Collaborative Learning in Industry 5: A Systematic Mapping Study and Taxonomy

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Abstract: Humans have always been the central focus of learning. Through interactions with others, we can develop the skills and knowledge necessary to survive and thrive in the world. However, the industrial revolution marked a shift in this focus as machines began to take on an increasingly important role in production. This trend continued with the development of Industry 4.0, which saw the adoption of emerging technologies in the industrial environment. This goal was to promote greater competitiveness, efficiency, and product quality. However, this strategy reflects a work environment that prioritizes machines over humans. Industry 5.0 aims to fill this gap related to the human perspective in this environment and enhance the collaboration between humans, robots, and digital systems. The present study seeks to understand how collaborative learning is undertaken in industrial workplace learning in Industry 5.0 context. Based on a systematic mapping study, this work analyzed 34 publications. The main scientific contributions of this study are mapping publications focusing on collaborative learning models in Industry 5.0, identifying future research opportunities and current challenges, and providing taxonomies of these topics. Collaborative learning has been defined in a variety of ways. Still, at its core, it is a process that involves two or more individuals working together to achieve a common goal. This type of learning has several advantages, including the ability to pool resources, share knowledge, accelerate the learning process, and promote creativity and problem-solving skills.

Industrial revolution, Industry 4.0, Industry 5.0, Human perspective, Collaborative learning, Industrial workplace learning

1. Introduction

Industry 4 can be understood as the digital transformation of the industry processes aiming to increase their value creation [2]. This digital transformation is achieved mainly by the adoption of emergent and smart technologies such as cyber-physical systems, internet of things, cloud computing, artificial intelligence, and others. The main goal is to increase automation to reach high efficiency and quality in industrial processes. Despite the benefits this approach provides to the industries, there are some challenges mainly related to the human-centric perspective. Human workers need to divide their workspace with diverse technologies and also make use of many of them to better perform their tasks.

As Industry 4 highlights the techno-centric paradigm, Industry 5 emerges to complement it with the vision of a more sustainable and human-centric approach [1]. This new vision is important since politicians and organizations are increasingly paying attention to sustainability and resilience, and the demand to put people back at the center [4]. Industry 5 promotes a view of the industry beyond efficiency and productivity as the sole aims and emphasizes the industry's role and contribution to society. It prioritizes worker well-being in the production process and employs new technology to bring wealth beyond employment and development while remaining mindful of the planet's productive constraints. It adds to the existing "Industry 4.0" strategy by emphasizing the role of research and innovation in the transition to a more sustainable, human-centered, and resilient industry [3].

On the other hand, collaborative learning is an educational technique that involves working in groups to improve learning. Individuals in groups of two or more collaborate to solve issues, perform tasks, or acquire new concepts. Rather than relying on mechanical memorizing of facts and statistics, this technique actively engages group members in the processing and synthesizing of information and concepts [23]. Individuals collaborate on projects and must work together to understand the topics taught. Researchers will better understand as a group than as individuals by defending their opinions, reformulating concepts, listening to various points of view, and communicating their opinion and values [16].

In collaborative learning methods, ontologies can be a knowledge representation that improves models. For example, it is possible to use this feature to formalize how a knowledge domain's concepts are described by creating semantic networks. Ontologies may also be a tool to help model decision-making by using domain knowledge in reasoning [26]. Various fields, including industry [13], project management [17], health [7], and mental health [8] are reported to utilize ontologies.

Contextual information from these models can help in decision-making. A context is a collection of details describing the conditions under which an entity, such as a person, item, or location, is present. The context often discusses the location, identity, and condition of individuals, groups, and physical and computational entities [15]. Context-aware computing has been made more popular by the widespread usage of mobile computing and the development of sensors. According to the perceived context, the computational application, in this case, modifies the behavior [7]. Setting histories are historical information about a user's particular context. By examining this historical and current data, predictive algorithms can determine the circumstances of users' future interactions [24]. Applications, in this case, keep track of past contexts, evaluate them, forecast upcoming situations, and suggest user actions based on context similarity analysis [17, 50].

This systematic mapping study makes the following contributions: (i) provide a mapping of the collaborative learning application domains in industry 5, considering how the works relate to these areas; (ii) describes the history of publications focusing on collaborative learning models in industry 5; (iii) propose taxonomies of industry 5 and collaborative learning categories; and (iv) identify future research opportunities and current challenges.

The remainder of the article is organized as follows. Section 2 lists and briefly details the articles related to this research and the academic differential of this work. Section 3 presents the methods used to conduct this systematic mapping study. Section 4 presents the outcomes, which include the answers to the research questions and the two taxonomies and section 6 summarizes the remarks and future research opportunities.

2. Related Works

This section presents the related works identified during the systematic mapping study. Theoretical studies identified in the review process, such as surveys, literature reviews, or systematic mapping studies were considered related works. Table 1 shows a comparison between these works and the present study, considering the following criteria: 1) the type of paper, 2) the research method applied, 3) the Industry paradigm involved and 4) the focus of the study.

Wan and Leirmo [57] conducted a systematic literature review based on the industry 5 paradigm. The main goal was to understand how humans can contribute to achieving zero-defect manufacturing. According to the authors, this new industry paradigm highlights the importance of humans as critical assets in the manufacturing sector. Despite innovative technology being important to keep up with the competition, investing in people skills and developing technologies to enhance human capabilities is vital. Focusing exclusively on emergent technology will not provide the required system's capabilities to reach the paradigm of zero-defect manufacturing. As the present study, this work employs the vision of the industry 5 paradigm to emphasize the importance of a human-centric approach in the industry transformation.

According to Simões et al. [54], collaborative robots are one of the critical technologies that helped Industry 4 become a tangible reality. The primary objectives of human-robot collaboration in the industrial setting are to improve employee safety and well-being while also raising profitability and productivity. With an emphasis on the control viewpoint, the study performed a systematic literature review on designing human-robot collaboration (HRC) workspaces in industrial settings to enable the proper division of labor. The study presents a set of guidelines and recommendations in physical, cognitive, social, organizational, environmental, and other relevant knowledge areas critical in manufacturing systems.

Proia et al. [43] surveyed to identify the advantages and gaps of the main control techniques for collaborative robotics that can be applied in industrial applications. These techniques are related to safety, ergonomics, and efficiency, enabling effective human-robot collaboration. In the safety dimension, the authors found several control algorithms that can be implemented to prevent collisions. In the ergonomics dimension, the cobots (collaborative robots) can reduce physical labor by helping operators with repetitive tasks. Finally, the efficiency dimension can be achieved by simplifying the operator's actions to complete a task by optimally planning the human-robot activities.

Galin et al. [19] argue that manufacturing companies have started to invest heavily in collaborative workspaces. Companies search for efficiency, productivity, and flexibility in production lines and their corresponding workstations. This study conducted a survey on safety methods for human-robot interaction during collaboration. The study presents a taxonomic classification for the level of shared interaction among humans and robots and a review

Reference	Type	Research method	Industry paradigm	Focus
Wan and Leirmo [57]	Article	Systematic literature review: 36 articles reviewed	Industry 5 and human-centric approach	Assistive technologies can enhance human capabilities in reaching the paradigm of zero-defect manufacturing
Simões et al. [54]	Article	Systematic literature review: 65 articles reviewed	Industry 4 and efficiency at work	Guidelines and recommendations for designing collaborative workplaces where humans and cobots successfully interact with each other
Proia et al. [43]	Article	Survey: 55 articles reviewed	Industry 4 and 5, safety and efficiency at work	Guidelines and recommendations for designing collaborative workplaces where humans and cobots successfully interact with each other
Galin et al. [19]	Conference paper	Survey	Industry 4 and safety in human-robot interaction	Safety methods for Human-Robot Interaction During Collaboration
Robla-Gomez et al. [49]	Article	Survey	Industry 4 and safety in human-robot interaction	Safety systems proposed and applied in industrial robotic environments
Present study	Article	Systematic mapping study: 34 articles reviewed	Industry 5 and collaborative learning at work	Collaborative Learning between humans and machines

Table 1. Related Works

of general safety standards. Types of collaboration and a list of potential risks of human-robot interaction during collaboration are also presented.

According to Robla-Gomez et al. [49], the collaboration between humans and robots is crucial in smart industries since it helps to increase efficiency and output. However, when the distinction between human and robot workstations is eliminated, this progress entails defying accepted safety protocols. The authors reviewed the main safety systems proposed and applied in industrial robotic environments. Discussion covers various multidisciplinary topics, such as methods for calculating and evaluating injuries in human-robot collisions, impact detection systems, mechanical and software devices designed to lessen the effects of human-robot impact, and collision avoidance strategies. Additionally, a review of the current regulations, along with new concepts that have been introduced in them, is presented.

The present study contributes to the results of the related works and aims to advance this research area in two main aspects. First, to the best of the authors' knowledge, this is the first systematic mapping that addresses a mapping of techniques used for collaborative learning in the light of the Industry 5 paradigm. Second, the present study contributes with a taxonomy that organizes the study areas of these topics and demonstrates the challenges of implementing collaborative learning in Industry 5.

3. Materials and Methods

This paper employs a systematic mapping study [30] as a methodology to perform a literature review on how collaborative learning is undertaken in industrial workplace learning in Industry 5 context. Systematic literature reviews summarize previous work on a certain topic and identify potential gaps, opportunities, and trends in research. Based on this research method it is possible to address research questions that yield impartial answers [9].

The following steps were used to conduct this systematic literature review [30]: (1) Define the research questions; (2) Define the search procedure; (3) Define the text selection criteria; and (4) Execute the text analysis and categorization. These steps are detailed in the next subsections.

3.1. Research questions

Table 2 depicts the research questions addressed by this study, which include one general question (GQ), six specific questions (SQ), and two statistical questions (STQ). Specific questions address specific technologies, techniques, data, challenges and other resources employed. The statistics questions assess the sources of the articles' publishing and the number of publications every year.

Type	Question
General Question	
GQ1	How collaborative learning is undertaken in industrial workplace learning in Industry 5 context?
Specific Questions	
SQ1	What are the collaborative learning techniques used in the industry 5 context?
SQ2	What are the challenges of applying collaborative learning towards industry 5?
SQ3	What technologies are being used in the industry 5 context?
SQ4	What are the data types, and devices used?
SQ5	In which scenarios are ontologies used for collaborative learning?
SQ6	Does the paper use context histories or context information?
Statistical Questions	
TQ1	Where were the studies published, and how many publications occurred per year?

Table 2. Research Questions

3.2. Search Process

The search process followed the guidelines provided by Petersen et al. [42]: (1) specify the search string, (2) select the databases to apply the string, and (3) execute the string to get the results. The search string considered three main terms: (I) collaborative learning, (II) Industry 4, and (III) Industry 5. Table 3 displays the major terms in the search string and their relations to alternative terms and synonyms applied in the search string.

Major Terms	Alternative Terms
Collaborative Learning	Collaborative learning; cooperative learning; interactive learning; learning group; Co(-)education; shared learning; joint learning; federated learning
Industry 4	Fourth industrial revolution; 4th industrial revolution; Industry 4; Industrie 4; 4 industr
Industry 5	Fifth industrial revolution; 5th industrial revolution; Industry 5; Industrie 5; 5 industr

Table 3. Search Terms

The search procedure requires representing each component of the string by at least one term in the selected articles. This constraint exists to limit the scope of the search, as early searches without particular terms yielded numerous articles. Furthermore, the preliminary searches aided in defining the specific terms, which cover various scenarios within the industry 4 and 5 research. As this evaluation was fairly broad initially, the filtering procedure pulled together publications that did not focus on industry 5. The third part of this research focused on coupling collaborative learning with industrial sectors (4 and 5).

The following is the standard search string applied:

(“fourth industrial revolution” OR “4th industrial revolution” OR “industry 4” OR “industrie 4” OR “4 Indutr” OR “fifth industrial revolution” OR “5th industrial revolution” OR “industry 5” OR “industrie 5” OR “5 Indutr”) AND (“collaborative” OR “cooperative” OR “Interactive learning” OR “learning group” OR “co education” OR “shared learning” OR “joint learning” OR “federated”).

Six databases were selected to apply this search string: ACM [1], IEEE Xplore [2], Science Direct [3], Wiley [4], Scopus [5] and Springer [6]. The materials chosen include work in computer science and engineering. Table 4 describes the database search method performed.

