ergonomics, Psychosocial Ergonomics, Work Organization	✓
Gualtieri *et al.,* 2023 [382]	Assembly station	Multicriteria algorithm	Economic, Social	Economics, Safety, Physical and Cognitive Ergonomics	✓
Ojstersek *et al.,* 2022 [383]	Assembly station	Simulation	Economic, Environmental, Social	Productivity, Efficiency, Economics, Financial, Energy consumption, Waste, Work Organization	✓
Colim *et al.*, 2021 [384]	Assembly station	Case study	Economic, Environmental, Social	Productivity, Waste, Physical Ergonomics, Worker Perception	✓
Huang *et al.*, 2021 [385]	Disassembly cell	Case study	Economic, Social	Efficiency, Safety, Physical Ergonomics	✓
Fager *et al.*, 2021 [386]	Picking system	Cost model	Economic	Productivity, Economics	×
Gualtieri *et al.*, 2021 [387]	Assembly system	Mathematical model	Economic	Productivity, Financial	✓
Gualtieri *et al.*, 2020 [388]	Assembly station	Case study	Economic, Social	Productivity, Physical Ergonomics	✓
Ojstersek & Buchmeister, 2020 [379]	Assembly system	Simulation	Economic, Environmental	Productivity, Economics, Energy consumption	×
Faccio *et al.*, 2019 [389]	Assembly system	Mathematical model	Economic	Productivity, Economics, Financial	✓

psychosocial aspects is crucial, quantitative research has predominantly concentrated on safety and physical ergonomics. Several scholars have integrated economic and social dimensions in order to enhance productivity levels and the physical working conditions of employees. Zhang *et al.* [393] developed a mathematical model to tackle an item storage assignment issue by taking into account both robots' picking efficiency and pickers' energy expenditure. In a study by Heydaryan *et al.* [270], the analytic hierarchy process (AHP) method was suggested in combination with ergonomic simulation to allocate tasks to humans and robots. The evaluation criteria for the two options included productivity, quality, safety, and human fatigue. Huang *et al.* [385] conducted an experimental collaborative disassembly with a focus on human-robot task allocation, considering ergonomic factors to ensure worker health and safety while enhancing efficiency (resource utilization ratio).

A multicriteria algorithm targeting task allocation, incorporating technical feasibility, safety and ergonomics, quality, and economics was proposed by Gualtieri *et al.* [382]. Their approach involved the computation and integration of four hierarchical indexes to provide an overall final assessment. Zhang *et al.* [394] aimed to minimize the completion time of a single job cycle by introducing a constraint related to the fatigue of human workers.

5.5. Growing trends and challenges in HRC development

Buxbaum *et al.* [395] discussed the future development of HRC, covering different aspect including ergonomic, technical-economic, psychological, human factors, and ethics. Their discussion is intended to establish a common and wider understanding of human centred HRC. Buxbaum *et al.* [395] also discussed the future road map for HRC design in safety requirements, flexibilization of safety technology, simplifying configuration and programming, approaches to achieving higher functionality via AI, and enhancing flexibility in the distribution of tasks. In the context of HRC for future factories, successful HRC implementation will require the assurance of human safety, integration of sensor data, dynamic planning, adaptive control, and in-situ decision support for operators [396]. This should be attained in addition to enabling multimodal communication between humans and robots through gestures, speech, haptics, and brainwave interactions, successful implementation of advanced AI technologies, as well as collaborative intelligence (CI) algorithms [397] to enhance the capabilities of future HRC systems [396].

An important factor that influences the inclination of individuals to work alongside a robotic companion is the robot's capacity to dynamically modify and adjust its operations in accordance with human behaviour and actions. It is crucial for the robot to comprehend the HRC context, specifically gauging the level of human adaptability, and respond appropriately [396]. The establishment of trust between humans and robots is critical for the success of any human-robot team, especially in high-risk situations like assembly, because it directly influences the acceptance of robot-produced information and the willingness of the human counterpart to follow robot suggestions/instructions. In uncertain or risky environments, an individual's level of trust in a robot affects their decision-making and the timing of interventions [398].

