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EXPLORING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON HUMANROBOT COOPERATION IN THE CONTEXT OF INDUSTRY 4.0

Abstract

The function of Artificial Intelligence (AI) in Human-Robot Cooperation (HRC) in Industry 4.0 is unequivocally important and cannot be undervalued. It uses Machine Learning (ML) and Deep Learning (DL) to enhance collaboration between humans and robots in smart manufacturing. These algorithms effectively manage and analyze data from sensors, machinery, and other associated entities. As an outcome, they can extract significant insights that can be beneficial in optimizing the manufacturing process overall. Because dumb manufacturing systems hinder coordination, collaboration, and communication among various manufacturing process components. Consequently, efficiency, quality, and productivity all suffer as a whole. Additionally, Artificial Intelligence (AI) makes it possible to implement sophisticated learning processes that enhance human-robot collaboration and effectiveness when it comes to assembly tasks in the manufacturing domain by enabling learning at a level that is comparable to human-human interactions. When Artificial Intelligence (AI) is widely applied in Human-Robot Cooperation (HRC), a new and dynamic environment for human-robot collaboration is created and responsibilities are divided and distributed throughout social and physical spaces. In conclusion, Artificial Intelligence (AI) plays a crucial and indispensable role in facilitating effective and efficient Human-Robot Cooperation (HRC) within the framework of Industry 4.0. The implementation of Artificial Intelligence (AI)-based algorithms, encompassing deep learning, machine learning, and reinforcement learning, is highly consequential as it enhances human-robot collaboration, streamlines production procedures, and boosts overall productivity, quality, and efficiency in the manufacturing industry.

1. INTRODUCTION

Industry 4.0, known as the fourth industrial revolution, involves many modern tech tools that link physical and digital spaces together. It discusses developments like digital computers, cloud computing, the Internet of Things (IoT), artificial intelligence (AI), and

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new manufacturing techniques like 3D printing. These tools help machines to work by themselves, make links stronger, and let smart devices talk with other devices and people. They then make things better in different companies, including health care. The IoT layer in the proposed system architecture generates high-rate tasks, which are then communicated to the upper layers. The main goal of Industry 4.0 is to serve customers better by making factories respond and change faster according to their needs (Ibrahim & Askar, 2023). This is done by using digital tools that allow fast data gathering and sorting. This helps improve areas like managing orders, delivering products, reusing items, and conducting studies to create new things.

Artificial intelligence plays a major role in Industry 4.0, a new paradigm for conducting business that includes data-driven decision-making and intelligent automation. AI's job is to create plans that let health authorities quickly and correctly respond in a crisis like the COVID-19 virus. AI programs, especially deep learning models like Convolutional Neural Network (CNN), are used to look at medical pictures (Ahmad et al., 2022). These make it easier to find and treat diseases early on. Examples include X-rays. These AI-based systems can work with lots of data, learning to see complicated patterns and make correct guesses. This helps improve how human-machine teams work together. Moreover, AI helps use picture processing methods to find important parts and make bigger datasets with extra information. This can fix problems of having not enough examples. Putting AI in Industry 4.0 has not just made healthcare better but also helped develop smart healthcare systems, making the whole management of healthcare more efficient. AI is very important for people working with robots (HRC). It helps cobots do difficult tasks together with humans, promoting a shared place to work and goals. In Industry 4.0, cobots using AI work together with people and need to help each other in tasks that are more than just working as a team. They work towards the same goal by doing things together. AI contributes to the dynamic communication, optimization, learning, and program adjustments necessary for effective collaboration. AI algorithms, including value-based, policy-based, and hybrid approaches, are employed to manage the complexity of decision-making in large-scale wireless networks with extensive action and state spaces (Abdulazeez & Askar, 2024). Figure1 shows the domains of AI, ML, DL, and popular algorithms where (RBFN) stands for Radial Basis Function Network, (LSTM) stands for Long Short-Term Memory Network, (CNN) for Convolutional Neural Network that has a broad range of applications in object recognition and is primarily employed in image classification to evaluate visual information (Sharma et al., 2023), (RNN) for Recurrent Neural Network, and (MLP) for Multi-Layer Perceptron (Rahman et al., 2023). Moreover, AI is integral to the design of interaction paradigms that allow humans to maintain control and responsibility in collaboration, despite the increased autonomy of cobots. AI-enabled sociotechnical configurations of HRC in Industry 4.0 contexts give rise to new configurations of distributed agency and shared control, in which human agency is shared with nonhuman agents such as robots and sensors rather than being the sole domain of humans. AI's role is also critical in ensuring that cobot behavior is predictable and transparent, allowing humans to recover from failures and maintain a sense of control over the collaborative process. AI is increasingly being used to enhance HRC and Human-Robot Interaction (HRI). AI can be used, for example, to control robots that combine head and eye gazing, analyze the effect of AR signals on human attention, and show robot operations or flaws to facilitate debugging. AI can also facilitate collaborative assembly between humans and robots, monitor workspace and robot volume, increase interaction efficiency by decreasing physical strength requirements, and assist operators in quickly and intuitively understanding the objectives of the robot.