[1] https://dl.acm.org
[2] https://ieeexplore.ieee.org/Xplore/home.jsp
[3] https://www.sciencedirect.com/search.
[4] https://onlinelibrary.wiley.com/.
[5] https://www.scopus.com/home.uri
[6] https://link.springer.com/

Database	Search Fields Description
ACM	The search filtered articles only by the abstract. The search considered the expansion "ACM Guide to Computing Literature".
IEEE Xplore	The search considered all metadata, filtering only the type by "Magazines", "Conferences", and "Journals".
Science Direct	The search filtered articles by the types "Review Articles" and "Research Articles", considering all metadata. The results consisted of the distinction of articles found in sub-queries based on the search string because of the limit of 8 boolean connectors per field.
Scopus	The search considered the article title, abstract, and keywords. Besides, the search contemplated only the document types "Article", "Conference Paper", and "Review".
Wiley	The search filtered articles only by the abstract.
Springer	The search considered all metadata, removing articles "Preview-Only" and selecting articles/conference papers categorized in the discipline "Computer Science".

Table 4. The definition of the database search method

3.3. *Study Filtering*

After querying the databases, the articles gathered passed by a filter, considering inclusion (IC) and exclusion criteria (EC). This review evaluated the studies that satisfied all the inclusion criteria. In contrast, this study excluded the articles that attended at least one exclusion criterion during the filtering phase. These criteria allow for eliminating any noise generated in the research. We did not filter studies by period; thus, there are no criteria regarding the year of publication. The inclusion criteria applied are:

- IC1: The study must have been published in a conference, workshop, or journal;
- IC2: The study must contain terms that match the search string;
- IC3: The study should be a full paper;
- IC4: The study must be written in English.

Because a group of articles may use the terms of the search string without fulfilling this study, this research evaluated exclusion criteria (EC) for removing papers. The following is a complete list of ECs:

- EC1: The study consists of a literature review or systematic mapping;
- EC2: Study needs do not focus on Industry 4 or 5;
- EC3: The study does not present an application of collaborative learning in industry 4 or 5.

EC1 screened works that review or map the literature regardless of the research subject. These works were removed from the mapping and considered related works. Studies that match the search term but do not include the industrial area as a target aim were excluded based on EC2. For example, some papers focus on the industry but don't always undertake studies on industry 4 or 5 contexts. Finally, as the focus of this review is collaborative learning applied in the industrial workplace, EC3 excluded works that do not present any mention of industry workplace learning.

Figure 1 displays the whole screening process, in which the first search yielded 6,877 studies after applying the search string to the databases and analyzing the inclusion criteria. In the search tools, all databases permitted this evaluation. We use the Parsifal application to manage the metadata of selected articles[7]. This tool supports the execution of systematic reviews, from protocol registration to outcomes interpretation via visualizations. To boost review agility and describe the causes and stages that excluded the work, we broke the filtering process into phases, taking different ECs and work information into account.

After removing duplicates, which yielded 6.657 works, the second phase accepted 1,249 studies based on the EC1 and EC2 elimination criteria. We only approved works that are not literature reviews or systematic maps focused on the industry in this phase, based on an inspection of the title and keywords in the publications. The Wiley database was responsible for the most research decrease in this phase, accounting for 72.8 percent of the total. Springer database displays a comparable rate, with 69 percent of eliminated works. Other databases revealed a near-fifty percent refusal rate.

We then confirmed the EC2 and EC3 criteria in phase 3, which considered the abstracts of the publications. Studies that met these requirements did not progress to the next round. We approved 92 studies at this point. The

[7] https://parsif.al/about

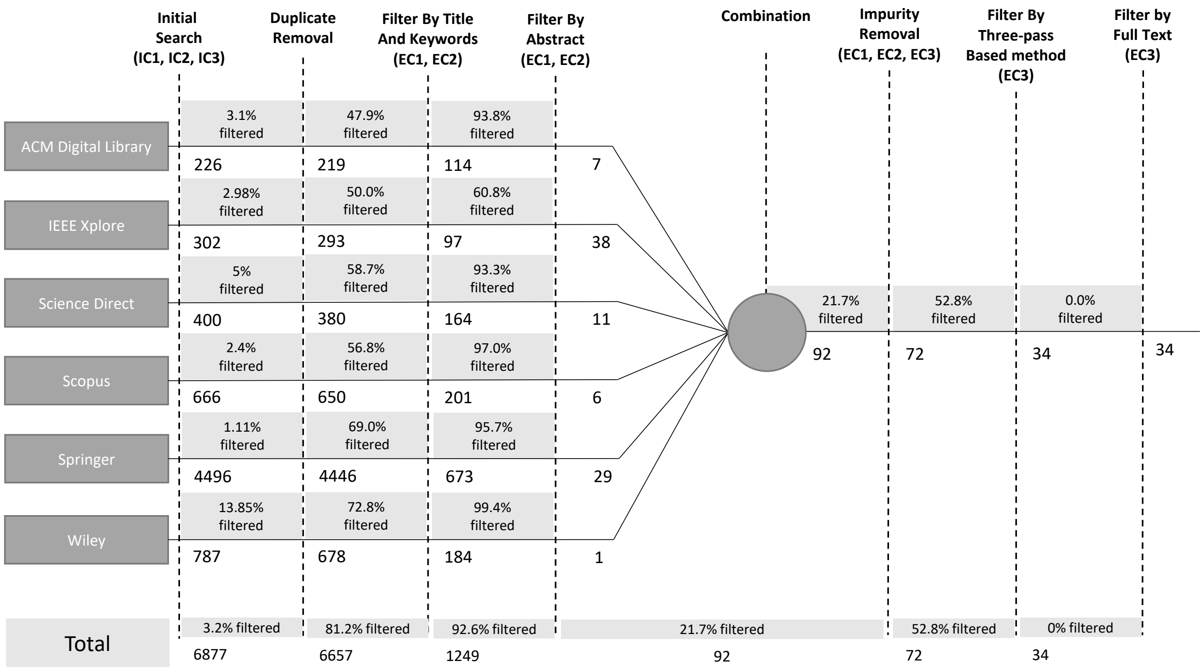

Fig. 1. Applied filtering steps

Wiley database had the highest elimination rate, with around 99 percent of the studies screened, followed by the Scopus database, which had 97 percent of the works rejected.

Phase 4 merged all works resulted and applied EC3, resulting in a 21.7 percent reduction in studies remaining. We subjected the remaining 72 studies to a screening phase based on Keshav's three-pass method [29]. This method divides the reading of an article into three steps. The depth of reading grows with each phase. The first step provides a high-level overview of the study. This stage comprises four tasks: (1) reading the title, abstract, and introduction; (2) reading the titles of sections and subsections while ignoring the body of the document; (3) an overview of mathematical content (if applicable); and (4) reading the conclusions. The next step entails examining the figures, diagrams, and other illustrations, focusing on the graphics. The last step is to read the entire document. We accepted 34 works in this phase. The final stage thoroughly examined the EC3 criterion in the selected works. There were no eliminations at this point. Finally, we looked into the research questions in the remained studies.

4. Results

This section presents the results of the systematic mapping study, organized by the specific research questions. Table 5 provides the final list of the 34 publications examined during the final phase of this study. The H-Index, Overall, Impact, and SJR rank, representing the impact of journals and conferences in the literature, were used to evaluate the quality of the publishers. The SJR indicator for a journal is a measure that reflects the number of citations obtained each year for articles published in that journal over the preceding three years, as indexed by Scopus. Greater journal prestige is intended to be shown by higher SJR indicator values. Journal rankings are used to assess the importance and influence of academic journals. The overall ranking of a journal is evaluated based on its position in the research area, its relative difficulty of being published, and its reputation. The impact factor measures the frequency of citations for a typical article in a journal within a given year. Counting the number of times an article is referenced may determine the prominence of a journal. Although some studies did not provide these indicators, we nonetheless examined them because of their content and value to the study. The following sections present the results of each specific research question (SQ) described in Table 2.

4.1. SQ1: What are the collaborative learning techniques used in the industry 5 context?

Elizabeth et al. [16] organized collaborative learning techniques into six broad categories. These collaborative learning techniques were used to map their occurrence in the selected articles. Table 6 presents the techniques mapped for each article, and the definition of each technique is shown in the following.

The first collaborative learning technique proposed by Elizabeth et al. [16] is "Discussion". When applying the method, communication and individual exchange are carried out mainly through spoken words. The second

ID	Reference	Year	Database	H-Index	Overall	Impact	SJR
A01	Ji et al. [28]	2021	Springer Link	134	4608	3.77	0.924
A02	Choudhury et al. [11]	2019	IEEE Xplore	103	3741	1.58	1.058
A03	Na and Dai [37]	2022	Springer Link	-	-	-	-
A04	Lee et al. [32]	2018	Springer Link	56	16439	0.71	0.25
A05	Yilma et al. [59]	2019	Springer Link	-	-	-	-
A06	García et al. [21]	2022	Science Direct	136	1544	7.81	1.775
A07	Koch et al. [31]	2017	Science Direct	-	-	-	-
A08	Cecil et al. [10]	2018	IEEE Xplore	93	1409	5.86	1.865
A09	García-Esteban et al. [22]	2021	IEEE Xplore	48	13941	1.15	0.329
A10	Shu and Solvang [53]	2021	IEEE Xplore	-	-	-	-
A11	Löcklin et al. [33]	2021	Science Direct	78	7683	1.94	0.639
A12	Schoen et al. [52]	2022	ACM	11	6645	4.69	0.716
A13	Illankoon et al. [27]	2021	Springer Link	-	-	-	-
A14	Rabelo et al. [46]	2019	Springer Link	-	-	-	-
A15	Nuzzi et al. [40]	2018	IEEE Xplore	-	-	-	-
A16	Pacaux-Lemoine et al. [41]	2022	Springer Link	40	6955	3.54	0.692
A17	Dang et al. [14]	2022	Springer Link	134	4608	3.77	0.924
A18	Raziei and Moghaddam [48]	2021	Science Direct	76	14074	0.92	0.324
A19	Niu et al. [38]	2021	Science Direct	92	8770	2.27	0.569
A20	Moniri et al. [36]	2016	IEEE Xplore	14	6785	3.13	0.707
A21	Gallala et al. [20]	2021	Science Direct	-	-	-	-
A22	Yu et al. [60]	2020	IEEE Xplore	158	4581	4.34	0.927
A23	Rai and Kannan [47]	2017	IEEE Xplore	36	20368	0.44	0.164
A24	Monakhov et al. [35]	2021	IEEE Xplore	67	6408	2.33	0.736
A25	Roveda et al. [51]	2020	Springer Link	82	5562	3.61	0.816
A26	Formica et al. [18]	2021	IEEE Xplore	67	6408	2.33	0.736
A27	Noureddine et al. [39]	2020	Springer Link	36	21274	0.30	0.148
A28	Zhang et al. [61]	2020	Science Direct	164	1316	5.50	1.937
A29	Ahmed et al. [5]	2019	IEEE Xplore	18	25196	0.32	0.104
A30	Tsarouchi et al. [55]	2015	Science Direct	78	7683	1.94	0.639
A31	Rabelo et al. [45]	2018	Springer Link	-	-	-	-
A32	Weichhart et al. [58]	2021	IEEE Xplore	-	-	-	-
A33	Cunha et al. [12]	2020	Springer Link	-	-	-	-
A34	Umbrico et al. [56]	2021	IEEE Xplore	-	-	-	-

Table 5. Selected studies

technique is “Reciprocal peer teaching”. It consists of some individuals helping each other in the mastery of the content and the development of skills based on the studied area. The third technique is named “Problem-solving”. In this technique, members focus on practicing problem-solving strategies as a team. The fourth technique is called “Graphic information organizers”. The main objective of this technique is to use visual tools to organize and display information to help the learners. The fifth technique is called “Writing”. In this approach, individuals write to learn the content and essential skills of the subject. After a thorough search, we could not find any articles or studies related explicitly to “Writing” as a technique for learning content and essential skills. While writing is a standard method used in education and has been studied as a form of self-reflection and self-expression, there is currently a lack of research specifically focused on its use as a learning technique in this research context. Finally, the sixth technique is “Games”. In this approach, members work together in teams to participate in a competitive activity guided by a pre-existing set of rules.

4.1.1. Reciprocal peer teaching

As presented in Table 6, **“Reciprocal peer teaching”** appeared in 17 studies, primarily to provide collaboration between machines and humans to enhance efficiency and productivity in task execution. Lee et al. [32] proposed a process model using a Virtual Reality interface based on the Human-Robot Collaboration system. The authors defined the work order, parts flow, and collaboration information for the electronic engine assembly process. Then, the study applies part flow-based manufacturing process modeling and reciprocal learning to improve processes via human-machine collaboration. Ji et al. [28] used technology to record the user’s brain activity and transform it

Technique	Studies
Reciprocal peer teaching	A01 A02 A03 A04 A05 A14 A18 A19 A20 A23 A21 A26 A27 A29 A32 A33 A34
Graphic information organizers	A06 A08 A10 A24 A25 A28
Games	A07 A11 A12 A15 A17 A22
Problem-solving	A09 A13 A16 A30
Discussion	A31
Writing	–

Table 6. Collaborative learning techniques mapped in the studies

into interaction messages. The work offers contextual visual feedback through an augmented reality headset and provides an interface of the reciprocal loop.