While social and emotional dimensions have been the subject of recent research [122,399,400], they remain challenging to formalize yet they are recognized as crucial for performance and mental health [401]. The way individuals perceive themselves not only affects their thoughts but also influences their actions and overall well-being [402]. This is evident in the self-positivity bias, where individuals tend to have a more positive self-perception than reality warrants, thus contributing to mental health. Hence, a self-positivity bias is commonly observed in healthy individuals [403]. The social and emotional dimensions can be studied through various approaches including surveys, physiological measurement, and ML techniques [404]. Trust and psychological effects and impacts are the most important challenges for HRC applications and need further exploration and a transdisciplinary approach is required where multiple different disciplines work together [297,309].

Another challenge is safety. Current standards primarily focus on distance and force/torque/energy limits to safeguard individuals against serious injuries. Despite this, there is a lack of comprehensive standards

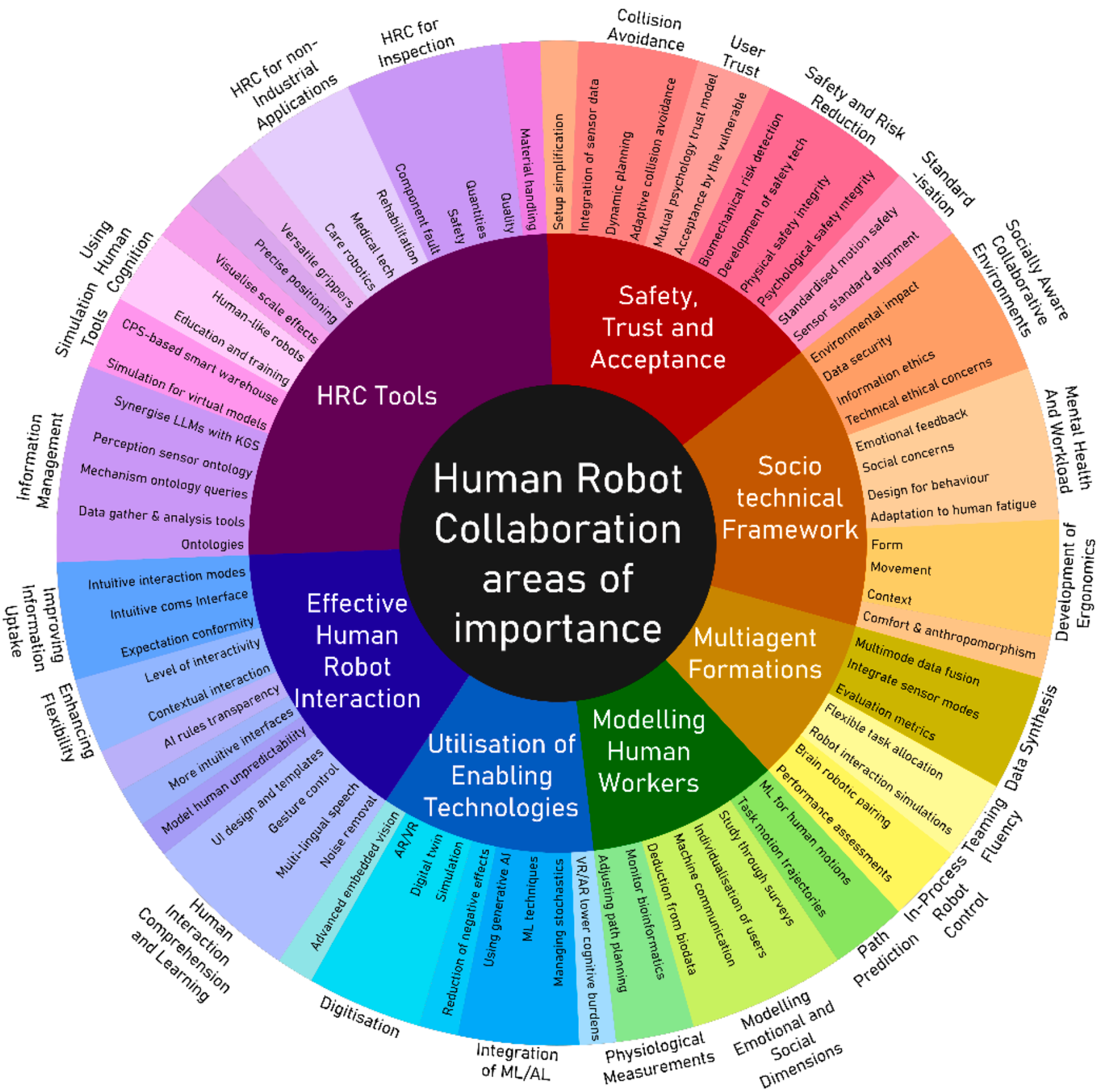

Fig. 18. Human Robot Collaboration areas of importance.

