DOI: https://doi.org/10.4038/jdrra.v2i1.30

The Journal of Desk Research Review and Analysis, Vol. 2, Issue 1, 2024, 110-126

REVOLUTIONIZING MANUFACTURING: THE ROLE OF ROBOTICS IN THE 21st CENTURY

DRI Dassanayake[1], MK Buddhika[2], IDK Maduranga[3], JA Seneviratne[4] and WGC Kumarage[5]

Abstract

The Industrial robotics sector is experiencing rapid growth driven by the escalating need for automation across various industries. This review systematically analyses the prevailing trends, challenges, and future directions of robotic technologies within the manufacturing sector. This review article delves into the prevailing trends, inherent challenges, and future directions of robotic technologies in the manufacturing sector. The study employed a comprehensive literature review and case analysis, focusing on key robotic methodologies such as collaborative robots (cobots), digital twin (DT) technology, and machine vision systems integrated with artificial intelligence (AI) for enhanced performance optimisation. Through the methodological approach of synthesising case studies and empirical findings from leading enterprises such as Amazon and DHL, this review leverages logistics robots, including autonomous pick-and-place systems, to enhance operational efficiency in their warehouse. Additionally, the integration of machine vision systems powered by convolutional neural networks (CNN) enables precise object recognition and positioning, fostering a collaborative human-robot interaction framework. Key findings indicate that cobots are increasingly pivotal in augmenting industrial efficiency while maintaining safety in human-robot collaboration. Furthermore, Digital Twin technology has proven instrumental in simulating real-time manufacturing environments, optimising assembly line performance and predictive maintenance strategies. However, several challenges persist, including the difficulty of programming robots to handle complex objects and the complexities of balancing human and robot activities in synchronised tasks. Despite the advantages of these robotic systems, significant challenges remain. A significant hurdle lies in programming robots to accurately identify and manipulate complex objects, often necessitating iterative trial-and-error methods. Besides that, balancing the assembly line and effectively scheduling the robotics and human activities is important. Additionally, industrial robots face technological limitations, including the complexity of multitasking, alongside social and ethical concerns. The review concludes that while industrial robots have revolutionised many aspects of manufacturing, ongoing research is required to overcome technological limitations, such as multitasking capabilities and ethical concerns related to human

[1] Department of Physics and Electronics, University of Kelaniya. Sri Lanka.
Email: dasanay-ec20040@stu.kln.ac.lk https://orcid.org/0009-0002-5993-5540
[2] Department of Physics and Electronics, University of Kelaniya. Sri Lanka.
Email: buddhik-ec20007@stu.kln.ac.lk https://orcid.org/0009-0003-6605-0377
[3] Department of Physics and Electronics, University of Kelaniya. Sri Lanka.
Email: madhura-ec20041@stu.kln.ac.lk https://orcid.org/0009-0009-3813-9589
[4] Senior Lecturer, Department of Physics and Electronics, University of Kelaniya. Sri Lanka.
Email: jehans@kln.ac.lk https://orcid.org/0009-0001-1273-1287
[5] Senior Lecturer, Department of Physics and Electronics, University of Kelaniya. Sri Lanka.
Email: ckumarage@kln.ac.lk https://orcid.org/0000-0002-9507-4146

Received date: 08.07.2024
Accepted date: 22.10.2024

labour displacement. Anticipated advancements in robotics and AI are expected to enhance manufacturing efficiency further and expand robotic applications beyond traditional industrial settings in the coming years.

Keywords**:** Cobots; Digital Twin; Manufacturing; Robotics

Introduction

In the 21st century, robotic systems have revolutionised numerous industries, finding applications in diverse fields such as healthcare (Lu et al., 2024; Patrício et al., 2024), agriculture (Yang et al., 2023; T. et al., 2024), space exploration (Morrell et al., 2024) and manufacturing and industrial automation (Evjemo et al., 2020) (Fig. 1). These advancements have made robotic systems indispensable, driving significant improvements in efficiency and productivity. Recent years have witnessed remarkable progress in robotics technology, fundamentally altering industrial operations. Advanced robotic systems have become integral to modern manufacturing processes, enhancing precision, reducing labour costs, and increasing overall productivity (Zhao et al., 2024; Duan et al., 2023; Chen et al., 2024).