Yilma et al. [59] proposed a meta-model of a Cyber-Physical-Social System to integrate human aspects with Cyber-Physical Systems (CPS). This meta-model can help design complex systems that involve a close collaboration of humans and CPS. Na and Dai [37] presented an immersive mixed-reality human-robot collaboration experience. The study proposed an immersive architectural experience in which the sensorial, including color, depth, materials, and geometries, are constantly blurred between the physical and digital worlds.

Niu et al. [38] aimed to teach robots about human discomfort in collaborative order-picking robotic mobile fulfillment systems. Gallala et al. [20] used Mixed Reality, including the definition of Human-Robot interaction, to propose a human-friendly and easy cobot programming method. Formica et al. [18] focused on predicting human intent to estimate the most likely future action or trajectory of a human operator through collaboration between hybrid teams. Ahmed et al. [5] showed an approach for reliability and quality control in a collaborative assembly process. Weichhart et al. [58] created an interaction between humans and robots to provide fewer defects and mistakes during the activities. This study provided an environment that allows a group of operators and engineers to model processes that can be re-used and executed across domains and robotic hardware.

Cunha et al. [12] proposed a fast learning system – based on neural dynamics – that permits collaborative robots to memorize sequential information from single-task demonstrations by a human tutor. Umbrico et al. [56] suggested using novel Artificial Intelligence technologies to enhance these collaborative systems' learning, flexibility, and adaptability. Choudhury et al. [11] recommended a distributed knowledge framework deployed modularly across multiple heterogeneous robots, enabling them to perform tasks through real-time knowledge mutual sharing and collaboration. Noureddine et al. [39] used an adaptive learning methodology and predictive analytics to provide efficient maintenance practices. The study proposed an architecture to support continuous and sustainable value creation.

Rabelo et al. [46] presented a collaborative soft-bots approach to address human satisfaction. The authors used constant loop feedback to make a learning network. Raziei and Moghaddam [48] attempted to leverage knowledge from previously learned tasks to accelerate learning new tasks through a deep reinforcement learning framework. Moniri et al. [36] described a research prototype that utilizes the user's visual attention in a collaborative dual reality environment. Rai and Kannan [47] created online distributed learning to facilitate collective decision-making in scalable, intelligent factories.

4.1.2. Graphic information organizers

Six studies applied **"Graphic information organizers"** collaborative learning technique. Cecil et al. [10] described a framework for assembling micro-devices in Industry 4.0, which utilizes a combination of cyber and physical components. The engineering life cycle includes assembly planning, virtual reality simulation, command generation, and physical assembly of micro-target components. A semantic approach was implemented to address interoperability issues between multiple organizations. A Cyber-Physical Manager was used to coordinate tasks, and a cloud of resources hosted cyber components for engineering activities. The framework was demonstrated to be feasible through multiple micro-device assembly demonstrations and can be applied to other manufacturing domains.

Shu and Solvang [53] proposed that the advanced human-robot collaboration system likely includes visual aids such as flowcharts, diagrams, and graphics to organize and present information on the different modules and components of the system, such as object localization, object classification, and remote control. These visual aids can help in understanding and navigating the system's architecture. They can be particularly useful for SMEs, who may have limited resources to invest in implementing advanced HRC systems.

Monakhov et al. [35] proposed a new development for a collaborative assembly system with a vision-based safety system, which is the introduction of a movable user interface for human-robot collaboration tasks. The interface allows the user to adjust its location based on their physical needs and the task at hand. Its technical maturity has reached a level where user studies can be conducted to evaluate its feasibility, robustness, and user-friendliness. The researchers plan to continue their work by focusing on the technical feasibility and scalability of the system, as well as studying the most suitable types of virtual instructions that can be projected on the UI for users' convenience.

Roveda et al. [51] described Model-Based Reinforcement Learning (MBRL) as a way of controlling the interaction forces in human-robot collaboration tasks in the Industry 4.0 context. This approach involves creating and updating a model of the human-robot interaction dynamics and optimizing impedance control parameters using Artificial Neural Networks (ANNs) and Model Predictive Controller (MPC) with a Cross-Entropy Method. The goal is to improve human-robot collaboration performance by accounting for uncertainties and adapting the human motor system. The approach was validated through an experimental procedure, where a lifting task was used as a reference.

Zhang et al. [61] developed an RNN-based method for predicting human motion trajectory, which aims to improve the accuracy of human motion recognition and corresponding robot action for authentic Human-Robot Collaboration. The method uses an RNN structure with two functional units to parse the evolutionary motion pattern of human body parts and their coordination. It investigates probabilistic inference using Monte-Carlo dropout to minimize uncertainty-induced robot mis-trigger and improve reliability in interpreting human motion. The result shows a 40% reduction in prediction error compared to standard RNN.

García et al. [21] aimed to improve maintenance efficiency in traditional manufacturing using Industry 4.0 technologies. They proposed a methodology for retrofitting older physical assets in a non-intrusive way to support collaborative maintenance processes. The study was applied in milling operations and manufacturing cycles of face shields during the COVID-19 pandemic. The solution proposed a connected infrastructure for data storage and pattern extraction of failure probability of critical components and assisted the workers via augmented human-machine interface (HMI) tools. The study aimed to reduce industrial investment in SMEs and improve the status of legacy systems with a portable, standard sensor-based system connected to cloud-based data analysis tools. However, it does not relate directly to the "Graphic information organizers" learning technique. Although the work mentions "data storage", "pattern extraction", and "cloud-based data analysis tools" which may process, store and manage a large amount of data, including data of graphic nature such as images or videos, the article does not specify the kind of data that is being stored.

4.1.3. Games

"Games" elements were observed in six papers. Koch et al. [31] described the implementation of an intuitive and adaptive GUI for a mobile manipulator-turned-collaborative robot to assist workers in maintenance tasks. The robot's screwing skills are highlighted, and the robot used was the Littler Helper 3. The authors plan to improve the robot's safety and expand its application to more industrial maintenance tasks. Relating to games, the implementation of an intuitive and adaptive GUI for a mobile manipulator is similar to the user interface design in video games. Video games often require players to use controllers or other inputs to manipulate on-screen characters, and a well-designed user interface can make the game more enjoyable and easy to play for players. Similarly, an intuitive and adaptive GUI can make it easier for inexperienced and untrained users to operate and control the mobile manipulator in the industrial setting. Additionally, as planned future enhancements, the adaptive vision algorithms mentioned in the article could be related to computer vision applied in games, such as tracking and predicting players' moves to adjust the gameplay accordingly.

Locklin et al. [33] presented the concept of the Human-Digital Twin (H-DT), which is a digital representation of humans in cyberspace and is seen as a crucial component in the implementation of the Digital Twin concept. The Operator 4.0 research area is focused on solutions for better integrating humans in production processes, and the H-DT provides up-to-date data and models for this purpose. Previous approaches for the H-DT have been tailored to a single application. Still, a common interface for all person-related data and models is needed for symbiosis effects and reuse. The article presents a reference architecture that serves as a guideline for the components of an H-DT. An advanced Digital Twin can provide many different models and data and increase the probability that models can be reused. The H-DT also enables data sovereignty through access control and transparency. The Digital Twin concept is becoming relevant for Industry 4.0. The paper suggests that the H-DT is a core technology for developing sophisticated solutions and making them accessible to companies with the best possible practical benefits. The concept of the Human-Digital Twin (H-DT) and its applications in production processes and Industry 4.0 can be related to using avatars or digital representations of players in video games.

Schoen et al. [52] introduced collaborative robots (cobots) in the workplace and how previous research has shown a disconnection between the capabilities of cobots and the current applications used. They argued that this is partly due to a lack of effective cobot-focused instruction in the field. To address this, the authors proposed to use expert insights in the collaborative interaction design space to develop a set of Expert Frames, which they integrated into a new training and programming system that can teach novice operators to think, program, and troubleshoot like experts. The paper presents the system and case studies that demonstrate the effectiveness of using Expert Frames to provide novice users with the ability to analyze and learn from complex cobot application scenarios. The challenges of introducing collaborative robots (cobots) in the workplace and the lack of effective cobot-focused instruction can be related to introducing new players to a complex video game. As with cobots, new players may not be familiar with the capabilities of the game and its mechanics, leading to difficulty in using and understanding the game. Similar to the authors' proposed solution of using expert insights to develop a set of Expert Frames, in game design, developers often rely on player testing and feedback to improve the game's mechanics and tutorial systems to help new players learn how to play and enjoy the game. Besides, in games, players are often motivated to share their experiences and strategies through guides and forums, which can be helpful for novice players to analyze and learn from.

Nuzzi et al. [40] developed a model to set up collaborative robots using simple and robust gestures to be detected by the model. The authors used a Faster R-CNN object detector algorithm and found some limitations. However, experiments have shown that the performance was good, and the inference time was suitable for real-time applications with a relatively small dataset. The best performance was observed when the model did not use face detection. The authors aimed to deploy the embedded version of the algorithm on an NVIDIA Jetson TX2 card. However, it was not possible because the Computer Vision Toolbox, which the Faster R-CNN object detector belongs to, is not currently supported by GPU Coder. Therefore, they will continue their work using a different programming language and framework to implement a dynamic hand gesture recognition model based on state-of-the-art research. They will then test it on a real robot to set up the operations to be performed upon recognizing the commands. This research can be related to games because game developers also use gesture recognition to control game characters. Just like the authors aimed to use simple and robust gestures that the model can easily detect, game developers also aim to create simple and intuitive controls for players to interact with the game.

Dang et al. [14] presented a human-robot cooperation system that can be used in the gaming industry, where a robot can perform complex and precise movements, such as grasping and moving objects, like in puzzles or adventure games. The system was integrated with machine vision that aims to enhance the safety of the system and operators. The authors used a robotic arm for complex and precise movements in sphere assembly problems. The study makes three contributions: 1) using image processing techniques to identify 16 types of component blocks, 2) creating a safety envelope of the robotic arm using simple image processing methods instead of 3D mapping, 3) results of the study show that at least two cameras and three separate modules are the minimum requirements for the assembly process. The study demonstrates that the proposed system is effective, robust, and highly applicable in industrial environments, allowing operators to participate directly in the assembly process and increasing product customization. The study has some limitations in image processing, but it is valuable for industrial applications.

Yu et al. [60] presented a method for task scheduling in Human-Robot Cooperation (HRC) assembly processes using a combination of Monte Carlo Tree Search (MCTS) and Convolutional Neural Network (CNN). The chess game and AlphaGo Zero inspired the method. The method is formulated as a reinforcement learning problem and inspired by the chessboard format and the algorithm used in AlphaGo Zero. It was evaluated using simulation case studies and an example of HRC assembly of a desk. The results show that the MCTS-CNN algorithm is a powerful and scalable method for achieving an optimal policy for online task scheduling and improving the efficiency of HRC assembly. The authors plan to investigate more complicated scenarios and safety concerns in future work.

4.1.4. Problem-solving

Four articles presented **"Problem-solving"** collaborative learning technique. García-Esteban et al. [22] discussed the need for human-robot collaboration in Industry 4.0 to increase industrial quality and productivity and reduce production costs. This is a problem that needs to be solved to achieve these goals. The text presents a strategy for contact prevention and a non-verbal communication interface based on hand gestures to ensure safety and facilitate effective collaboration between humans and robots. This problem-solving strategy addresses the issue of safely and effectively incorporating robots into industrial environments. Additionally, the article mentions advanced computer vision techniques and future work to improve the system further, such as implementing a filter to avoid abrupt changes in robot speed and using an adapted Kalman filter to estimate hand position in blind spots. These additional improvements to the system are also problem-solving measures aimed at increasing the efficiency and effectiveness of human-robot collaboration in industrial settings.

Illankoon et al. [27] proposed a new approach to addressing the issue of collaboration and situation awareness among technicians and intelligent systems in maintenance domains. The authors identified gaps in current technology and decision support systems, specifically the lack of learning from the user and hindering of implicit knowledge development in augmented reality systems. They then provided a solution to these problems by recommending new technologies such as eye-tracking. They also recommended future work in the form of formal notations, such as ontologies, to validate the propositions of their proposed model, the DCAM.

Pacaux-Lemoine et al. [41] described the identification and evaluation of an issue, specifically the lack of autonomy of the technical agents at the operational level and the need for more cooperation between those agents when designing an assistance system to support humans at controlling an Intelligent Manufacturing System in Industry 4.0. The evaluation of the Cognitive Work Analysis methodology was conducted through a micro-world simulation with 23 participants as a way to gather data on the issue. Based on the findings, the authors proposed a solution by suggesting the incorporation of the Human-Machine Cooperation approach to the Cognitive Work Analysis methodology and plan to continue research on possible combinations of both methods and conduct further experiments to strengthen the results and refine the demonstration system.