for emerging technologies such as vision, ultrasonic, and depth-based sensing systems. In the same context, a recent tragic example from South Korea where a man met his untimely demise when he was crushed by a robot. This unfortunate incident occurred as the robot failed to distinguish the man from the boxes of food it was tasked with handling [405]. It is imperative to employ more sophisticated devices (high end sensors and cameras) with higher safety integrity levels to avoid such accidents and research needs to be in this direction.

5.6. Future research in HRC

This study has critically examined technologies, emerging trends, and current research challenges, and in so doing has enabled the authors to give a measured prediction of the future direction of research in the field of HRC. These challenges and trends have been organized and outlined to create a map of HRC themes for future research and development endeavours.

Fig. 18 illustrates the critical HRC future research areas which area categorised into different sub-domains namely, effective human robot interaction, utilization of enabling technologies, modelling human workers, multi-agent team formations, sociotechnical framework, safety, trust, and acceptance, and HRC tools. These sub-domains are further segmented, and particular research areas are indicated where future research in HRC needs to be focused.

Some of the specific themes are further elaborated in the subsequent sections of the paper.

5.6.1. HRC standards, and multiagent formation

The current standards, such as ISO 10,218–1/-2 [406,407] and ISO/TS 15,066 [408], primarily focus on physical aspects and fail to address mental, emotional, social concerns and the stress burden placed on users [409]. Although ISO 26,000 [410] provides guidance on social responsibility, advocating for more comprehensive rules for socially aware collaborative environments in industrial settings, this is an area in which the field has need for further development. Redundancy in robot degrees of freedom offers opportunities for optimization and adaptation, but when executing tasks in a complex work environment, constraints on technology and geometry must be met. This requires a bidirectional transition between task and configuration spaces [411]. Further, current computational methods are too demanding for real-time control and more efficient algorithms are needed for adaptive collision avoidance. In the area of assembly, collaborative workstations already exist [388, 412], however they lack the necessary characteristics for accommodating multiple humans and robotic agents. In a multi-agent setting, successful collaboration and coexistence require agents to be aware of each other's states and intentions as well as the state of objects, which necessitates effective communication and information acquisition channels [411].

5.6.2. Modelling, trust and multiple mode integration

AI-based methodologies for forecasting the trajectory of human movement and identifying human activities have been developed [409, 413,414]. Leaving aside reliability and transparency concerns in such models, there is scope for further investigation into the development of an adaptable strategy for predicting motion trajectories that prioritizes distinct functional components based on specific tasks and pertinent body segments. Currently, there is little research in the implementation of continual observation of human behaviours and emotions in the workplace for regulating assembly workstations. This area for development emphasises the necessity for models accommodating individual human worker preferences, worker statuses, and passive and low-cost modes of communication [409].

One potential area of exploration for data fusion in HRC assembly is the integration of multiple modes of human commands. Although gestures and voice commands are increasingly used in HRC for robot control, they may not be as natural and practical in busy and noisy work environments. Furthermore, these commands often suffer from ambiguity. Instead of relying solely on predefined gestures and voice commands, deep learning techniques [133] can be employed to recognize and predict human motions, leading to improved context awareness and reduced disruption caused by gestures. These methods are however deeply unaccountable, and subject to major legal and ethical concerns [143,415]. Another approach to achieve programming-free robot control is through haptic interaction, particularly for legacy industrial robots with limited embedded sensors. Brain robotics or brainwave-driven robot control is an emerging research direction that can enhance symbiotic HRC in the manufacturing assembly industry [8,416,417].

Previous research has already explored methods for modelling emotional and social processes, as well as acquiring individual or cultural profiles and adapting them to newly perceived changes [163,391, 392,418]. These existing findings serve as a strong starting point for developing similar solutions for industrial applications in the context of HRC. However, a critical element that is currently lacking is the establishment of mutual models of trust [419].