The fourth industrial revolution, Industry 4.0, is central to this transformation, characterised by the convergence of physical and digital technologies. Industry 4.0 encompasses advanced technologies such as the Internet of Things (IoT) (Kareemullah et al., 2023; Ozer et al., 2022; Chehri et al., 2021), artificial intelligence (AI) (Leutert et al., 2024; Mukherjee et al., 2024; Dzedzickis et al., 2021; Arkouli et al., 2021), big data analytics (Ma et al., 2024; Kunecová et al., 2024), robotics (Dzedzickis et al., 2021; Xu et al., 2024), and cyber-physical systems (Pedone et al., 2024; Brennan & Lyu, 2024). This integration facilitates significant communication and coordination between machines, devices, sensors, and humans, enhancing data collection, autonomous decision-making, and automating complex processes (George et al., 2021; Rahman et al., 2023).

Robotic systems are pivotal in this industrial revolution, addressing critical challenges and revolutionising operational efficiencies. They have become essential for automating repetitive tasks, minimising errors, and significantly boosting profitability (Çalık et al., 2020; Javaid et al., 2021). The deployment of robotic systems across various sectors, such as electrical/electronics, automotive, and food processing, has seen remarkable growth, underscoring their expanding applications in enhancing industrial capabilities.

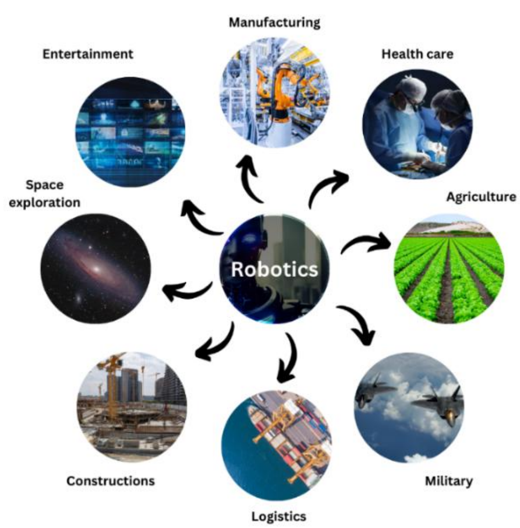

Figure 1: Robotics in Different Fields.

As depicted in Fig. 2, the increased utilisation of robotics is evident across these sectors (IFR et al. of Robotics, n.d.). Data from the International Federation of Robotics (IFR), shown in Fig. 3, highlights a significant global increase in robot density within manufacturing industries. This trend signifies a profound transition from manual labour to automation, reflecting the critical role of robotics in driving industrial advancements. The growing prevalence of robots in various sectors enhances efficiency and productivity. It marks a transformative shift in industries' operations, paving the way for future technological innovations and economic growth.

Within manufacturing, robotics has significantly optimised production processes through various innovations. One of the most noteworthy advancements is the development of collaborative robots (cobots). Cobots are designed to work alongside human operators and enhance operational efficiency by safely coexisting with human workers in shared environments (Nourmohammadi et al., 2024; Javaid et al., 2021; Buhl et al., 2019). Unlike traditional robots, which might disrupt workflows when humans are present, cobots facilitate seamless collaboration, addressing issues such as production line flexibility and mitigation of physical strain on workers (Ferraguti et al., 2019; Bragança et al., 2019; Song et al., 2023). This development represents a critical evolution in industrial robotics, aiming to optimise productivity and worker safety.