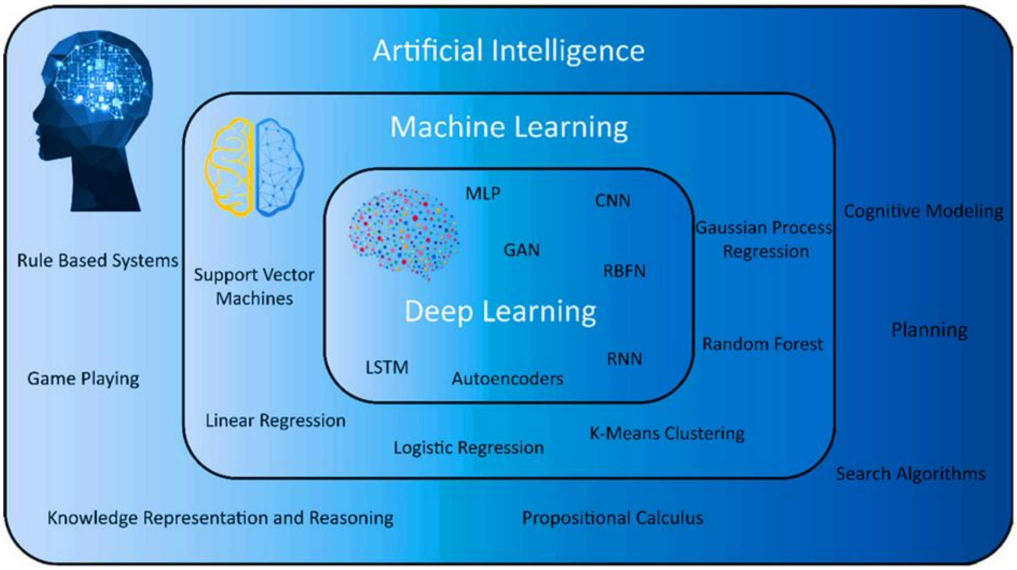

Fig. 1. Domains of AI, ML, DL, and widely used algorithms (Baduge et al., 2022)

1.1. Human-robot Collaboration

Human-robot Collaboration (HRC) is an advanced interaction paradigm used in smart manufacturing environments where humans and robots live together and work together to accomplish tasks that utilize each other's skills. In Human-Robot Collaboration (HRC), robots more specifically, collaborative robots, or "cobots" are intended to operate alongside human operators in a shared workspace, free from the customary safety barriers that apply to standard industrial robots. These systems can adapt to different jobs and environments because they are designed to be safe, user-friendly, versatile, and secure. Ensuring that these interactions are effective, safe, and dynamically sensitive to the changing demands of the human partner is a major problem for the HRC sector. To construct HRC systems, issues including shared understanding, communication, trust, and the distribution of labor between people and robots must be resolved. By giving robots the ability to carry out laborious or physically taxing jobs, HRC hopes to improve production processes and free up human workers to concentrate on jobs requiring higher cognitive skills, dexterity, and problem-solving abilities. In addition to protecting worker safety, this partnership seeks to improve the manufacturing process's overall productivity, efficiency, and flexibility. Fig. 2 shows the concept of HRC.

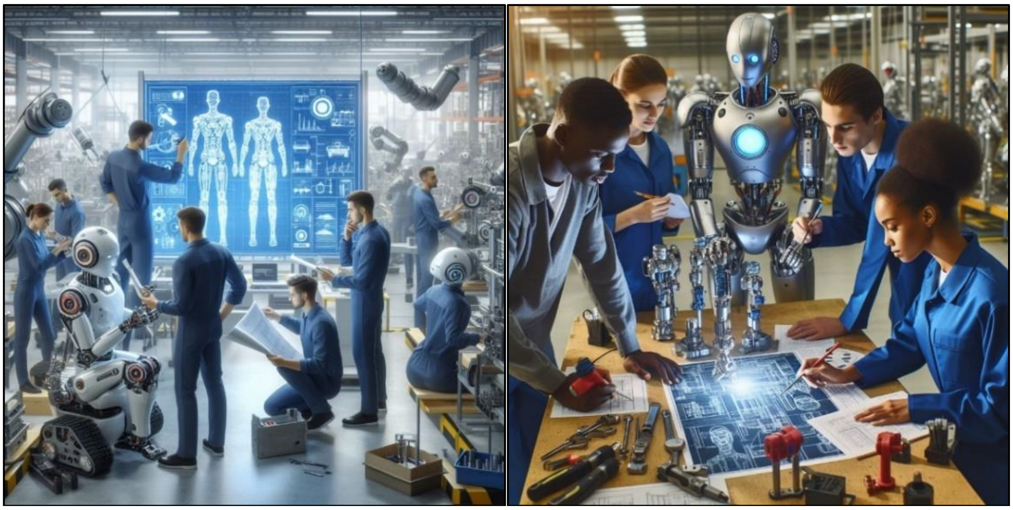

Fig. 2. Cobots and humans can work together to enhance each other's strengths

2. LITERATURE REVIEW

Human-Robot Interaction (HRI) aims to unify the field's vision and discuss key themes and future challenges. It emphasizes the importance of a coherent narrative over exhaustive citation, focusing on cross-application themes in HRI, Conducting experiments with human subjects to evaluate proof-of-concept technologies and identify key design attributes. Blending results from simulated and physical robots to address cost, reliability, and real-world challenges. Utilizing ethnographic methodologies for real-world observation and designing interventions. Establishing standards and common metrics for HRI research. Implementing longitudinal studies to observe long-term interactions between humans and robots. Involving multidisciplinary experts in research efforts from fields such as robotics, cognitive science, and human factors engineering. Developing and evaluating real systems for robot autonomy and interaction modes. Building multimodal interfaces to reduce workload and make interactions more natural. Investigating sensor technologies and information presentation techniques for telemanipulation in space exploration and standardizing test areas, performance measures, and robot-assisted efforts in urban search and rescue (USAR). The paper highlights the importance of haptics and telemanipulation in HRI and suggests increased interaction between these research communities. Urban search and rescue (USAR) is identified as a high-profile area of HRI research with significant social impact, and efforts to standardize USAR test areas and performance measures are noted. Contributions from human factors and automation science to HRI are acknowledged, including key concepts like mental workload, situation awareness, mental models, and trust in automation (Goodrich & Schultz, 2007).