To be effective collaborators with humans, robots must be able to model human behaviour, and their role. There is significant room for improvement in robotic hardware for alternate forms of communication (audio, visual, tactile). Robot collaborators have the potential to expand the capabilities of humans, enhancing their well-being, sense of purpose and quality of life.

6. Conclusion

This paper provides detailed analysis on the current state-of-the-art and the future outlook of HRC in I4.0, its potential in I5.0 and application of HRC in manufacturing processes (assembly, inspection). The review's focus was on the last 10 years from 2013 to 2023. In addition, the role of artificial intelligence, machine learning, large language models, information modelling (ontologies), and new emerging digital technologies (augmented reality, virtual reality, digital twins, cyber-physical system) in the development of HRC and I5.0 is documented and discussed adding a new perspective to the growing literature in this area. Other HRC related aspects namely, safety and trust, difficult to work with/ challenging materials handling, socio-economic factors, and ethical considerations have been extensively documented and discussed. The outputs from this are then used to drive the future perspectives in HRC. It has been seen that despite recent advancements in HRC, there are still limitations and challenges that need to be addressed. In order to design robots that effectively support human work, it is imperative to gather input from various scientific disciplines such as robotics, design, psychology, sociology, and others, a fact that is widely acknowledged within the HCI and HRI research community. Furthermore, input from stakeholders who are directly affected, such as operators, maintainers, and shift leaders should be taken into consideration as they play a crucial role in the development process. By harnessing the latest technologies in sensing, communication, augmented reality, AI/CI, and robot control, HRC research will be able to translate into practical applications on the shop floors of the intelligent factories of the future. Overall, this review paper sheds new light on the emerging paradigms in context of I5.0 and the transformative role of human-robot interaction in shaping the future of manufacturing. The review logically explains why, when, and how far HRC will benefit manufacturing in years to come, and how a robot could supplement creativity and enhance the decision-making potential to enable real synergy between it and its human counterpart.

CRediT authorship contribution statement

Mandeep Dhanda: Writing – original draft, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Benedict Alexander Rogers:** Writing – review & editing, Software, Resources. **Stephanie Hall:** Writing – review & editing. **Elies Dekoninck:** Writing