Tsarouchi et al. [55] addressed the issue of difficulty and inefficiency in using Offline Programming (OLP) tools to design and simulate industrial cells and carry out initial robot programming, particularly in environments with various types of robots and for small and medium-sized enterprises (SMEs). The study proposed a solution to this problem by suggesting exporting OLP data in a neutral XML format, which eliminates the need for different export tools for different robot programming languages. This approach enables cost-efficiency, and remote checking, modifying, processing, monitoring, and structuring of all data used by robots. Furthermore, the method allows for easy integration of human tasks by linking files from OLP software with the SOA framework. It facilitates the use of sensors for programming or controlling robots.

4.1.5. Discussion

Only one work focused on the collaborative learning technique **"Discussion"**. Rabelo et al. [45] presented a proof-of-concept of using softbots as a feasible approach for implementing the "Smarter Operator 4.0 type" and the results of the study in a controlled and emulated shopfloor environment. The text highlights the potential benefits and limitations of the approach, discussing the ARISA framework's usage, the prototype's limitation in certain aspects such as security, semantic interoperability, and more, and possible mitigation using external services. Additionally, the article presents the next steps of the ongoing work, which includes improvements on the voice and natural language recognition, evaluation of softbots in other types of the Operator 4.0 typology, and deeper analysis of integration approaches between the softbot and real smart industrial equipment's wrappers and controllers, all of which would require the collaboration of multiple stakeholders for further development and research.

4.1.6. Collaborative learning techniques taxonomy

The reviewed articles contributed to developing a taxonomy according to collaborative learning techniques proposed by Elisabeth et al. [16]. The taxonomy created is depicted in Figure 2. This result expands on the investigation of collaborative learning, and its relevance to Industry 5. Elisabeth et al. [16] have spent years researching, creating, and refining methods and strategies to enhance team learning, making them an authority on the issue. These authors think collaborative learning is crucial for teams' success because it fosters the development of cooperation, communication, and problem-solving abilities, all of which are vital for personal and professional growth.

"Reciprocal teaching" emphasizes individual contact and active participation through various roles, such as summarizing, posing queries, providing clarification, and making predictions, to promote active engagement with the subject. Through reciprocal instruction, the critical thinking, teamwork, communication, and digital literacy skills required for Industry 5's automated and inventive data-driven work environment are created [16].

The goal of the problem-solving technique also known as "note taking pairs" is to increase individuals' collaboration, communication, and knowledge and retention by having two people or machines working together to note down a task or problem. It aids in data organization, comprehension, and sharing, fosters teamwork and communication, boosts productivity and efficiency, and promotes active involvement and innovation in Industry 5 [11, 12, 28, 32, 36, 38, 47, 48, 56].

A "learning cell" consists of a small group of people who work together to accomplish a particular learning goal, typically through self-directed and collaborative learning. It is associated with Industry 5 because it promotes teamwork, problem-solving, and ongoing learning—skills that are crucial in the highly collaborative and dynamic workplace of Industry 5 [5, 18, 20, 37, 39, 58]. In order to practice and develop abilities, "role-players" act out a certain scenario or event. In a virtual setting, it enables employees to practice and build collaborative skills, which might help prepare them for challenging and dynamic circumstances in Industry 5 [46, 59].

The discussion technique is a type of collaborative learning in which participants argue and discuss a particular subject or issue to agree and share information. This technique fosters strong teamwork, critical thinking, and effective communication—skills essential in today's highly collaborative and dynamic workplace. Discussions enable groups to collaborate on original and creative responses to difficult problems. Prior to group discussion, the Think-Pair-Share method promotes independent reflection. There are three phases to it: thinking (individually),

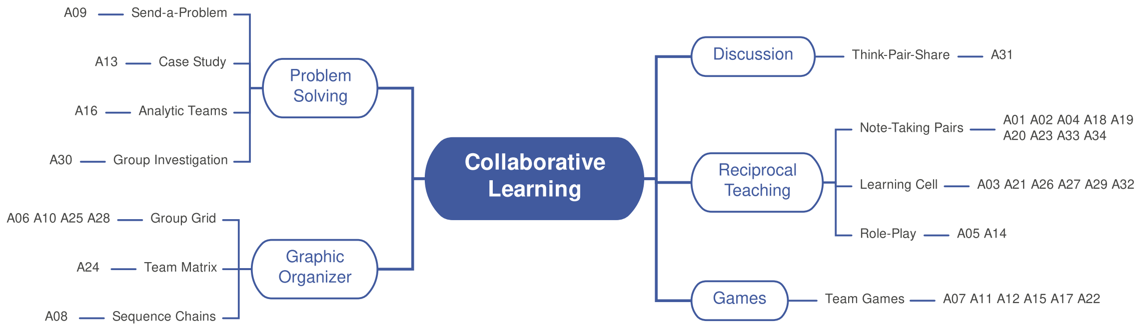

Fig. 2. Collaborative learning techniques taxonomy

sharing (in pairs), and discussing (in groups). Participants think about and record their views on a particular problem or topic during the first stage. Participants exchange their concepts with a partner in the second step. The third and final step involves group discussion to agree. Before expressing their opinions, participants can process and think about the topic, which improves the quality of talks and helps people develop their critical thinking abilities. By exchanging ideas in pairs, participants can learn from others' perspectives, which can broaden their own perspectives and improve their capacity for creativity and problem-solving [45].

The "Games" technique uses games as a training tool for concepts and skills. Games are a fun and interesting way to teach and may be made to promote particular abilities like problem-solving, critical thinking, teamwork, and communication. Games can be created expressly to develop abilities necessary for this type of workplace, like coping with complex data, making data-driven judgments, and using cutting-edge technology. In addition, games can imitate actual circumstances and difficulties, offering practical instruction for groups and individuals. This improves employees' capacity for innovation and decision-making while also preparing them to meet the demands of Industry 5 [14, 31, 33, 40, 52, 60].

The "Graphic information organizers" technique is a collaborative learning tool that aids students in clearly and logically visualizing and organizing difficult knowledge. It is a successful method for assisting kids in comprehending abstract concepts and drawing connections between various ideas. Using the graphic information organizers technique, employees can be assisted in understanding and adjusting to technological advancements and new processes. It can be used, for instance, to teach staff members how various technologies, including automation, artificial intelligence, and the Internet of Things, interact with and complement each other. Additionally, it can assist staff in comprehending how technological advancements impact their duties and responsibilities at work.

The Group Grid approach, for instance, enables people to organize and evaluate information while working in small groups. This approach can be applied in the workplace to assist staff members in comprehending and putting new technology and procedures into practice. It can be used, for instance, to teach staff members how various technologies, such as the Internet of Things (IoT), artificial intelligence (AI), and automation, can be leveraged to boost the effectiveness and caliber of processes. Additionally, it can assist staff in identifying issues and possibilities brought on by technological advancements and in coming up with creative solutions [21, 51, 53, 61].

Another application of "Graphic information organizers" technique can be made through the "team matrix" method. Employees can divide and manage tasks in teams using this method. Each team consists of members with various knowledge and skill sets, and each member is accountable for completing particular duties. On projects involving cutting-edge technologies and procedures, staff can benefit from using this strategy to work productively together. For instance, it can assist staff members in organizing and managing duties connected to adopting technologies like automation, artificial intelligence, and the Internet of Things. Additionally, it can be utilized to maximize each employee's unique abilities and expertise so that they can all contribute successfully to the project [35].

"Sequence chains" allow groups to work together to develop a logical flow of ideas or occurrences. Each group member must add a sequence item and explain how it links to the preceding parts. Employees can utilize this strategy to assist them to discover issues and opportunities related to technology transformation and come up with creative solutions [10].

"Problem solving" technique focuses on resolving actual issues and relevant difficulties in a group setting. This can involve collaborating with others to find solutions to issues with automation, robots, artificial intelligence, and other cutting-edge production and manufacturing technology. Participants can use this method to practice their theoretical knowledge in practical settings while honing their critical thinking and teamwork abilities.

Sending problems to other team members or learners ("Send a problem") includes identifying and communicating actual issues or difficulties. Sharing concerns about manufacturing and production are included in this. The method can produce original and creative answers. Sharing difficulties also enables participants to improve their communication and teamwork abilities and fosters the development of a larger learning community [22].

The "Case Study" approach examines a particular instance of a genuine circumstance or issue. Techniques can include case studies of businesses or sectors using cutting-edge technology like automation, robots, artificial intelligence, and big data to boost productivity, cut costs, and increase efficiency. Participants can practice critical thinking and problem-solving techniques by analyzing and discussing a real-world scenario. Additionally, examining specific cases offers insight into how cutting-edge technology is being used and deployed in the sector and how businesses are addressing possibilities and difficulties [27].

The "Analytic Teams" technique calls for creating teams to evaluate and resolve complicated issues. Multidisciplinary teams are formed to examine and resolve issues relating to cutting-edge technologies. Engineers, production managers, data specialists, and other experts can be team members. The method enables participants to collaborate to examine and resolve complicated issues, strengthening their ability to think critically, cooperate with others, and solve challenges. Multidisciplinary team building gives members access to many viewpoints and inventive and unique solutions, which is crucial in Industry 5 [41].

The "Group Investigation" approach involves working in groups to research a topic. It is predicated on the notion that learning is most successful when individuals collaborate to find solutions to issues. This approach can teach staff members in Industry 5 how to comprehend and use AI concepts. Groups of workers might look into how these technologies can be applied to boost the effectiveness and standard of production processes. Additionally, they can cooperate to create fixes for particular issues like raising output or cutting expenditures. By using this strategy, employers can be actively involved in the transformation process and the implementation of the industry. By doing this, the company is ready to tackle the difficulties and take advantage of the opportunities presented by the fifth industrial revolution [55].

In summary, the study of Elisabeth et al. [16] on collaborative learning reveals various strategies that can be applied to enhance cooperation, communication, and problem-solving abilities. Multiple strategies can be used to encourage active participation and teamwork in the learning process, including graphic information organizers, role-playing, discussion, Think-Pair-Share, and reciprocal teaching. These abilities are crucial for the dynamic and highly collaborative work environment of Industry 5, where automation and data-driven decision making is essential. These methods can increase productivity and efficiency, encourage ongoing learning in Industry 5, and assist staff members in comprehending and adapting to technology changes.

4.1.7. Collaborative learning techniques technologies

A mapping of the technologies used to support the collaborative learning techniques is presented in Figure 3. In Industry 5, robotics can cooperate in a variety of ways with other devices [11], systems [22], and people [41]. Human-Robot Collaboration (HRC) is one of the most popular types of teamwork where robots assist human workers in carrying out hazardous or challenging tasks for them [20, 36, 48]. Due to the robots' ability to work continuously without rest intervals and their improved accuracy and precision, this collaboration promotes greater efficiency and production [47].

The ability of the robots to make judgments and adjust to changes in the production process is another benefit of the integration of IoT and AI capabilities, which raises the quality of the finished product as a whole [55]. Another method is multi-robot collaboration, where multiple robots work together to fulfill a task that a single robot can solely do. This is clear in the logistics of warehouses, where robots collaborate to pick and sort products, boosting production and lowering the need for human workers. Additionally, collaborative robots (cobots) can be employed in various contexts, such as manufacturing, assembly, and packaging, and are intended to function safely alongside humans [20].

Problem-solving techniques enable robots to make decisions and solve problems in the production process [5]. For example, if a robot encounters an obstacle or malfunction, it can use problem-solving techniques to determine the best action to continue working and minimize downtime. This can be done using algorithms or artificial intelligence to analyze data and make decisions based on that data [47].

Robots in the robotics Industry 5 can learn from one another and share performance data using the reciprocal teaching technique [28]. For instance, robots operating on a production line can communicate information about their progress and modify their course of action as necessary [20]. Robot collaboration could become more effective and efficient, boosting output and product quality [11].

Robots can learn from one another through reciprocal teaching by observing one another's performance and exchanging knowledge [56]. This can be achieved by allowing robots to guide the group in learning new knowledge and abilities on a rotating basis. On the other hand, machine learning is a technique for teaching computers to learn from data without being explicitly programmed. It is a subset of AI that enables the system to gain knowledge and develop over time [20].

Robots can gain knowledge from their peers and the data by integrating reciprocal teaching and machine learning. For instance, a group of robots in a production line can communicate information about their performance and modify their behavior accordingly [48]. The final output's productivity and quality may increase due to more effective collaboration between the robots. The robots can also use machine learning algorithms to learn from the data and enhance their capacity for decision-making [59].