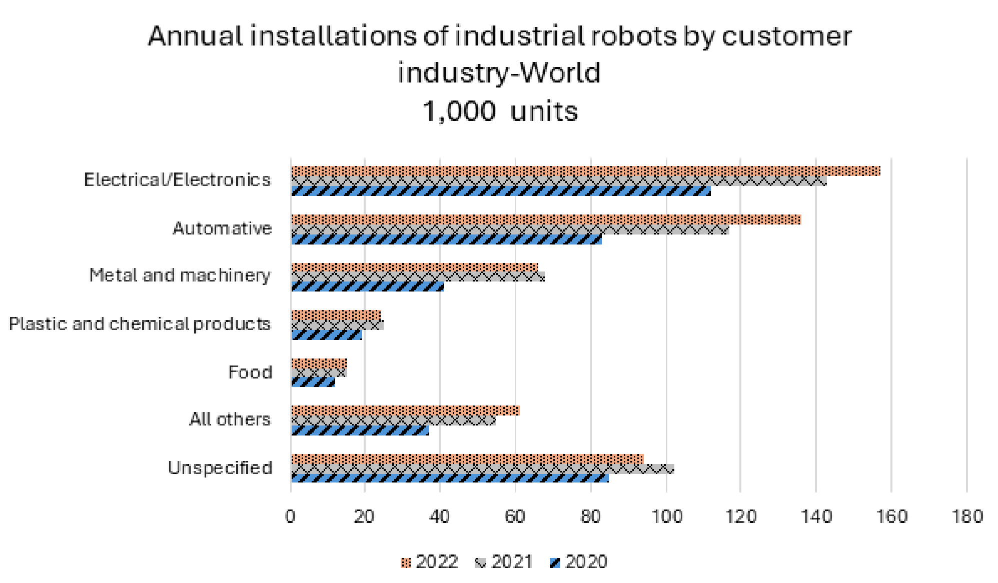

Figure 2: Annual Installations of Industrial Robots by Customer Industry World (IFR et al. of Robotics, n.d.)

In addition to collaborative robots (Fig. 4), Digital Twin (DT) technology is revolutionising industrial robotics (Tavares et al., 2017; Vachalek et al., 2017; Aivaliotis et al., 2019). By creating a virtual replica of a physical system or components, digital twins mirror their lifecycle and operations in real time (Mazumder et al., 2023; Jones et al., 2020; Tao et al., 2019). This innovative technology allows for real-time monitoring and simulation, enhancing optimisation and predictive maintenance.

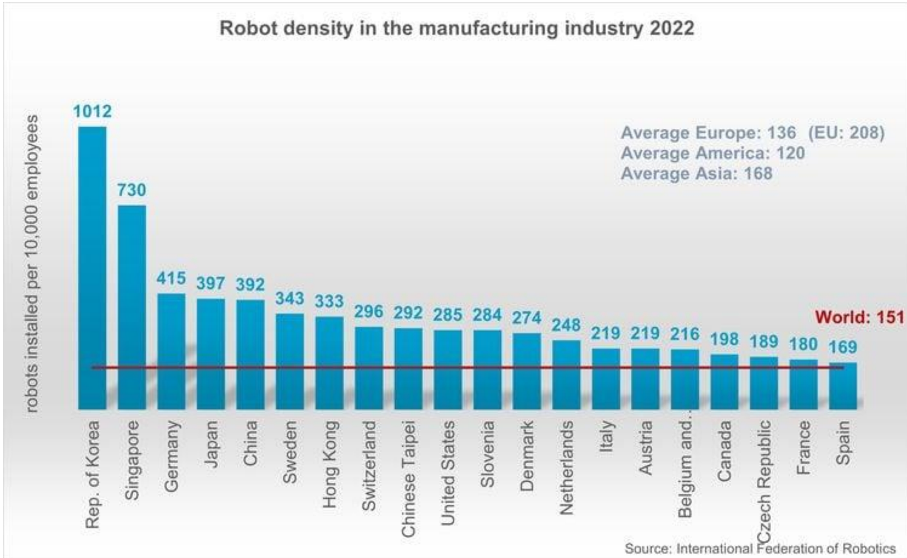

Figure 3: Robot Density in the Manufacturing Industry 2022. Reprinted with permission (IFR International Federation of Robotics, n.d.)

As illustrated in Fig. 5, the evolution of digital twin technology underscores its growing significance in advancing industrial robotic systems, paving the way for more innovative, more efficient manufacturing processes. Despite its advantages, using digital twin technology in industrial robotics faces challenges such as computational demands and data security risks. These issues can be addressed through advancements like blockchain technology (Lee et al., 2021; Tao et al., 2022). Subsequently, Another assembly line balancing problem (ALBP) is another significant challenge involving efficient allocation and scheduling of tasks to synchronise human and robot activities effectively (Fathi et al., 2024; Boysen et al., 2022). Addressing ALBP is essential for maintaining high efficiency and productivity on assembly lines, ensuring that human and robotic resources are utilised optimally.