Figure Reference

Figure of use	Image	Author	Date Accessed	URL	Licence Type
11	Robot Arm	Freepik	07/12/2023	https://www.flaticon.com/free-icon/industrial-robot_3253587?term=robot&page=1&position=14&origin=search&related_id=3253587	CC by attribution
11	Human	Gajah Mada	07/12/2023	https://www.flaticon.com/free-icon/user_12828907?term=human&page=4&position=25&origin=search&related_id=12828907	CC by attribution
11	Waving Hand	Prashanth Rapolu	07/12/2023	https://www.flaticon.com/free-icon/hand_7127808?term=wave&page=1&position=29&origin=search&related_id=7127808	CC by attribution
11	Speaker	POD Gladiator	07/12/2023	https://www.flaticon.com/free-icon/speaker_9777119?term=speaker&page=1&position=93&origin=search&related_id=9777119	CC by attribution
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11	Button	Pixel Perfect	07/12/2023	https://www.flaticon.com/free-icon/button_2107968?term=button&page=2&position=1&origin=search&related_id=2107968	CC by attribution
11	Gauge	Icon Baandar	07/12/2023	https://www.flaticon.com/free-icon/pressure-gauge_4519248?term=dial&page=1&position=37&origin=search&related_id=4519248	CC by attribution
11	Robot Icon	Good Ware	07/12/2023	https://www.flaticon.com/free-icon/robot_2432846?term=robot&page=1&position=2&origin=search&related_id=2432846	CC by attribution
4	Steam Train	Freepik	04/04/2024	https://www.flaticon.com/free-icon/train_5731977?term=steam±engine&page=1&position=8&origin=search&related_id=5731977	CC by attribution
4	Pylons	berkahicon	04/04/2024	https://www.flaticon.com/free-icon/electric-pole_2962268?term=electric&page=1&position=32&origin=search&related_id=2962268	CC by attribution
4	Production Line	juicyfish	04/04/2024	https://www.flaticon.com/free-icon/worker_6755076?term=production±line&page=1&position=46&origin=search&related_id=6755076	CC by attribution
4	Robot Arm	shmai	04/04/2024	https://www.flaticon.com/free-icon/robot-arm_4518817?term=robot±arm&page=1&position=9&origin=search&related_id=4518817	CC by attribution
4	Brain-Computer Interface	Umeicon	04/04/2024	https://www.flaticon.com/free-icon/artificial-intelligence_2586590?term=ai&page=1&position=10&origin=search&related_id=2586590	CC by attribution
12	Human Team	Freepik	04/04/2024	https://www.flaticon.com/free-icon/group_554724?related_id=554724	CC by attribution
12	Camera	dreamicons	04/04/2024	https://www.flaticon.com/free-icon/cctv-camera_2642550?term=camera&page=1&position=8&origin=search&related_id=2642550	CC by attribution
12	Robot Arm	Design Circle	04/04/2024	https://www.flaticon.com/free-icon/robot-arm_9791676?term=robot±arm&page=1&position=8&origin=search&related_id=9791676	CC by attribution
12	Microphone	Freepik	04/04/2024	https://www.flaticon.com/free-icon/microphone_1186562?term=microphone&page=1&position=3&origin=search&related_id=1186562	CC by attribution
12	Speaker	monkik	04/04/2024	https://www.flaticon.com/free-icon/speaker_860330?term=speaker&page=1&position=8&origin=search&related_id=860330	CC by attribution
12	Encoder	Good Ware	04/04/2024	https://www.flaticon.com/free-icon/decode_4010793?term=encoder&page=1&position=1&origin=search&related_id=4010793	CC by attribution
12	Speech-text conversion	Uniconlabs	04/04/2024	https://www.flaticon.com/free-icon/speech-synthesis_13063588?term=text-speech&page=1&position=5&origin=search&related_id=13063588	CC by attribution
12	Cloud Data	RaftelDesign	04/04/2024	https://www.flaticon.com/free-icon/server_2318786?term=cloud±data&page=1&position=2&origin=search&related_id=2318786	CC by attribution
12	OpenAI ChatGPT Logo	N/A - Official Logo, not from flaticon			
13	ICONS: Clouds	FreePik	10/10/2024	https://www.flaticon.com/free-icon/clouds_414876?k=1728914784503	CC by attribution
13	Human And Robot	Darius Dan	10/10/2024	https://www.flaticon.com/free-icon/boy_4275576?term=human±and±robot&page=1&position=6&origin=search&related_id=4275576	CC by attribution
13	Robot Arm	Design Circle	10/10/2024	https://www.flaticon.com/free-icon/robot-arm_9791676?term=robot±arm&page=1&position=7&origin=search&related_id=9791676	CC by attribution
13	Sensor	Zero_wing	10/10/2024	https://www.flaticon.com/free-icon/sensor_10731298?term=sensor&page=1&position=62&origin=search&related_id=10731298	CC by attribution
13	VR headset	FreePik	10/10/2024	https://www.flaticon.com/free-icon/virtual-glasses_2274634?term=vr&page=1&position=38&origin=search&related_id=2274634	CC by attribution
13	Human	Prosymbols Premium	10/10/2024	https://www.flaticon.com/free-icon/accountant_8660988?term=manager&page=1&position=16&origin=search&related_id=8660988	CC by attribution
16	Robot arm	Design Circle	14/10/2024	https://www.flaticon.com/free-icon/robot-arm_9791676?term=robot±arm&page=1&position=7&origin=search&related_id=9791676	CC by attribution
16	Human And Robot	Darius Dan	14/10/2024	https://www.flaticon.com/free-icon/boy_4275576?term=human±and±robot&page=1&position=6&origin=search&related_id=4275576	CC by attribution
16	HRI Robot Arm	FreePik	14/10/2024	https://www.flaticon.com/free-icon/robot_120581?term=robot&page=1&position=5&origin=search&related_id=120581	CC by attribution
16	HRI Worker	FreePik	14/10/2024	https://www.flaticon.com/free-icon/packing_1372903?term=human±worker&page=3&position=12&origin=search&related_id=1372903	CC by attribution

– review & editing. **Vimal Dhokia:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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