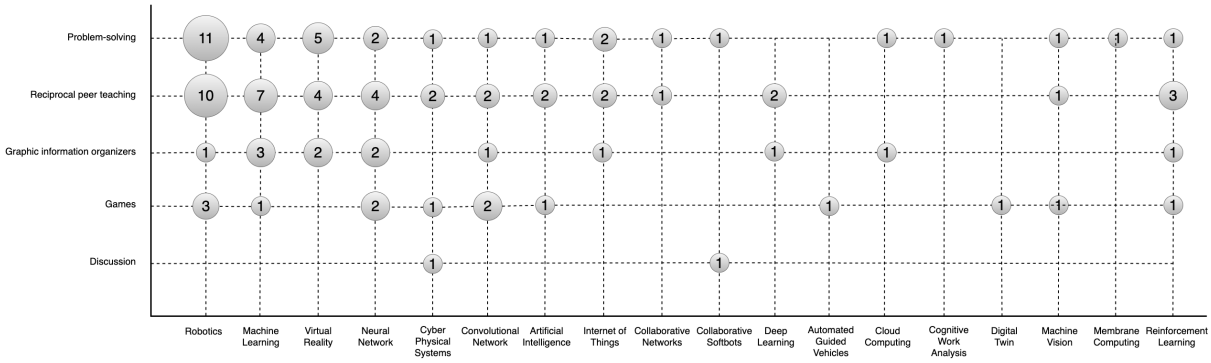

Fig. 3. Technologies used in Collaborative Learning techniques

4.2. *SQ2: What are the challenges of applying collaborative learning to industry 5 context?*

The fifth industry raises a variety of potential challenges in applying collaborative learning. The academic community has highlighted several issues that often need to be resolved for Industry 5 advancements. Table 7 shows the challenges and the respective articles. The remainder of this section explains how the articles relate to the cited difficulties and how they overcame them.

Challenges	Studies
Collaborative robot	A01 A02 A04 A05 A07 A09 A11 A16 A18 A20 A23 A24 A25 A30 A31 A33 A34
Pattern recognition	A01 A03 A04 A10 A15
Assembly works	A08 A17 A22 A29
Robot manipulation	A09 A20 A21
Business objectives	A11 A12 A16
Human satisfaction	A11 A14 A19
Costs of maintenance	A06 A13
Machine level decision	A02 A23
Behavioral prediction	A11
Intelligent maintenance	A27
Program quality	A12

Table 7. Challenges in applying collaborative learning in Industry 5.0

4.2.1. Collaborative robots

The successful implementation of "**Collaborative robots**" (cobots) in Industry 5.0, the following stage of industrial automation, which is characterized by the integration of cutting-edge technologies, presents several challenges. Since collaborative robots will coexist with humans in shared workspaces, safety must be taken into consideration throughout design [57]. Advanced safety features like force-limiting sensors and emergency stop buttons must be created. Collaborative robots need to be able to change with their surroundings and coexist with various human and robotic species. Human-robot communication and cooperation must be optimized. Businesses will have to spend money training their employees to work with cobots. In the Industry 5.0 environment, collaborative robots must be able to effortlessly exchange information and communicate with other equipment, and systems [43].

Because they are connected to the internet and other networks, collaborative robots are susceptible to cyber-attacks. For collaborative robots to be embraced in Industry 5.0, they must be affordable and simple. AI and machine learning will be the driving forces behind collaborative robots, but their implementation and upkeep can be complicated. Collaborative robots must be regularly maintained and upgraded to stay current with emerging technologies [49].

Ji et al. [28] described the steps taken to transform a mobile manipulator into a collaborative robot with a focus on safety enhancement by implementing adaptive vision algorithms that control execution according to the presence and intentions of the human operator. Choudhury et al. [11] introduced a distributed semantic knowledge-based multi-robot system and its performance compared with a centralized system, emphasizing testing the system's robustness and working on a backup strategy for any failure of one or multiple robots in the team. Lee et al. [32] proposed a process model-based HRC system that uses an AR interface. It is expected to reduce human error in part model identification and work sequence while also increasing production flexibility by using image processing to improve part recognition of AR.

Yilma et al. [59] proposed a CPSS approach to improve human-machine collaboration and safety in Industry 4.0 by incorporating human aspects into current CPS-based system designs. The CPSS approach effectively integrates human dynamics and AI to enable machines and robots to better understand and adapt to complex human behaviors and needs. Future studies are planned to investigate this approach further. Koch et al. [31] focused on developing a collaborative robot (cobot) to work alongside humans in a shared workspace. It also highlights the importance of an intuitive human-robot interface for effective HRC, allowing for smooth communication and cooperation. The article also presents a practical application of HRC through a skill-based approach and communication through the human-robot interface for a screwing task.

García-Esteban et al. [22] addressed HRC regarding industrial productivity and operator safety. It highlights the need for a seamless collaborative work environment between humans and robots to achieve high productivity, low failure rate, and ensure safety. To achieve this, the article proposes an intuitive HRI strategy that includes a high-precision safety layer for gestural human-robot communication and monitoring of the operator's hands to avoid collisions during human-robot collaboration. The safety layer is created using advanced machine learning and computer vision, specifically Convolutional Neural Networks (CNN), and is independent of the cobot and the environment. The approach aligns with the goal of ensuring safe and efficient collaboration between humans and robots in industrial settings, which is a key aspect of HRC.

Löcklin et al. [33] applied a Human-Robot Collaboration (HRC) in the context of AGV (Automated Guided Vehicles) and Human-AGV interaction. The proposed reference architecture uses a Human Digital Twin (H-DT) to improve automation and human-AGV interaction in position-based automation. AGVs are used to achieve flexible intralogistics solutions and share the same traffic space with operators on the shop floor. To optimize AGV performance, models are used to predict human movements, allowing AGVs to act more efficiently, such as rolling out in case of a temporarily blocked route rather than going fast and braking hard. The prediction of human motion can also be used for other applications such as starting maintenance routines in advance to allow a maintenance technician to start work as soon as he reaches the machine. This approach aligns with the goal of improving the efficiency and safety of collaboration between humans and AGVs in industrial settings, which is a key aspect of HRC.

Pacaux-Lemoine et al. [41] evaluated the Cognitive Work Analysis (CWA) methodology and its use in designing an assistance system to support human control of Intelligent Manufacturing Systems in Industry 4.0. The methodology is applied to identify functions the assistance system should have, including integrating a digital twin of the intelligent manufacturing system. The methodology was evaluated through experiments using a micro-world, a manufacturing cell with robots, products, and a human supervisor. Results showed that the assistance system allows for correct awareness of the situation, accurate evaluation of decisions, and management of mental workload while reaching expected production performances. The article suggests coupling CWA with human-machine cooperation principles as a potential avenue for research to improve cooperation between humans and robots.

Raziei and Moghaddam [48] affirmed that robots (cobots) are a new generation of robotic arms designed for direct human-robot interaction and have built-in safety features as collision detection and force feedback. They are commonly used in Industry 4.0 for assembly, material handling, machine tending, and inspection tasks. Research focuses on stable and safe operations in manufacturing processes, but cobot structures must be enhanced with computational methods such as AI, specifically deep Reinforcement Learning (RL), to improve adaptability and resilience in unstructured environments. The article relates to Human-Robot Collaboration, illustrating how cobots are designed for direct interaction with humans and how AI can improve their adaptability and resilience in dynamic and unstructured environments.

Moniri et al. [36] described a scenario of Human-Robot Collaboration in which two humans work together with one robot. One person physically interacts with the robot, while the second person monitors the setup through a Virtual Reality (VR) system. The VR system allows the user to manipulate objects in a 3D representation of the environment, which is updated in real-time. This includes the position and orientation of objects, as well as the head position and gaze of the other user. This system allows for novel forms of collaborative factory work, as the collaborators can follow the visual attention of the tutor in 3D and in real time.

Rai and Kannan [47] proposed an algorithmic framework that enables distributed learning and decision-making for coordinating industrial machines. The goal is to achieve scalable global coordination between these machines. The self-modeling approach is intended to allow for high learning rates for high-dimensional, on-demand control services. It has been tested and validated in multiple mobile robotic settings. This is an example of Human-Robot Collaboration as it allows multiple robots to work together in coordination, with the help of a central algorithm, to achieve a common goal.

Monakhov et al. [35] presented a Human-Robot Collaboration as the interface aims to improve the collaboration between humans and robots in assembly processes. This article describes a prototype for a projector-based adaptive portable user interface that aims to improve the ergonomics of human-robot collaboration cells. The interface is said to provide additional benefits, such as improving safety awareness inside the robot cell and providing additional help annotations to the assembly process.

Roveda et al. [51] designed a model-based reinforcement learning (MBRL) variable impedance control schema for human-robot interaction dynamics. The goal was to empower and assist the human operator in collaborative onerous tasks by minimizing human forces applied to the robot and minimizing human effort. The article proposes an impedance controller for compliant robot behavior, a human-robot interaction dynamics modeling approach using an ensemble of Artificial Neural Networks, and a Model Predictive Controller using a Cross-Entropy Method for the online optimization of impedance parameters (stiffness and damping). The article also details the specific elements of the approach, such as the impedance controller, the ensemble of ANNs approach, and the MPC with CEM in different sections.

Tsarouchi et al. [55] characterized a method for coordinating human and robot tasks using OLP (Off-Line Programming) data. The method does not require software modules for robot-specific program generation. Instead, it proposes a software framework based on the Robot Operating System (ROS) as a middleware to enable the interaction between different robot controllers and OLP tools. The simulation data is generated in a neutral XML format and a "command handler" converts the XML file data into the robot maker language. This method aims to enable human integration in a hybrid assembly cell and coordinate assembly tasks sequence. This approach is a form of Human-Robot Collaboration (HRC) as it allows the coordination of human and robot tasks in the assembly process.

Rabelo et al. [45] presented a proof-of-concept and qualitative work to investigate the extent to which 'softbots' (soft robots) can support the implementation of the Operator 4.0 concept, particularly the "Smarter Operator 4.0" type. This type of operator is aided by softbots such as Intelligent Personal Assistants (IPAs) to interface with smart machines and robots, computers, databases, and other information systems, to assist the operator in the execution of different tasks in a human-like interaction. This type of Operator 4.0 is based on the Industry 4.0 reference architectures principles, such as the Reference Architecture Model for Industrie 4.0 (RAMI 4.0) from Germany and the Industrial Internet Reference Architecture (IIRA) from the USA. This research is focused on how softbots can assist the operator in the execution of different tasks.

Cunha et al. [12] presented a model for natural human-robot interaction using Dynamic Neural Fields (DNFs). DNFs provide a theoretical framework for giving robots cognitive functions such as working memory, prediction, and decision-making. The model is based on the concept that task-relevant information is expressed by supra-threshold bumps of neural populations, which enable an auto-sustained multi-bump pattern that can be used as a memory mechanism for sequential processes. The research likely focuses on Human-Robot Interaction (HRI) to improve how robots interact with humans.

Umbrico et al. [56] proposed a solution for open issues in Human-Robot Collaboration by integrating AI and AR technologies to create a user-aware approach for enhancing the flexibility and adaptability of collaborative systems. The proposal includes three technology modules: an AI-based knowledge representation and reasoning module to encapsulate the user model, an AI-based task planning module to synthesize collaborative plans, and an AR-based human-system interaction module to realize advanced interaction mechanisms. The goal was to adapt the behavior of collaborative robots and the collaborative process to different users by considering the users' characteristics and preferences.

4.2.2. Pattern recognition

Pattern recognition in the context of Industry 5 involves the complexity and variety of data generated, the need for real-time processing, privacy and security concerns, difficulty in handling noise and outliers, and lack of labeled data for training and testing. Overall, advanced techniques and technologies are required to take the complexity, variety, and volume of data generated in Industry 5 [54].

Ji et al. [28] discussed using augmented reality feedback to create a close-loop brain-computer interface (BCI) for controlling a robot in an industrial scenario applying pattern recognition. The input for the BCI is voluntary eye blinks, which are easy to perform and generate stable pattern recognition. An Optical See-Through (OST) AR headset is used to provide visual feedback for the input of the BCI user to achieve complex robotic operations. The effectiveness of this approach is verified by comparing its performance with a hand gesture-based AR interface in an industrial HRC task.

Na and Dai [37] presented a project that focuses on using a system of sensors in a spatial context to bridge the physical and digital world by expanding upon current forms of mixed reality experience. The human body and robots are designed as "aggregated" characters whose behavior and performance help build an "aggregated" environment. The process culminates in an architecturally augmented robotic performance. The observer's position and point of view are tracked in real-time to reveal an augmented environment, with avatars of telepresent participants and digitally augmented physical robots. The digital avatar and augmented robots interact with each other based on participants' input and distinct behavioral pattern recognition through machine learning.

Lee et al. [32] proposed a conceptual framework for a human-robot collaboration (HRC) system for a semi-automated process to produce electric motors. The process consists of automated machines, a handling robot, and a human worker. The robot assists the human worker in material handling operations and transfers the partially processed parts to the assembly section, which is performed by the human worker. In current practice, there is no interaction between the robot and the human worker on part information. The human worker does not receive information about the type of parts the robot picks up before the part arrives at the assembly section. This can lead to delays when the human worker needs to measure and identify the part. To address this, the research applied machine vision technology to identify the part in the collaboration process. The researchers use Part-flow based Manufacturing Process Modeling (PMPM) to define the work order and part information and an augmented reality (AR) device to transmit the work order and product specification information. The study proposes a conceptual framework for the HRC system using a process model and AR interface.