The presenting article emphasises the challenges and opportunities of implementing robotics in emerging sectors where robotic technology is nascent. By focusing on the early stages of robotics integration, we examine the specific issues faced by industries just beginning to explore the potential of robotics. This exploration provides valuable insights into the foundational aspects of robotic implementation, including initial setup, adaptation strategies, and the development of industry-specific solutions.

Figure 4: A Workspace with Collaborative Robot. Reprinted with permission (Technical Articles Archives - Industrial Robotics, n.d.)

By addressing these critical aspects, the article aims to deepen the understanding of two types of robot technologies, the materials used, and how robotics can be effectively introduced and utilised in emerging industrial contexts. This knowledge paves the way for future advancements and broader adoption, ultimately driving innovation and efficiency across various sectors.

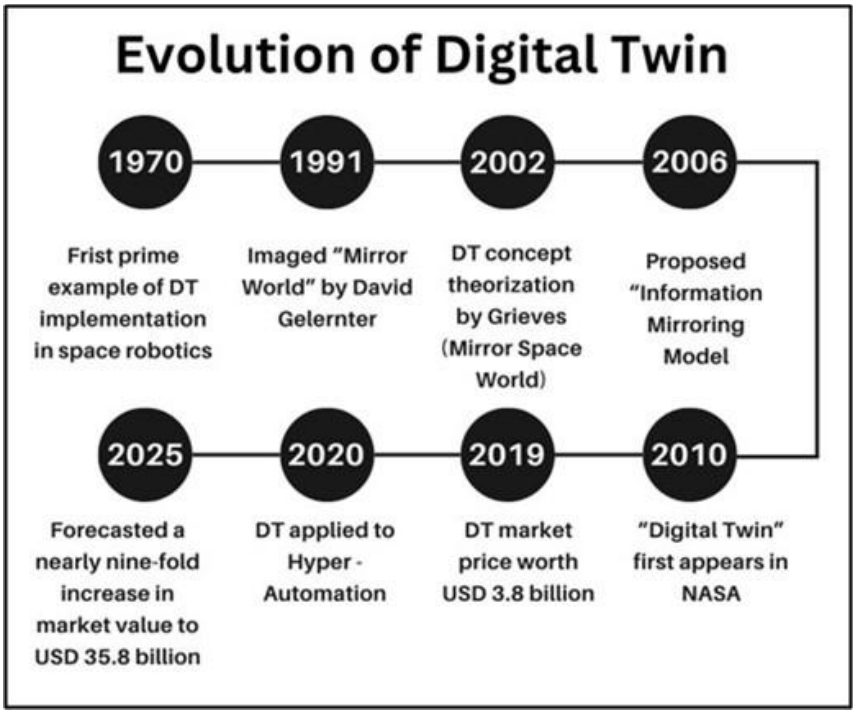

Figure 5: Evolution of Digital Twin Over Past Years (Mazumder et al., 2023).

Methodology

Collaborative robots represent a significant advancement in industrial automation, designed to operate collaboratively with humans in open workspaces (Ferraguti et al., 2019; Javaid et al., 2022; Buhl et al., 2019). The efficacy of cobots is closely linked to the quality and sophistication of their hardware components. These robots are adept at performing physically demanding or highly repetitive tasks, thereby enhancing productivity and reducing human physical strain (Hamza Zafar et al., .2024). Cobots are equipped with sophisticated actuation systems, combining rigid actuators for precision with under-actuated soft actuators that mimic human flexibility (Vicentini et al., 2020). Contemporary production robots boast a high degree of freedom (ranging from 6 to 12 degrees of freedom) and exceptional precision (Mukherjee et al., 2022). Furthermore, integrating torque sensors and obstacle detection systems elevates safety standards, ensuring cobots operate safely alongside their human counterparts (Nicole Berx et al., 2024).