(Michalos et al., 2015) discusses designing collaborative human-robot assembly stations, focusing on safety, control, and productivity by integrating technologies like safety sensors and augmented reality. It evaluates these design concepts through three pilot cases to ensure operator safety and system efficiency. Safety sensors are utilized for real-time monitoring of the workspace to prevent accidents and ensure human safety. Certified robot control functionalities are integrated to manage the robot's actions safely. Augmented Reality (AR) is used to enhance the operator's perception and interaction within the collaborative environment. The results indicate that with the proper implementation of control, safety, and operator support strategies, it is possible to create a collaborative environment where human safety is ensured without compromising the system's productivity. emphasizes the importance of integrating safety-induced restrictions into design and planning tools to simulate their effect on the manufacturing process, thereby improving the overall safety and efficiency of human-robot collaboration in industrial settings. The survey would have included studies on the remote operation of robots, the introduction of Intelligent Assistant Devices (IADs) or Cobots, and motion planning for safety in HRI. It would have also considered the categorization of HRI systems based on workspace sharing and the level of interaction between humans and robots.

Industry 4.0's integration in food processing is explored, highlighting benefits like automation and systematic management, and challenges for smaller enterprises. The paper discusses nine key technologies, including Big Data and IIoT, and their applications in areas like food safety and intelligent manufacturing. Review of technological advancements in Industry 4.0 and their application in the food sector. Analysis of simulation software for modeling and optimizing manufacturing systems. Examination of 3D food printing technologies and their customization capabilities. Utilization of visioning and inspection systems for quality control and safety. Implementation of QR codes and RFID for supply chain traceability. Discussion on additive manufacturing for personalized food products. Exploration of automated process monitoring and control in manufacturing. Case studies on the use of simulation software in plant operations. Application of vacuum gripper technology for handling food products. Industry 4.0 technologies improve resource efficiency, cost reduction, and customer satisfaction in the food sector. Visioning and inspection systems enhance food safety by detecting foreign bodies and reducing waste and recalls. Quick Response (QR) codes and Radio Frequency Identification (RFID) enhance traceability in the food supply chain. Augmented Reality (AR) aids in faster and more effective training processes (Noor Hasnan & Yusoff, 2018).

(Tosello et al., 2019) introduces a master course at the University of Padova focused on training students in autonomous and industrial robotics within Industry 4.0 through a lab project called the "Industry 4.0 Robotics Challenge". It emphasizes a constructionist learning approach, where students program robots and a 3D vision system to perform industrial tasks, aiming to foster innovation and practical skills relevant to Industry 4.0. Students programmed robots using the Robot Operating System (ROS) for various tasks such as manipulation and navigation. The AprilTag library was used for object detection. MoveIt was utilized for planning the manipulation of objects. The ROS navigation stack was employed for robot navigation, with parameters tuned to avoid collisions. For navigating through narrow passages, a routine was implemented that allowed the robot to travel equidistant from the passage walls. An ad-hoc routine exploiting potential fields was developed for obstacle avoidance and narrow passage navigation in one of the solutions. The Kinect2 library was provided for controlling the Kinect sensor, and the Point Cloud Library (PCL) was used alongside AprilTag for perception tasks. Students were overall satisfied with the lab experience, with 58.3% assigning an average grade of 2 on a 1-5 scale for the perceived quality and usefulness of the teaching and lab experience. The survey results indicated that students felt personal growth and gratification from the lab experience. Working in teams was found to be effective, with students acknowledging that they achieved results they could not have reached alone. Students reported that working with real robots was more interesting and challenging than simulations, and it improved their programming skills. The feedback highlighted a need for better integration of theory and tutorials with hands-on activities, which was attributed to the pilot nature of the project. Students felt that they had acquired good Industry 4.0 capabilities by the end of the course. The best solutions proposed by students included using the AprilTag library, MoveIt, and the ROS navigation stack for object detection, manipulation, and navigation.

Collaborative robots, key to Industry 4.0, significantly improve the manufacturing sector by working with humans. They offer enhanced productivity, flexibility, and safety, and can be programmed by non-experts. These robots support human workers by performing tasks that require strength and precision. The paper reviews the current importance of collaborative robots and their future potential in the industry. Review of control strategies and approaches for Human-Robot Interaction (HRI) applications. Analysis of task planning and task allocation in collaborative robotics. Examination of shared control and multi-modal user interfaces in industry. Static optimization technique for efficient and safe parallel operations. Dynamic sequencing for task allocation to enhance human safety. Gesture-based control technologies and machine learning for gesture recognition. Collaborative robots enhance productivity, flexibility, and safety in manufacturing, they can perform repetitive tasks with high accuracy, improving worker health and safety. Research shows collaborative robots can adapt to different environments, which is crucial for their versatility. Studies indicate that dynamic task allocation and optimized robot trajectories can improve human safety in HRI. Gesture-based control and machine learning are suggested to improve interaction with collaborative robots.(Sherwani et al., 2020)

(Angelopoulos et al., 2020) surveys machine learning solutions for fault detection, prediction, and prevention in the Industry 4.0 era, discussing architectures, cybersecurity, and human-machine interaction. It highlights the importance of cloud/fog/edge architectures for data acquisition and the role of human operators in manufacturing processes, stimulating further research in these areas. The paper discusses machine learning (ML) methods for fault detection, prediction, and prevention in industrial settings, It examines cloud/fog/edge architectures for data acquisition to train ML algorithms, Supervised learning techniques like artificial neural networks (ANNs), and support vector machines (SVMs) are used for classification and regression, Unsupervised learning methods, including principal component analysis (PCA), are utilized for finding patterns in data, ML-based diagnostic systems allowed more faulty boards to be successfully repaired, with accuracy up to 77.5% in low volume and 98.7% in high volume manufacturing. Weighted kernel-based SMOTE (WK-SMOTE) improved the performance of SVM classifiers in detecting insulation degradation in high-voltage electrical machines. Ensemble learning with AdaBoost.NC and SMOTE effectively detected abnormal machine operation with over 94% accuracy in minority-class data. With unbalanced data, instance-based algorithms demonstrated the highest performance in fault detection during semiconductor fabrication.