Shu and Solvang [53] focused on human-robot collaboration and proposes a new system architecture that offers a low-cost solution to allow traditional industrial robots to perform human-robot collaboration tasks. The architecture includes advanced features such as dynamic tracking, high-level abstraction control, and the possibility for multi-method controlling to improve manufacturing agility and flexibility. However, safety regulations do not currently allow the use of general industrial robots in human-robot collaboration tasks, especially in real production processes. Therefore, the experiments are conducted through computer simulations and simplified safe laboratory setups. The researchers also note that ongoing research is working to apply safety features to general industrial robots.

Nuzzi et al. [40] applied Machine vision which is a critical component in robotics because it enables the robot to understand and interact with its environment. It allows the robot to see and focus on specific tasks, making the robotic system more flexible and automated. For example, with machine vision, the robot can identify the position of objects to be picked up, even if they are not fixed, allowing greater autonomy and efficiency in the robot's actions. Both machine vision and pattern recognition are used in many applications, including robotics, surveillance, medical imaging, and autonomous vehicles. Together, these technologies enable machines to make sense of visual data and make decisions based on that data, improving many systems' accuracy, efficiency, and automation.

4.2.3. Assembly works

In the Industry 5 environment, **Assembly works** refers to the use of advanced technologies, such as robotics and automation, to increase efficiency and precision in the assembly process. This can include using sensors, machine learning algorithms, and other digital technologies to optimize the assembly process and improve overall performance [5]. Industry 5 assembly work often involves using connected systems, such as the Internet of Things (IoT), to share data and improve communication between different parts of the assembly process. It complements the goal of Industry 4.0 assembly, which aims to create a more flexible and responsive manufacturing process that can adapt to changing market conditions and customer needs [60].

Cecil et al. [10] proposed an advanced collaborative framework to support the planning, simulation, and assembly of microdevices. The framework is designed in the context of Industry 4.0, which emphasizes the integration of advanced technologies such as Cyber-Physical Systems (CPS) and the Internet of Things (IoT) to improve manufacturing processes. The framework consists of a set of cyber and physical components that collaborate using next-generation networking technologies to accomplish a series of tasks in assembling a target micro part. Data and information exchange among these components are crucial in supporting this cyber-physical life cycle. The various assembly activities are monitored and communicated to the relevant software entities through cloud-based infrastructure. Cameras monitor the assembly activities, and feedback is provided to distributed sites as the physical assembly tasks progress.

Dang et al. [14] used a human-robot collaboration system to apply assembly works to resolving the Taiwan pyramid sphere puzzle. The system uses a 2D calibration model to determine the locations and orientations of component blocks in operating zones and machine vision to recognize and categorize them. The robot then applies this knowledge to the assembly challenge by precisely grasping and moving the bricks to the proper places. In order to operate securely alongside human operators without the need for safety barriers, a safety monitoring module was also installed to detect the presence of external objects, such as an operator's arm. The goal of this system was to improve the precision and efficiency of the assembly process using advanced technologies such as machine vision and robotics.

Yu et al. [60] sought to simplify the assembly process by structuring it as a game of chess with set rules. The objective was to tackle challenging assembly jobs using potent techniques like deep neural networks and reinforcement learning (RL). The researchers also created a self-play RL job scheduling system that does not need supervision or human input. Overall, the project aimed to use machine learning to automate and improve assembly activities.

Ahmed et al. [5] described a research project focusing on the Human-Robot Collaborative assembly process as a crucial element of modern manufacturing. The authors stated that quality and reliability are important factors that need to be considered in this area and that both robot and human factors play a role in these factors. The article presents an approach for addressing quality and reliability in the HRC assembly process, which considers the robot's and human's critical parameters that affect the key quality and reliability characteristics. The approach was demonstrated using an industrial case study of an HRC assembly process. Overall, the research aimed to improve the quality and reliability of the HRC assembly process.

Assembly processes are used to improve and automate the assembly process using advanced technologies such as Cyber-Physical Systems (CPS), the Internet of Things (IoT), machine vision, robotics, and machine learning. The authors discussed approaches to addressing quality and reliability in the assembly process, and some cases, structuring the process as a game or using self-play algorithms to improve scheduling and decision-making.

4.2.4. Robot manipulation

In the perspective of Industry 5, **"robot manipulation"** refers to the collaborative employment of robots and humans in industrial settings [20]. This entails utilizing cutting-edge technology like computer vision and machine learning to provide robots the ability to interact with people safely and productively in a shared workspace. The goal is to bring together the best qualities of humans and robots to boost efficiency and productivity while assuring everyone's safety. Building a reliable and secure human-robot communication interface includes methods like non-verbal communication utilizing the hands and safety features like collision avoidance [36].

Robot manipulation is utilized in García-Esteban et al. [22] study, which emphasizes the application of robotics in industrial settings, particularly in the context of collaborative robotics. The creation of appropriate safety measures and interfaces is necessary to achieve the objective of improving performance by enabling robots and people to cooperate and communicate. The suggested approach enhances human-robot interaction and manipulation tasks by utilizing cutting-edge technologies like machine learning and computer vision.

Moniri et al. [36] utilized a robot to carry out duties in a manufacturing environment, and people may interact with and manage the robot using virtual reality technology. Visual sensor systems enable tracking of the user's gaze for extra information for teaching purposes. The VR system allows the user to manipulate things in a 3D representation of the world that is updated in real-time. The study prototype that the authors have suggested intends to enable new types of collaborative industrial work, including the manipulation of things by the robot while being controlled remotely by human partners.

Gallala et al. [20] explained how markers and AR technologies allow a robot arm made up of joints and linkages to move and position itself in the real world. The control interface enables the joints to move precisely, enabling the robot to attain desired positions. The robot may operate things or perform tasks in the natural environment thanks to markers and coordinate transformations, which align the robot's movements with the surroundings. In conclusion, the authors highlighted how crucial precise positioning and control are when manipulating robots.

Studies in industrial robotics, which seek to enhance performance by developing safeguards and interfaces for human-robot interaction and manipulation tasks, primarily focus on manipulating robots. Modern techniques for interacting with and controlling robots are used in these investigations, including machine learning, computer vision, and, in some instances, virtual reality. With the help of these techniques, robot arms can move and position themselves precisely in actual settings, allowing them to operate items and carry out tasks. The studies presented emphasize the need for precise positioning and control in robot handling.

4.2.5. Business objectives

"Business objectives" in the era of Industry 5 refers to the goals and objectives that businesses seek to achieve through the adoption of Industry 4 technologies, such as increased productivity and efficiency, enhanced quality and flexibility, improved customer experience, cost reduction, and data-driven decision making. These technologies enable businesses to develop new opportunities by creating more intelligent, efficient, and adaptable processes [41].

Given that it has a generalizable structure, the suggested usage of a Human Digital Twin (H-DT), proposed by Löcklin et al. [33] in the business objectives, can help with reuse. An H-DT architecture consists of a unique ID, information about the represented person, models of the embodied human, relationships with other Digital Twins, and interactions between models. The H-DT also needs several interfaces for data collection, co-simulation, and model and data access. The H-DT may be given to a particular individual, person/operator role using the unique ID. The data that has been kept consists of important information acquired by sensors, organizational information, and work information. Models include behavioral, intention, and capacity models representing various human behaviors, goals, and capacities.

Schoen et al. [52] implemented an Expert Model based on research that found experts in cobot application design balance safety concerns with Performance Objectives (cycle-time, speed, payload), Business Objectives (robot wear-and-tea) and Safety concerns (collaborative/shared space collisions, pinch-points, risk-assessment, force sensing, and tool/part manipulation). Experts bring a deep understanding to weigh cost, flexibility, and usability with safety. They considered the use case, specific robots, necessary integrations and sensors, and the impact on the safety of the process structure. They evaluated the cost of having a robot producing the part compared to a human operator. The concepts were organized into four Expert Frames: Safety Concerns, Program Quality, Robot Performance, and Business Objectives to align with learning outcomes.

Pacaux-Lemoine et al. [41] examined the human-machine interaction in an Industry 4.0 flexible cell from the perspective of business objectives. They found that the cell, composed of mobile ground robots and robots connected by a conveyor system, is managed by a human supervisor at the tactical level who evaluates the manufacturing plan and takes corrective actions as needed. The manufacturing plan is assigned at the strategic level, and the decision support system provides information on the cell's condition. The shuttles self-organize in response to events and manufacturing processes, but this method has limitations in achieving production goals and addressing restrictions. To improve performance and meet business objectives, the HUMANISM project recommends adding a human supervisor to oversee the self-organizing system. The integration of the human and the IMS is designed and evaluated using the CWA approach to ensure it considers both capabilities and limitations.

All of these studies examined the human-machine interaction in the context of business objectives to improve performance and achieve production goals. They involved a human supervisor at the tactical level who evaluates the manufacturing plan and takes corrective actions as needed. They also involved a decision support system that provides information on the cell's condition and recommended adding a human supervisor to oversee the self-organizing system.

4.2.6. Human satisfaction

In the scope of Industry 5.0, **"human satisfaction"** refers to how Industry 5.0 practices and technology might raise the general level of satisfaction of human workers in industrial settings. It is expected that Industry 5.0 focus on improving the human-centered approach, where the industry will be more focused on the well-being and pleasure of the workers [38].

Löcklin et al. [33] proposed that the H-DT may be used to store information about the represented person, such as vital information gathered by sensors, job information, and organizational information. The individual's present position, work performance, access permissions, and salary group may all be understood using this data. This information may be used to evaluate a person's performance and pinpoint strategies to raise their job happiness. The individual's data privacy and pleasure are also guaranteed by the capability to encapsulate sensitive data and selectively erase it after a certain time.

Rabelo et al. [46] proposed applications of softbots, commonly referred to as software assistants, in Industry 4.0. According to the consulting company BCG, softbots may be helpful in ten general scenarios, including operational excellence, inclusivity, happiness and motivation, safety, and continuous learning. These ten scenarios can produce various circumstances and instances. The authors decided to concentrate on five particular use scenarios as proof of concept. They offered a broad overview of the use scenarios and some illustrations of graphical user interfaces (GUIs) and how the ARISA tool handles them.

Niu et al. [38] highlighted the usage of robots with retrieval shelves in warehouses and the need to enhance productivity by keeping both people and robots active. The authors also pointed out that it might not be the greatest idea to give duties to employees who are uncomfortable or exhausted because it may negatively influence their productivity and well-being. The authors argued that worker discomfort levels should be considered when making operational decisions in warehouse operations and seek to identify the optimal workstation for the robot with a retrieval shelf to distribute picking employees' suffering moderately.

These works discussed the use of technology to enhance various business operations and employee satisfaction, including data privacy, happiness, and discomfort levels, to boost productivity and efficiency. Examples of this technology include Human Digital Twins (H-DT) and software assistants.

4.2.7. Costs of maintenance

In the domain of Industry 5, **"costs of maintenance"** refers to the expenses related to the upkeep and repair of Industry 4 technologies and equipment. Industry 4 would be defined by incorporating cutting-edge technologies like blockchain, IoT, and artificial intelligence, which might result in a more proactive and predictive maintenance strategy. This could potentially lower the overall expenses of maintenance by allowing the early detection and adjustment of possible faults [21, 27].

García et al. [21] stated that maintenance costs significantly impact the industrial sector's competitiveness. The most recent epidemic has raised the requirement for industrial facilities to adjust to unforeseen developments and guarantee real-time production continuity. Developing innovative human-machine collaborative maintenance models and intelligent monitoring is beneficial to streamlining industrial operations. However, SMEs still encounter difficulties putting Industry 4.0 principles like interoperability, virtualization, decentralization, real-time capabilities, service orientation, and flexibility into practice. The labor force must also improve its ability to deal with digital technology. Real-time collaborative maintenance may be implemented quickly and at a lower cost in traditional production with the help of a flexible and linked retrofitting method.

Illankoon et al. [27] presented a model called DCAM for problem-solving in operational-level maintenance. The model comprises four main knowledge components: team synchronicity, corporate environment, diagnosis to prognosis, and work safety. Since the task environment interacts in covert and overt ways with internal and external issue representations, the model recognizes the dynamic character of these knowledge pieces. The author contends that various SA interventions, such as those detailed in the author's sources, can help the DCAM.

4.2.8. Machine level decision

"Machine level decision" refers to the capability of Industry 4 technologies, particularly those leveraging cutting-edge AI and machine learning, to make decisions at the machine level without human interaction. This could entail modifying manufacturing procedures, keeping an eye on equipment, and spotting and resolving possible problems. Industry 4's utilization of machine-level decision-making can boost productivity, improve quality, and minimize downtime.