Introduces a deep learning and IoT-based system to optimize air conditioner usage for energy savings in smart buildings by detecting the number of people present using the YOLOv3 algorithm. Results show the system can accurately count people and adjust air conditioning, accordingly, potentially reducing energy consumption and costs. Utilization of the Internet of Things (IoT) architecture for smart energy management in buildings. Deployment of sensors and microcontrollers for data acquisition and transfer to the cloud. Real-time data analysis and decision-making control are transmitted to microcontrollers to manage air conditioner units. Application of the YOLOv3 deep learning algorithm for people detection to control air conditioner operation. Use of the contact elements for IoT platform for device monitoring and data visualization. Implementation of MQTT protocol for data acquisition and communication within the IoT system. The YOLOv3 model trained on the WiderFace dataset showed a steady decrease in loss function and high accuracy in detecting persons in various scenarios. The proposed approach's accuracy was confirmed with a sample photo from the WIDER dataset, where it detected all 16 people without error. Energy control decisions were effectively influenced by the IoT platform's comparison of the number of occupants and the condition of the air conditioner. The system provided both automatic and manual operation modes for the air conditioner, ensuring continuous operation even if automatic systems encountered problems (Elsisi et al., 2021).

Reviews how Robotic Process Automation (RPA) and Artificial Intelligence (AI) enhance digital services in Industry 4.0 by automating and optimizing business processes. It discusses the integration of AI techniques like neural networks, text mining, and natural language processing with RPA tools to improve organizational operations. Literature review of RPA tools associated with AI in the context of Industry 4. Analysis and comparison of several proprietary and open-source RPA tools and their functionalities. Examination of AI techniques and algorithms used by RPA tools, such as Artificial Neural Networks, Text Mining, and Natural Language Processing. Comparative study of technologies specifying AI objectives and algorithms used by different RPA tools. Proprietary RPA tools implement AI algorithms for tasks like recognition, optimization, and knowledge extraction from documents and processes. Open-source RPA tools are growing in functionalities and depend on the developer community. AI techniques used include computer vision, statistical methods, decision trees, neural networks, fuzzy logic, text mining, and natural language processing. Integration with ERP systems is a common feature among RPA tools, enhancing their utility in organizational processes. The paper identifies a need for further development in open-source tools to match the functionalities of proprietary tools.(Ribeiro et al., 2021)

Identifies and proposes structural components for the design of human-robot collaborative systems (HRCS) in the manufacturing industry. In highlighting the development and applications of HRCS over the past five years, it provides a systematic review of fifty case studies from manufacturing environments. Conducted a systematic literature review focusing on practical aspects of HRCS in various environments. Analyzed case studies of real manufacturing settings and experimental works, including simulated tasks in digital manufacturing software. Followed the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) framework, adjusted for the research objectives. Classified interaction levels based on human-robot work dynamics, workpiece, and process. Identified four structural components such as Safety control modes, interaction levels, work roles, and communication interfaces. Found that physical contact-based collaboration is suitable for automotive industry tasks like screwing assembly and heavyweight material handling. Highlighted certified augmented and virtual reality devices as beneficial for safety and training in manufacturing. Observed that in real industrial environments, multiple safety control modes are used to ensure the well-being of human operators. Noted improvements in cycle time reduction, decreased robot idle time, and enhanced ergonomic and safety indicators.(Segura et al., 2021)

Safety assurance in collaborative robots (Cobots) used in manufacturing, focusing on safety requirements and challenges. It highlights the need for new technologies and methods to ensure cobot safety, including data processing, real-time control updates, and cost reduction. An object-oriented approach to building a Cobot workcell simulator. Reduced computation using a genetic algorithm to prevent collisions. Enabling harmonious human-robot collaboration (HRC) in assembly processes through speech processing, gesture recognition, and context awareness. Strain gauges measure strains and convert them into gripping forces in grippers. Specifying a safe, ever-changing work environment through the use of speed and separation monitoring. Robotic programming framework for runtime assurance of complexity and uncertainty. A cobot's power output during hand guiding can be regulated using an impedance controller. Found that in order to classify risks in cobot safety assurance, it is necessary to acquire, process, and fuse diverse data. Highlighted the importance of updating control systems in real-time to avoid interference and ensure safety. Emphasized the development of new technologies to improve human-machine interface (HMI) performances, particularly in workloads and speeds. Pointed out the necessity to reduce the overall cost of safety assurance features for cobots. Discussed the safety assurance of integrated robotic systems with two development examples. Presented a new feature in gripper design that allows adjustment of the gripping operation direction. Showed the development of a sensing technology for grippers using strain gauges to measure forces (Bi et al., 2021).

(Prati et al., 2021) presents a UX-oriented method for designing human-robot interaction in manufacturing, focusing on human needs rather than just technology. It applies this method to an industrial case involving assembly tasks with collaborative robots and AGVs, demonstrating its effectiveness in guiding interface design. Creation of a multidisciplinary team involving various experts such as system engineers and UX designers. User analysis through observations, focus groups, and interviews. Activity analysis using task analysis. Interaction visualization with tools like the UserTask Matrix and Experience Maps. Interface design and prototyping. UX assessment based on user testing. The UserTask Matrix was completed, and the Experience Map was defined to describe the interaction fully. The analysis provided insights into the complexity of tasks, their types and durations, and communication needs. The Experience Map focused on the human operator's experience and did not include emotions, which could be added later. The UX analysis revealed that in regular conditions, the operator interacts only with AGVs, not with collaborative robots.

(Pagani et al., 2021) compares user frame calibration methods for cobots, focusing on accuracy, complexity, and calibration time. It finds that traditional methods with more calibration points outperform the built-in vision-based method in repeatability performance. Built-in Robot Positioning System (RPS) calibration method using a fiducial marker and wrist camera for image analysis. Traditional three-points and five-points calibration methods involving rigid markers. Quantitative analysis of the limitations of the RPS approach that computes local calibration planes. Comparison of repeatability performances between RPS and traditional methods. Use of a custom-made centering tool to ensure the end-effector's correct positioning over the markers during calibration. Computation of the calibration plane using robot software. Analysis of calibration times for different methods to evaluate efficiency. Traditional calibration methods outperformed the RPS method in terms of repeatability performance. The RPS method showed poor repeatability, especially for the z-axis, with values significantly higher than the reference. Three-points and five-points calibration methods achieved lower repeatability values, closer to the reference repeatability The five-points calibration method had the best performance, with repeatability values very close to the reference. Increasing the number of calibration points beyond five did not significantly improve performance, indicating a plateau effect.

Evolution of Human-Robot Collaboration (HRC) in the context of Industry 4.0 and its potential in the upcoming Industry 5.0, analyzing research trends and case studies. It defines HRC, discusses its characteristics, and explores its applications across various fields, emphasizing the shift towards robots as partners rather than tools. Bibliometric analysis to identify research trends related to HRC. Analysis of the scientific state of the art regarding HRC. Case studies to report significant examples of HRC applications. Utilization of SCOPUS for keyword-based research trend analysis. Classification of approaches for safe collaboration into pre-collision and post-collision categories. The paper identifies major research trends in HRC, including safety, ergonomics, assembly, welding, medical, agricultural, and educational applications. It presents a general definition of HRC that encompasses its industrial applications and other fields. The study highlights the role of HRC as a key concept in Industry 4.0 and its potential to shape Industry 5.0. The bibliometric analysis shows a dense network of keywords, with clusters around artificial intelligence, assembly, safety, and ergonomics. The paper discusses the evolution of HRC and its acceleration due to technological advancements and the COVID-19 pandemic (Baratta et al., 2022).

Cobots, or collaborative robots, work alongside humans in manufacturing, enhancing safety, flexibility, and efficiency in various industries. This paper reviews the capabilities of Cobots and their significant applications in the manufacturing sector. Conducted a literature review from databases such as ScienceDirect, Scopus, Google Scholar, ResearchGate, and other research platforms using keywords "Cobots" or "Collaborative robots" for manufacturing applications. Analyzed the capabilities of Cobots in manufacturing and their role in improving production automation in a safe and cost-effective manner. Explored the advancements in edge computing and distributed artificial intelligence that enable Cobots to make real-time decisions and process information efficiently. Investigated how Cobots enhance human talent by working alongside humans and improving safety and performance in shared workspaces. Cobots are widely employed in various industries, enhancing man-machine collaboration and competitive edge. They are user-friendly, reliable, safe, and precise, with capabilities for handling hazardous tasks. Cobots are increasingly being integrated into manufacturing workflows, offering adaptability and precision. The technology is expected to become more complex and connected, improving manufacturing processes and data analytics (Javaid et al., 2022).

The field of human-robot collaborative disassembly focuses on safety, communication, and design in recycling processes to enhance sustainability. It discusses the challenges and progress in the area from 2009-2020, aiming to guide future development in human-robot collaboration for industrial disassembly. Conducted a broad literature survey and reviewed over 400 papers related to human-robot collaboration (HRC) within disassembly from 2009 to 2020. Utilized web-based databases like Google Scholar, Scopus, and Web of Science for the initial search. Applied specific search terms related to disassembly and HRC to filter relevant literature. Excluded studies not directly contributing to the analysis of technology enabling human-robot collaborative disassembly systems. Identified that research on fully automated disassembly systems is mainly focused on consumer electronics due to the high volume of waste electrical and electronic equipment (WEEE) produced annually. I noted that existing automated disassembly systems struggle with the complexity of end-of-life products, leading to an increase in human-robot collaboration solutions. Highlighted the importance of safety in human-robot collaboration, with various methods analyzed to ensure safe interactions during disassembly tasks. Pointed out the lack of post-collision control schemes in current human-robot collaborative disassembly (HRCD) systems, which is crucial for safe physical interactions. Emphasized the need for skill acquisition interfaces to allow humans to teach and transfer knowledge to robots more intuitively. Mentioned the absence of practical implementations for complete frameworks supporting HRCD, despite the existence of theoretical frameworks. Observed that human-robot interaction (HRI) techniques common in social and service robotics are rarely implemented in HRCD system (Hjorth & Chrysostomou, 2022).

Collaborative robots (cobots) work closely with humans in manufacturing, adapting to changes and performing complex tasks without confined safety zones, as well as their varied uses and prospective future developments are examined in this article. The review delves into the benefits of cobots in the industry and their place in a tech-driven world, drawing from a comprehensive literature survey of seventy-six papers. Following a short introduction, the study looks into a comprehensive literature review that was organized based on an analysis of seventy-six research papers and articles. The authors discuss the diverse applications of cobots in the manufacturing sector and their advantages. The paper also highlights the future of cobots and how they will be a boon for a technology-driven world. The authors have not disclosed any funding for this study. Data availability is mentioned, stating that the datasets generated during the study are available from the corresponding author upon reasonable request. The study reviewed around 65 technical papers to analyze the applications of collaborative robots in manufacturing. Research is extensive in areas like assembly, quality inspection, and welding, with material handling and pick and place also being significant. The paper provides a list of various cobot brands, their payload, reach, and suitable manufacturing applications. It concludes that cobots are highly beneficial in modern manufacturing, with material handling, assembly, and pick and place applications having the highest weightage. FANUC holds the largest market share for cobot variants used in assembly, palletizing, packaging, and machine tending. The paper identifies a lack of precision, limited payload capacity, limited speed, and higher cost as drawbacks for cobots in certain applications (Kakade et al., 2023).