Choudhury et al. [11] compared and contrasted two distinct methods for selecting robot tasks. The first tactic involves having one robot calculate the cost and then tell the others what it is. The second tactic is to have all robots figure out the price. The author contends that while both procedures are equally effective, the second can take longer if the network capacity is low. The job execution may start later as a result of this. Weak bandwidth networks are the author's main area of interest.

Rai and Kannan [47]

4.2.9. Behavioral prediction

The term **"behavioral prediction"** emphasizes how Industry 4 technologies, particularly those that use cutting-edge AI, can predict and forecast how machinery, equipment, and processes would behave in an industrial setting. Predicting equipment failures, spotting possible inefficiencies in manufacturing processes, and streamlining production schedules are a few examples of duties that may fall under this category [33].

In order to represent global machine coordination, Löcklin et al. [33] developed an algorithmic framework for scalable distributed learning and decision-making. The method uses self-modeling, enabling a fast learning rate in high-dimensional on-demand control services. The authors found that the method can be effectively implemented with a minimum of 200 computational agents across multiple machines. Also, they suggested extending the technique to more complex domains, such as distributed sensing and medical cyber-physical systems.

4.2.10. Intelligent maintenance

The terminology **"intelligent maintenance"** refers to the enhancement and improvement of industrial equipment and system maintenance through cutting-edge technologies like AI, IoT, and machine learning. Predicting equipment breakdowns, spotting possible inefficiencies in production processes, and improving maintenance schedules are a few examples of duties that may fall under this category [39].

The idea of Cyber-Physical Systems (CPS) in Industry 4 was covered by Noureddine et al. [39]. They described CPSs as intelligent systems with embedded circuits that can communicate with their surroundings. They can speak and engage with their environment and respond to predefined stimuli. Because CPSs are networked, they can send and receive data from various places. This enables the creation of programs that can interact with their surroundings and take appropriate action. The authors also provided an example of a CPS framework for self-maintaining machines.

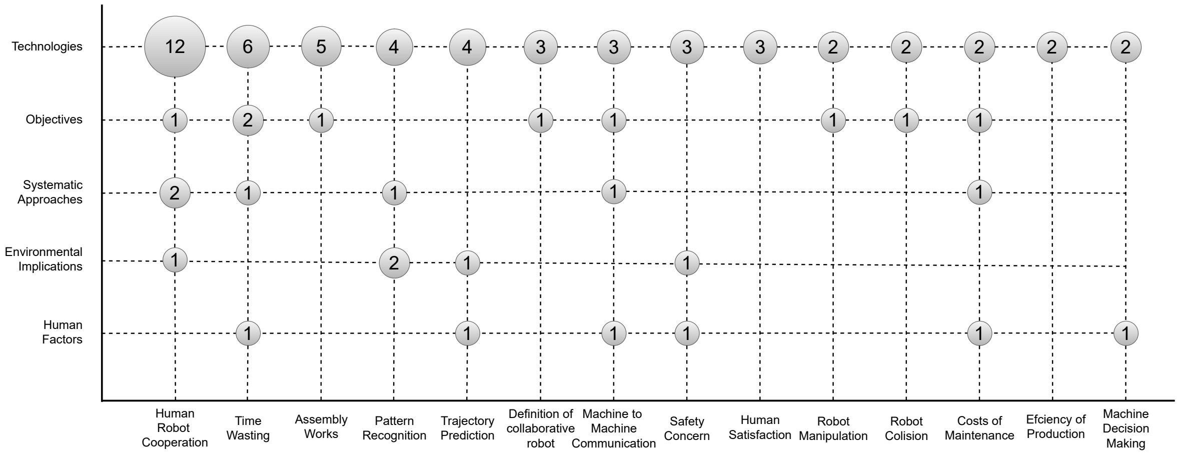

Fig. 4. Challenges and Industry 5 categories

4.2.11. Program quality

The expression **"program quality"** in the context of Industry 5 refers to the general efficacy and quality of the software systems and applications utilized in Industry 5. This encompasses the software's dependability, performance, and maintainability, among other things. The effective operation of the systems decreased interruption, and improved decision- and problem-solving capabilities depend on good program quality, which is why it is crucial for Industry 5 [25].

The Program Quality feedback frame was described by Schoen et al. [52] about the Expert Model. They pointed out that this important and valuable feedback frame combines numerous topics, including programming, integration, application, and operator. According to the authors, many additional frames rely on the program's appropriate specification to deliver helpful feedback. Both straightforward program qualities, like parameter satisfaction, and more complicated ones, such as the robot's capacity to adjust to the length of various machine operations, are included in the Program Quality frame. The authors also state that elements like missing parameters and code blocks, talents and features that aren't being used, empty code blocks, and any logical problems with machine integration will be considered when evaluating the program.

4.3. SQ3: What technologies are being used in the industry 5 context?

Industry 5 refers to integrating advanced technologies, such as the IoT and Cloud Computing, into manufacturing and industrial processes to improve efficiency and productivity. User-Awareness [11], collaborative assembly [10, 21] and efficient maintenance [39] are also critical components of Industry 5, allowing for greater customization, collaboration, and maintenance optimization.

Digitization refers to the process of leveraging digital technologies to enhance the capabilities of AI systems.

4.4. SQ4: What are the data types and devices used?

Table 8 shows the devices used in the studies. Due to their adaptability in monitoring [10], inspection [53], and quality control, cameras are the most used gadgets in Industry 5. They can give data in real-time that boosts output [22], lowers downtime, and improves security in the manufacturing process [31, 55]. Machine learning algorithms are also frequently used with cameras to evaluate images and extract useful data [14, 18].

The Industry 5 environment benefits itself by using camera devices to identify product flaws, track the effectiveness of automated systems [61], and forecast probable equipment breakdowns. With cameras, remote monitoring is also possible [36]. This device is effective for Industry 5 since it calls for constructing cyber-physical systems, which connect and communicate between the physical and digital worlds [28, 37]. Additionally, cameras can be employed for augmented reality (AR) and virtual reality (VR) applications, which enhance visualization and training while also giving operators remote help [40].

Sensors are essential to Industry 5 because they enable data collection from a realistic environment and make it accessible for digital processing [27]. Maximizing efficiency, decreasing downtime, and improving safety during the production process permits the monitoring, measurement, and control of different factors, including temperature, pressure, humidity, and motion [37, 61]. Sensors can monitor product quality, check for industry conformity, and spot potential equipment faults. Additionally, they link machines, gadgets [35], and systems [47], enabling real-time data collection, analysis, and action [5, 51], resulting in a more effective and adaptable manufacturing

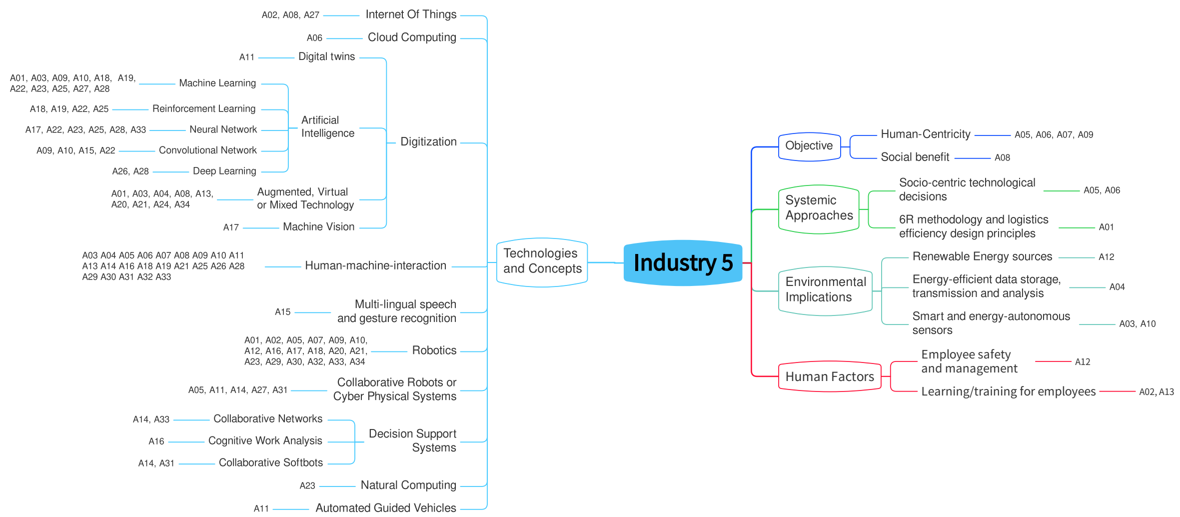

Fig. 5. Industry 5 concepts, technologies, and categories taxonomy

process [12]. Sensors can also be used with cutting-edge technologies like AI and ML to evaluate data and generate predictions. These devices help to improve safety [31], optimize industrial processes, consume less energy, and recognize human intentions [55].

The integration of conventional devices, such as traditional computers, smartphones, and other devices, into Industry 5 can be achieved through the use of their capabilities to gather [52], analyze [46], and transmit [36] data from the factory floor in real-time. For example, smartphones can be employed as mobile data collection tools [11, 32], and traditional computers can be used to analyze the data and make informed decisions based on the findings [39, 45]. Additionally, glasses [20, 36] and Kinnect [18, 35, 40] can be employed to visualize the manufacturing floor, providing employees with real-time updates on the state of the machines and the production process. In general, the key to effectively utilizing these devices is to leverage their capabilities to gather, analyze, and transmit data in real time, enhancing the production process's efficiency, adaptability, and productivity.

Devices	Studies
Camera	A01 A03 A07 A08 A09 A10 A15 A17 A20 A26 A28 A30
Sensors	A03 A07 A13 A23 A24 A25 A28 A29 A30 A33
Computer	A06 A10 A11 A12 A14 A16 A20 A27 A31
Smartphone	A02 A04 A10 A14 A20 A27 A31
Glasses	A03 A13 A20 A21 A34
Kinnect	A15 A24 A26
Joystick	A08
Projector	A24
Watch	A13
Balance	A25

Table 8. Devices used in the studies

Table 9 shows the data used by the mapped studies. Data is essential to Industry 5 since it helps to increase the productivity, adaptability, and efficiency of the production process. Different kinds of data are gathered to accomplish this. Production data [32, 59], for instance, contains details on the production procedure [21, 60], such as machine usage [41], production output [52], and product quality. On the other hand, sensor data is gathered from sensors on machinery [31], apparatus [27], and other areas of the plant and offers information on variables like temperature, humidity, impedance [51], and vibration [14]. A significant role is also played by maintenance data, which includes details regarding the upkeep of machinery and equipment [39], such as service intervals [5], repair histories [48], and spare parts inventories [21].

Environmental data, including information related to the factory environment [20, 22, 35, 47], such as energy consumption, emissions, trajectories [39], collaborators [18], and waste management, as well as logistics data, including data related to the logistics of the production process [10, 11, 55], such as inventory levels [46], supply chain management, and transportation, are both crucial. Human data, which includes information on the workers' whereabouts [28], motions [36, 37, 40, 53], historical data [45, 56], sentiment [38], location [33] is also being gathered. These data types are gathered, evaluated, and used to guide choices about managing logistics and the supply chain, enhancing manufacturing productivity and efficiency, decreasing downtime, and improving product quality.

Because it offers helpful information on the effectiveness and efficiency of industrial processes, production data, also known as operational data, is frequently employed in industry 5. Bottlenecks are located, and total productivity is increased, providing improved production. It can also anticipate maintenance requirements and boost overall equipment efficacy. IoT devices and sensors are used in Industry 5 to gather and analyze production data in real-time, enabling businesses to make data-driven decisions that can enhance their overall operations and competitiveness [10].

Data	Studies
Production data	A02 A05 A06 A08 A12 A13 A16 A18 A22 A30
Human data	A01 A03 A10 A11 A15 A19 A20 A31 34
Environmental data	A04 A09 A21 A23 A24 A26 A28
Sensor data	A06 A07 A17 A25
Maintenance data	A27 A29
Logistics data	A14

Table 9. Types of data used by authors

4.5. SQ5: In which scenarios are ontologies used for collaborative learning?

Ontologies are formal representations of the conceptual structure of a specific domain, including concepts, relations, and axioms. They are widely used in many areas, including artificial intelligence, information science, and systems engineering. In the context of the presented work, ontologies are used to improve the semantic interoperability between physical and cybernetic resources. Ontologies are particularly important for Industry 5 implementation, as they allow systems to be more flexible and adaptable. The use of ontologies also enables the generation of new knowledge and facilitates access to stored information, which is critical to support decision-making and process optimization [44].