(Borboni et al., 2023) reviews recent research on the role of AI in collaborative robots (cobots) for industrial applications, highlighting their ability to work closely with humans and improve tasks like material handling and automation. It discusses the advancements in AI that make cobots more adaptable, cost-effective, and user-friendly, and identifies challenges and future research directions. Utilized the PRISMA model for systematic review and meta-analysis methodology. Conducted my searches using resources like PubMed, Research Gate, Scopus, Web of Science, ScienceDirect, and IEEEXplore. The phrases "artificial intelligence in robots," "cobots," and "human-robot interaction" (HRI) were used throughout the literature search. All reviews, conference papers, and peer-reviewed academic journals published in English after 2018 were considered. We didn't include papers that were already published or had an improper research design, as well as those that came out before 2018 or didn't deal with artificial intelligence or cobots. The paper conducted a systematic literature review of research publications between 2018 and 2022 to identify the existing and potentially expanding role of artificial intelligence in collaborative robots for industrial applications. Initially, 156 articles related to collaborative robots and applications were identified through database searching. After screening and reviewing, 43 full-text articles published between 2018 and 2022 were included in the review. It highlights the growing interest in creating a collaborative workspace where people and robots can work cooperatively, and the need for AI-based human-robot collaboration to address challenges in cognitive and dexterity tasks. The authors of the paper have made significant contributions to the conceptualization, methodology, analysis, investigation, and writing of the manuscript.

(Othman & Yang, 2023) reviewes key technologies in smart manufacturing for Human-Robot Collaboration (HRC), focusing on design and interaction levels, and discusses the benefits and challenges of HRC implementation in industries like automotive and food. It highlights the integration of AI, Cobots, AR, and Digital Twin technologies in HRC systems, emphasizing the need for future research to improve these collaborations. Review and discussion of key technologies in smart manufacturing for HRC systems. Examination of various levels of Human-Robot Interaction (HRI) in the industry. Analysis of applications of AI, Cobots, AR, and Digital Twin in HRC systems. Evaluation of benefits and practical instances of deploying HRC technologies. Addressing limitations and providing insights for future HRC system design. Enhanced efficiency and productivity in smart manufacturing through the integration of HRC systems. Improved performance of HRC systems with the use of pivotal technologies like AI, Cobots, AR, and DT. Demonstrated successful implementation of collaborative robots in the food and automotive industries.

(Li et al., 2023) analyzes challenges in collaborative innovation systems within public higher education during the Industry 4.0 era, focusing on developing countries, and develops an integrated framework to assess these challenges. It identifies holistic acceptance of innovation and lack of technical infrastructure as the top challenges in these systems. IF-Entropy-SWARA-MARCOS approach for evaluating challenges in collaborative innovation systems. Entropy method under the PFS environment for objective weight determination. IF-SWARA procedure for deriving subjective weights. Comparative analysis with IF-WASPAS and IF-TOPSIS methods. Linguistic decision matrix (LDM) construction. Data collection through surveys and expert interviews. Holistic acceptance of innovation was identified as the most significant challenge in collaborative innovation systems in public higher education with a weight value of 0.0614. Lack of technical infrastructure emerged as the second most significant challenge with a weight value of 0.0594. Educational policy was ranked third in terms of significance with a value of 0.0588. The research applied an integrated framework to five areas of China's public higher education system to assess these difficulties. Option PHE-IV (p4) was deemed most important by public higher education organizations when evaluating the primary obstacles.

Systematically reviews the adoption of Industry 4.0 in supply chains within thirteen emerging markets, highlighting benefits, challenges, and mitigation strategies. It reveals the use of IoT, big data, and AI is common, while other technologies like cloud computing and robotics are less utilized in these markets. Followed the PSALSAR framework for systematic literature review (SLR) methodology. Integrated the PRISMA 2020 statement within the PSALSAR framework. Utilized Zotero for managing search results and screening papers based on inclusion/exclusion criteria. Applied thematic analysis to analyze the uses of Industry 4.0, challenges, and mitigation measures. Employed bar graphs to present the frequency of publication years, journal names, countries, and industries. The majority of studies on Industry 4.0 were conducted in 2021 and 2022, with a significant increase in research from 2020 to 2021. The journal "Production Planning & Control" had the highest frequency of publications on the topic. Elsevier was the leading publisher, followed by Emerald, Taylor & Francis, and MDPI, indicating high-quality research. India had the most studies, followed by China, together representing over half of the research in emerging markets. The manufacturing sector was the most studied, with automotive, circular economy, and food processing also being significant. Most studies were original research, with a few being a combination of systematic literature review and original research (Alshahrani, 2023).

Figure 3 Synthesizing this information into a network form highlights relationships between the major concepts in the area of collaboration of human and robots in Industry 4.0. The circles drawn in the diagram are the nodes which include concepts like; artificial intelligence, collaborative robot, human operator, industrial environment amongst others; the sizes of the nodes depict either their importance or the frequency of occurrences in the literature. The bottom left: it depicts how often these topics are researched together in that the edges (lines) represent the connections between them. Each color bar represents a particular type of nodes that are themed together, including the AI technologies nodes (blue), the industrial applications nodes (red), and the collaboration nodes (green). This visualization assists in deciphering the relationships and potential scenarios of interaction between distinct aspects of human-Robot collaboration and the overall context of Industry 4. 0.

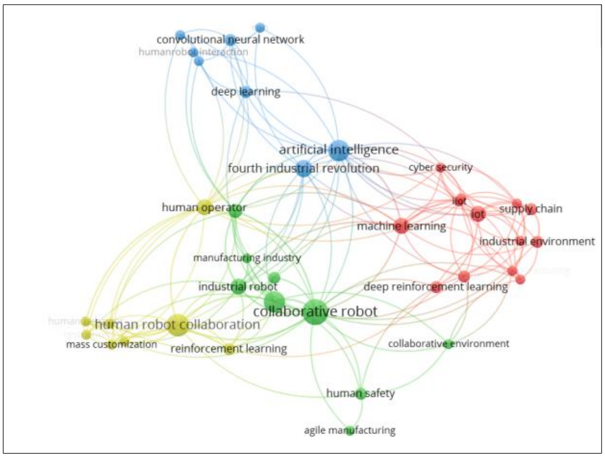

Fig. 3. A relationships between the major concepts in the area of collaboration of human and robots in Industry 4.0

3. RESULTS AND DISCUSSION

AI plays an important role in HRC during Industry 4.0. AI technologies including machine learning algorithms are being used to optimize and enhance collaborative assembly tasks. AI technology in HRC enables the emulation of real human behavior, minimizing unpredictability and increasing productive cooperation and safety. Also, AI-based algorithms can be used for fault detection and forecasting to make the reactions timely based on these predictions With the view of Industry 4.0, AI can be used to automate and advance processes, process large volumes of data in real-time, and enhance the accuracy levels of automated systems. Moreover, AI methods including deep convolutional neural networks can be used for quick identification of COVID-19 patients through clinical imaging to facilitate early diagnosis and treatment.