Two articles presented the utilization of ontologies. Cecil et al. [10] employed an ontology-based approach to summarize semantic interoperability that involves physical and cyber resources. The feasibility of the proposed method was evaluated by utilizing the projected ontology. Based on the part design input, the authors incorporated the cyber-physical life cycle and related activities into the ontology for each cyber-physical activity. For example, in the context of assembly plan generation, the potential assembly generation methods from different engineering organizations can be analyzed with associated costs and constraints before selecting a specific supplier or organization.

Umbrico et al. [56] presented a module in their work titled "knowledge base". This module stores a semantically rich representation of the current status of the production environment using an ontology. The knowledge base aggregates information from other modules and uses reasoning to produce new knowledge, serving as an information repository and providing reasoning capabilities. In particular, this module is responsible for storing, updating, and providing access to the ontology-Engineering vendors identified for a system of workers, objectives, tasks, procedures, and constraints.

Processes for Industry 5 benefit from using ontologies since they give knowledge about physical and digital resources a common terminology and structure. Better interoperability may result from this as it can make communication and system integration easier. Furthermore, ontologies can combine data from diverse sources and make it available for analysis and decision-making, which is essential for Industry 5 since it requires linking and analyzing data from all stages of the production process. Ontologies represent production process knowledge, including rules, limitations, and goals, which may then be used to automate operations and make decisions like choosing the optimal assembly method or supplier [44].

Ontologies can also be used to represent knowledge, which can be used to increase a system's self-adaptiveness and ability to respond to environmental changes. It is simpler to adapt systems to new domains or applications due to the flexibility of ontologies in describing the structure and behavior of systems in a domain-independent manner. Overall, using ontologies can aid Industry 5 processes by establishing a common language, easing data integration and analysis, enabling automation and reasoning, and increasing the self-adaptiveness and flexibility of systems [44].

4.6. TQ1: Where were the studies published, and how many publications occurred per year?

Figure 6 shows the distribution of articles according to the year of publication and database. The IEEE Xplore database had a total of 14 publications (41%). Springer Link obtained 12 studies (35%). Science Direct received the mark of 7 publications (20%) and the ACM Digital Library 1 publication.

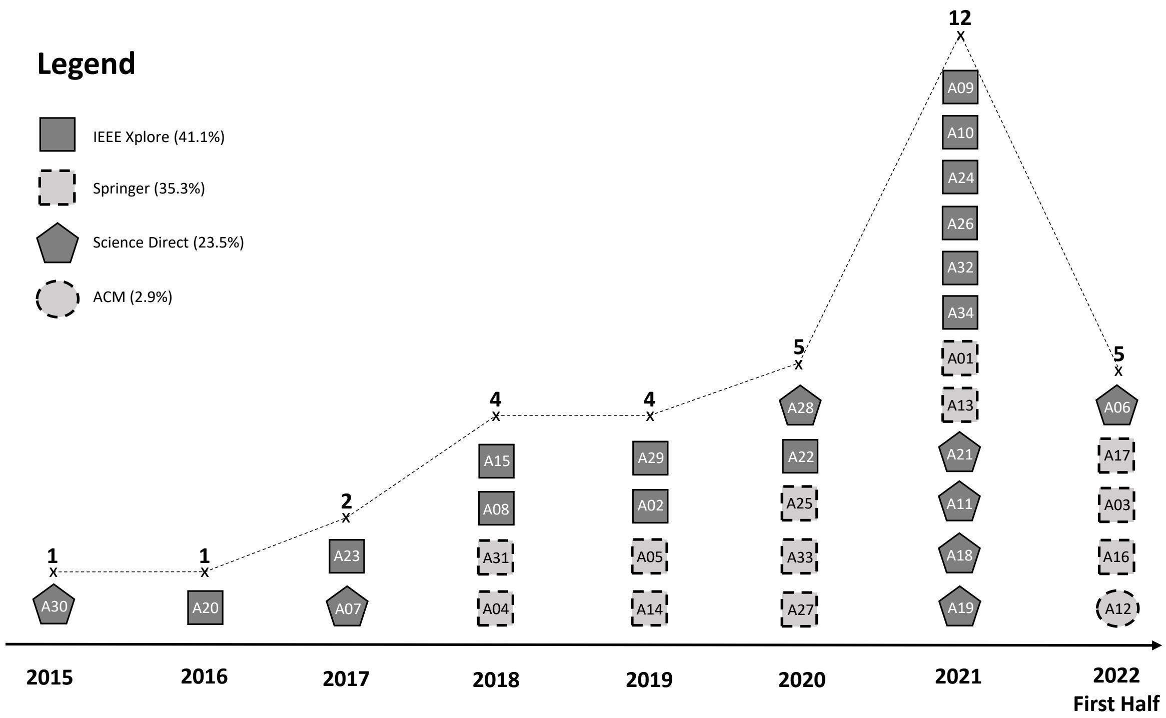

Fig. 6. Publications per Year

Data collection took place in June 2022, impacting the number of studies this year. The focus of research on collaborative learning in industry 5 began in 2015, when the first article was published, which discusses a method for coordinating assembly tasks that require the cooperation of humans with a robot. The researchers expanded the publications from 2018 onwards. The year the topic obtained the highest number of publications was 2021, with 12 articles. In the first half of 2022 alone, another five articles were published.

The growth of research shows that collaborative learning is a prevalent concern among scholars. Additionally, the increasing number of publications in recent years suggests that this field will continue to attract more attention.

5. Discussion

Industry 5 uses cutting-edge technologies to boost productivity and competitiveness [34]. Collaborative learning is essential to improve decision-making and manufacturing processes [6, 18]. We will discuss the advantages and drawbacks of using collaborative learning strategies in Industry 5.

The integration of collaborative robots in Industry 5 presents several challenges. One of the main challenges is ensuring the safety of both humans and robots in shared workspaces. Advanced safety features such as force-limiting sensors and emergency stop buttons must be incorporated into the design of these robots. Additionally, cobots must adapt to their surroundings and effectively communicate and cooperate with humans and other robots. Businesses will also have to invest in training their employees to work alongside cobots.

Another challenge is the integration of collaborative robots with other technology systems, such as the internet and networks. This increased connectivity makes them susceptible to cyberattacks. Collaborative robots must be affordable and easy to use to be successful in Industry 5. AI and machine learning will be crucial in developing these robots, but implementing and maintaining these technologies will also present difficulties.

The field of pattern recognition is complex and multifaceted, with a wide range of data types, real-time processing requirements, and concerns around privacy and security. The articles discussed in this section highlight the challenges and opportunities presented by pattern recognition in Industry 5, and showcase several innovative approaches to addressing these challenges.

The use of advanced technologies, such as robotics and automation, to increase efficiency and precision in the assembly process is a crucial element of Industry 5. Assembly works involve the integration of sensors, machine learning algorithms, and other digital technologies to optimize the assembly process and improve overall performance. Additionally, Industry 5 assembly work often involves using connected systems, such as the Internet of Things (IoT), to share data and improve communication between different parts of the assembly process.

Robot manipulation involves utilizing cutting-edge technology such as computer vision and machine learning to provide robots the ability to interact with people safely and productively in a shared workspace. The goal is to bring together the best qualities of humans and robots to boost efficiency and productivity while assuring everyone's safety. The authors used methods such as non-verbal communication utilizing the hands and safety features like collision avoidance.

Business objectives in the era of Industry 5 refer to the goals and objectives that businesses seek to achieve through the adoption of Industry 5 technologies, such as increased productivity and efficiency, enhanced quality and flexibility, improved customer experience, cost reduction, and data-driven decision-making. These technologies enable businesses to develop new opportunities by creating more innovative, efficient, and adaptable processes.

In the scope of Industry 5, human satisfaction refers to how Industry 5.0 practices and technology might raise the general level of satisfaction of human workers in industrial settings. It is expected that Industry 5.0 will be focused on improving the human-centered approach, where the industry will be more focused on the well-being and pleasure of the workers.

Industry 5.0 is defined by incorporating cutting-edge technologies like blockchain, IoT, and artificial intelligence, which could result in a more proactive and predictive maintenance strategy. Predictive maintenance allows for the early detection and adjustment of possible faults and lowers overall maintenance expenses.

Machine-level decision refers to the capability of Industry 5 technologies to make decisions at the machine level without human interaction, leveraging cutting-edge AI and machine learning. Machine decisions entail modifying manufacturing procedures, keeping an eye on equipment, and spotting and resolving possible problems. Industry 5.0's utilization of machine-level decision-making can boost productivity, improve quality, and minimize downtime.

The term "behavioral prediction" emphasizes how Industry 5 technologies, particularly those that use cutting-edge AI, can predict and forecast how machinery, equipment, and processes would behave in an industrial setting. Predicting equipment failures, spotting possible inefficiencies in manufacturing processes, and streamlining production schedules are a few examples of duties that may fall under this category.

The concept of intelligent maintenance is becoming increasingly important as industries look for ways to improve equipment and system maintenance through the use of advanced technologies. AI, IoT, and machine learning can help predict equipment breakdowns, identify inefficiencies in production processes, and improve maintenance schedules. These technologies can lead to significant cost savings and increased efficiency for industrial operations.

The authors also discuss the role of Cyber-Physical Systems (CPS) in Industry 4.0. CPSs are intelligent systems that can communicate with their environment and respond to predefined triggers. Because they are networked, they can send and receive data from various sources, which enables the creation of programs that can interact with their surroundings and take appropriate action on their own. This role can lead to more advanced and efficient maintenance processes and the development of self-maintaining machines. Integrating advanced technologies such as AI, IoT, and CPSs into industrial maintenance processes can improve efficiency, reduce costs, and increase safety. However, it is essential to note that implementing these technologies also requires careful consideration of their potential impact on existing systems and processes and the necessary infrastructure and personnel to support their use.

Software performance and maintainability are essential for the smooth operation of systems and improved decision-making capabilities. The Program Quality feedback frame, as described by Schoen et al. [52], is created by combining several topics such as programming, integration, application, and operator.

The concept of "reciprocal peer teaching" has been explored in a variety of studies, with a focus on collaboration between machines and humans to improve efficiency and productivity. Researchers have proposed various methods to enhance human-machine collaboration, including Virtual Reality interfaces, brain activity recording, and immersive mixed-reality experiences.

The use of "graphic information organizers" as a collaborative learning technique has been explored in several studies. These studies show that graphic information organizers can be a helpful tool for improving human-robot collaboration in various industries, particularly in manufacturing and assembly. The studies also highlighted the importance of addressing interoperability issues and accounting for uncertainties and human motor systems for improved performance.

The use of games and gaming technology in industrial settings is a growing area of research. Several papers have explored intuitive and adaptive user interfaces and digital twin technology in mobile manipulation and collaborative robotics. A well-designed user interface can make the game more enjoyable and easy for players. Similarly, an intuitive and adaptive GUI can make it easier for inexperienced and untrained users to operate and control the mobile manipulator in the industrial setting.

The topic of problem-solving in collaborative learning techniques was a common theme among the articles reviewed. Four articles presented strategies for addressing human-robot collaboration, situation awareness, autonomy, and efficiency in industrial settings. These articles demonstrate the importance of problem-solving in collaborative learning techniques to address issues related to human-robot collaboration, situation awareness, autonomy, and efficiency in industrial settings. They propose solutions using advanced technologies and methodologies and plan for future work to continue improving and validating their proposed solutions.

6. Conclusion

This study presents a systematic review of the literature on collaborative learning in Industry 5.0. We analyzed different approaches and aspects. We were considering data collection to the detailed characteristics of the studies. The final list contains 34 articles. First, we selected by a filtering process 6,877 studies from six databases. Then, we thoroughly read these articles to explore eight research questions.

The study covered the application domains as well as additional data, devices, techniques, and resources present in the studies. Finally, we assess challenges and future directions for research in the area of collaborative learning. Collaborative learning is a current research concern, especially about the importance of the human being as an industry 5 focus.

Since the authors' primary interest is the interaction between humans and machines, there are still many unresolved research questions that the academic scientific community needs to fill. For example, the intrinsic environmental risk of Industry 5 received little attention. Possible topics for future research are: prevention and recycling, renewable energy sources, data analysis, and transmission to improve energy efficiency, autonomous energy sensors, sustainability, environmental management, humanization, and social benefit.

Human elements, including training and learning, managing industrial personnel' safety, and other related themes, are also not included in the research included in this paper. Systemic methods, such as the moral use of technology to meet human wants and values, and technical choices to advance and enhance social life are other issues pertinent to industry 5 and may be covered in future research.

Future work should investigate proactive models that allow machine-departure decision-making. In addition, new studies need to consider temporal information since collaboration can occur in a specific context. Fusing information is also a research challenge because state-of-the-art models combine different data only from the same domain. New models can explore other data-collection devices, considering ubiquitous computing aspects and the user's context.

Future reviews may extend this study by considering other industry 5 techniques and collaborative learning, as this is a newly established research branch. Finally, there are opportunities to analyze the current ways to provide the best collaboration flow in the industry environment.

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