The role of AI in Human-Robot Cooperation in Industry 4.0 is multifaceted and pivotal for the evolution of industrial processes. AI enhances the capabilities of cobots, making them more adaptive, efficient, and safe for human interaction. The move towards AI-enabled moral decision-making signifies a new era where robots can make decisions considering ethical implications, crucial in close human-robot collaborations. AI's role in evaluating and optimizing cobots is critical for their wider adoption in the industry. By enabling cobots to understand and adapt to human behavior and task variability, AI is making these collaborations more effective and intuitive. Furthermore, as Industry 4.0 transitions to a more human-centric Industry 5.0, AI stands as a crucial enabler. It is shifting the focus from purely technological efficiency to enhancing human capabilities and well-being within the collaborative framework. Lastly, AI-driven advancements in control systems are crucial for ensuring safety and robust interaction in human-robot collaborations. By addressing challenges such as human intention prediction, disturbance handling, and safety assurance, AI is enabling a safer and more productive collaborative environment.

In summary, AI is a key driver in enhancing human-robot cooperation in Industry 4.0, leading to more intelligent, adaptable, and human-centered industrial processes. AI is an important contributor to increased efficiency of decision-making and safety in Integrating HRC into Industry 4.0 in smart manufacturing environments, Table 1 and 2 show the recent works on Industry 4.0, Artificial Intelligence, and Human collaboration, AI enables humans and robots to learn together at a human-human level mediating the advanced learning process in HRC, Cobots can perform many tasks in different sectors.

Fig. 4 shows the Pie chart that illustrates the impact of various individual approaches on key aspects of Industry 4.0. Each slice represents the impact across different approaches such as Internet of Things (IoT), Artificial Intelligence (AI) and Machine Learning (ML), Big Data and Analytics, Cyber-Physical Systems (CPS), Cloud Computing, Augmented Reality (AR) and Virtual Reality (VR), Additive Manufacturing (3D Printing)

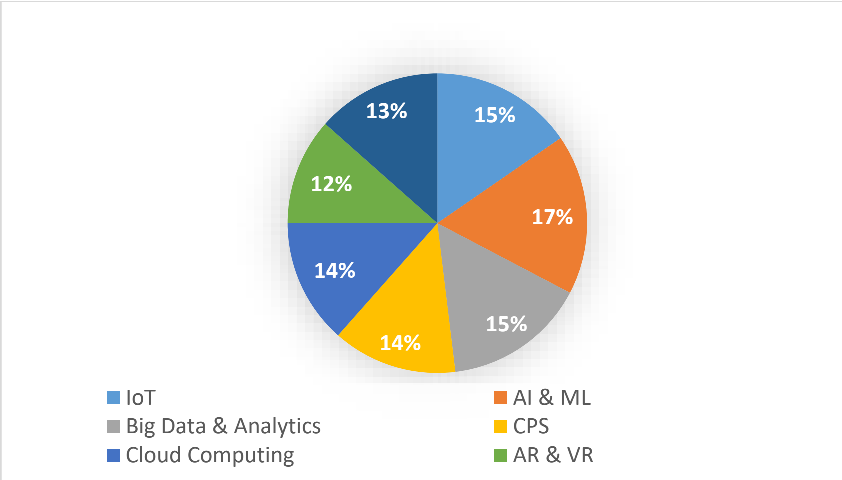

Fig. 4. Impact of Individual Approaches of Key Aspects in Industry 4.0

Fig. 5 shows the bar chart illustrating the impact of artificial intelligence on human-robot cooperation in the context of Industry 4.0. The chart shows the following key metrics:

– Productivity Improvement: 80%
– Error Reduction: 75%
– Operational Efficiency: 85%
– Job Satisfaction: 70%
– Innovation Rate: 90%

These percentages represent the positive impact AI has on various aspects of human-robot cooperation, enhancing productivity, reducing errors, improving efficiency, maintaining job satisfaction, and boosting innovation.

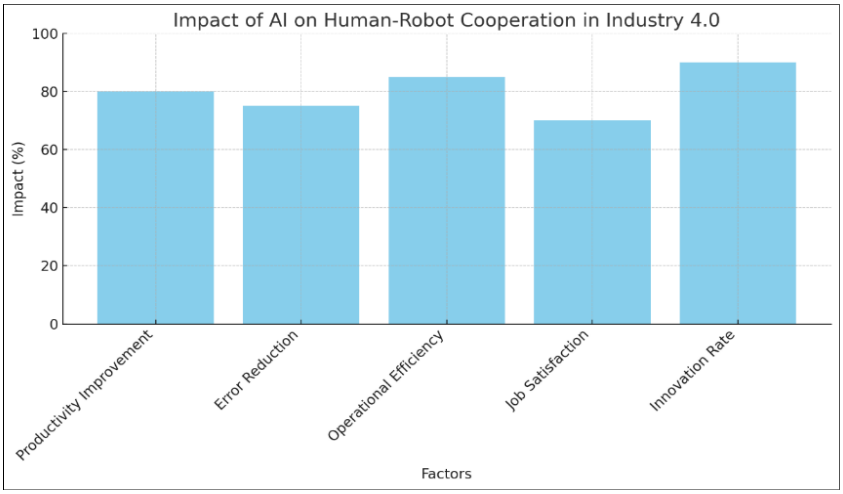

Fig. 5. Impact of artificial intelligence on human-robot cooperation

Tab. 1. A summary of the most recent research on Industry 4.0, Artificial Intelligence, and Human Collaborative Robot workspaces

Reference	Robot Type	Task Type	Simulation Tool	Technique
(Tosello et al., 2019)	ROS	Manipulation and navigation	object detection and Kinect sensor	Point Cloud Library (PCL) used alongside AprilTag for perception tasks
(Angelopoulos et al., 2020)	-	importance of cloud/fog/edge architectures	ANN, SVM, PCA	Machine Learning
(Elsisi et al., 2021)	-	for energy savings in smart buildings	YOLOv3 algorithm	deep learning and IoT-based
(Gomes et al., 2022)	UR3	Pick and place	RGBD camera	Reinforcement learning (CNN)
(Buerkle et al., 2021)	UR10	Assembly tasks	mobile EEG Epoc+	Long short-term memory recurrent neural network
(Zhang et al., 2022)	UR5 robot	Simulated alternator assembly	Deep image sensor	Reinforcement learning
(Ghadirzadeh et al., 2020)	ABB YuMi robot	Pick, place, and packing	Rokoko motion capture suit	Graph convolutional networks, recurrent Q-learning
(Silva et al., 2022)	Baxter mobile base	Homograph pixel mapping	2D cameras with 1280x720, 30 FPS	Deep learning (Scaled-Yolo V4)
(Chen et al., 2020)	Robotic arm	Sawing wooden piece	Force sensor	Neural learning
(Akkaladevi et al., 2019)	UR10 with SCHUNK 2-finger parallel gripper	Assembly task	RGBD and 3D sensors	Reinforcement learning
(Heo et al., 2019)	Indy-7	Collision detection	Force sensitive resistor	Deep learning (1- D CNN)
(Li et al., 2023)	-	Determining objective weights using the Entropy method under the PFS environment	Linguistic decision matrix (LDM)	IF-Entropy-SWARA-MARCOS
(Wang et al., 2024)	Universal Robot 10	detect humans and robots and classify their actions under various conditions	Unreal Engine 4, Sim2Real, Unity3D, UE4, and OpenGL	deep learning-enhanced Digital Twin framework
(Zhang et al., 2024)	AUBO i5	human-robot collaborative assembly (HRCA)	digital twin model of the HRCA system	two-stage skeleton-RGB integrated model for human action recognition, an online prediction approach for human action prediction
(Fu et al., 2022)	-	Design and analysis of a Tri-DSU (Discrete Variable Stiffness Unit)	FEA (Finite Element Analysis) simulation	force gauge and test stand to measure force

Tab. 2. A summary of the most recent research on Industry 4.0, Artificial Intelligence, and Human Collaborative Robot workspaces, cont.

Reference	Robot Type	Task Type	Simulation Tool	Technique
(Park et al., 2024)	commercial 7 degree-of-freedom (DOF) collaborative robot arm	Collision estimation for robot manipulators in human-robot collaborative environments	Robot Operating System (ROS Melodic	Dynamic Bayesian network with Markov model
(Gómez-Hernández et al., 2024)	UR3 robot for adhesive application	Automated bonding in footwear manufacturing	Robot Operating System (ROS) for control and coordination.	KDL (Kinematics and Dynamics Library)
(Fiestas Lopez Guido et al., 2024)	Sophia	Investigating the effect of robot intelligence and speciesism on customer perceptions in retail settings	Online experiments conducted on the Prolific platform	Logistic regression and PROCESS 4.0 for mediation and moderated-mediation analysis
(Maniscalco et al., 2024)	Pepper	Human-robot interaction system assessment in a museum context	UEQ Data Analysis Tool	Three-level architecture for processing and merging heterogeneous sensory information
(Hopko & Mehta, 2022)	UR10	Surface finishing task	Functional near infrared spectroscopy (fNIRS)	Monitoring neural responses to assess trust in human-robot interaction
(Guerra-Zubiaga et al., 2023)	FANUC robot model M-16iB/20	Multi-task industrial robot operation	Tecnomatix used for the virtual simulation of the robotic drilling system	Design of Experiments (DOE)
(Asad et al., 2023)	-	Biomechanical modeling of human-robot accident scenarios.	ANSYS	Quasi-static and dynamic analyses according to ISO TS 15066 conditions
(Cimino et al., 2022)	-	Modeling & Simulation (M&S) for manufacturing process design and optimization	Minitab software	Design of Experiments (DOE), Analysis of Variance (ANOVA)
(Mayr et al., 2023)	KUKA iiwa, Universal Robots UR5e	Robot-agnostic skills for contact-rich wiping tasks	-	Automatic selection of skill implementations based on input parameters
(Ferrarini et al., 2024)	KUKA KR210 R2700 Prime	Evaluation of Industrial Robot (IR) pose and path accuracy	KUKA.Sim or RoboDK	Novel online compensation approach for position corrections using an industrial PC and a laser tracker

4. CONCLUSIONS

In Conclusion, the integration of Artificial Intelligence (AI) with Human-Robot Cooperation (HRC) represents a leap transformation for manufacturing processes in the Industry 4.0. Leveraging AI technologies such as Machine Learning and Deep Learning help to balance the relationship between man and robot for more productive working conditions in terms of efficiency, quality, and safety. The evolution through the interplay of the two concepts fosters a dynamic environment in which new products and technologies evolve through shared control and distributed agency in the workspace, being redefined as something more adaptable and responsive to human needs. Transition to a more human-centric Industry 5.0 will put even more emphasis on AI use in the building of capabilities and satisfaction from work. Last but not least, the contribution of AI is a must in HRC for smart, sustainable, and inclusive manufacturing ecosystems—showing its indispensability to realize the full potential of human-robot collaboration.

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