Intended, direct real-time interaction, cobots can work securely beside humans when appropriate safety measures and advanced control algorithms are implemented. This human-robot collaboration underscores a pivotal shift in industrial practices, fostering more efficient and ergonomic work environments (Al-Yacoub et al., 2021; Zafar et al., 2024). Even though these methods are efficient, one of the major concerns is enhancing safety, which requires a multifaceted approach. One innovative method combines Learning from Demonstration (LfD) with ensemble machine learning, employing techniques such as Random Forest and Weighted Random Forest for effective knowledge transfer and task execution (Al-Yacoub et al., 2021).

Random forest regression consists of several decision trees, where each node is split based on the best variable amongst a randomly chosen subset at each node.

Moreover, trees outperforming others are identified, and their weights are increased to improve the overall performance in the weighted random forest regression. Time Series K Means and LSTM-RNN are other approaches to enhance safety. For instance, these approaches predict human upper-limb movement intentions, refining reaction times and ensuring safety (Buerkle et al., 2021) in here. Mobile electroencephalogram (EEG) sensors detect human perception of potential emergencies. This method processes real-time EEG data using decision tree models and wavelet transforms for hazard detection (Buerkle et al., 2021). During this approach, an experimental 9-12 second recording of EEG data is obtained from several participants simulating an emergency. That data set trains and validates a machine-learning model to detect any danger. Moreover, integrating workspace monitoring and augmented reality interfaces based on depth sensor information enhances real-time safety (Hietanen et al., 2020). Another significant contribution involves using sensor-less haptic control for collaborative assembly tasks through adaptive admittance control (Liu et al., 2021; Zhu et al., 2021).

Consequently, a novel human-robot collaborative (HRC) assembly framework has been developed to increase the demand for medical equipment following the COVID-19 pandemic (Lv et al., 2021). These shared environment frameworks are now being improved by incorporating Digital Twin (DT) technology. A real-time visual representation of the system is made possible by DT integration into the assembly process, providing a smooth human-robot interface (HRI) for effective control and monitoring.

This framework's central component is an advanced data management system that compiles datasets from the DT space so that a Deep Deterministic Policy Gradient (D-DDPG) module can be used. This module is crucial for optimising HRC strategies and action sequences in dynamic scenarios where continuous adaptation is necessary. Physical sensors enable real-time data collection by capturing and synchronising environmental conditions with the assembly process. This allows the assembly line to be optimised for both speed and accuracy. Additionally, the framework employs laser scanners to obtain point cloud data from the environment, which is subsequently segmented using a point cloud segmentation algorithm. This segmentation is crucial for defining the spatial parameters of the assembly environment, allowing for better navigation and task execution by the robotic systems. Testing of this HRC framework on an alternative case revealed substantial improvements in both productivity and robustness, indicating its potential for broader industrial application.

Moreover, a haptic-touch detection method has been developed for Industry 4.0 scenarios, such as collaborative welding. This method has demonstrated remarkable accuracy (99.9%) and a low miss rate (10%), as measured by the 3-Sigma rule evaluation and Hampel identifier. The high precision of this approach ensures its viability for real-time industrial applications (Tannous et al., 2020). Thus, the combined use of DT technology, real-time data management, and advanced sensory feedback systems in HRC frameworks represents a significant leap forward in the automation and efficiency of modern industrial processes.

Results and Discussion

Integrating robotics into industrial environments is intricate and varied, influenced significantly by the sector in question. In established industries like automotive manufacturing, robotics implementation is relatively seamless, benefiting from long-standing practices, advanced tools, and sophisticated control algorithms that facilitate the smooth adoption of new technologies (Einabadi et al., 2019). Conversely, emerging sectors at the forefront of robotics innovation face distinct challenges. These industries must grapple with the complexities of initial system deployment, which includes developing novel integration methods, designing bespoke control systems, and establishing tailored quality assurance protocols. This variation in integration practices highlights the diverse landscape of robotics adoption and emphasises the need for sector-specific approaches. This discussion will explore two pivotal technological advancements: Digital Twin (DT) technology and collaborative robots (cobots), and how materials are employed to drive robotic advancements in various industrial sectors.

Technology

DT technologies are applied to create digital twins, virtual replicas that simulate real behaviours in some physical objects, systems, or processes. DT technology created a virtual model to analyse and predict performance, diagnose problems, and optimise operations (David et al.,2021). DT technology has hugely advanced in several key areas (Ariansyah et al., 2023). One of the most significant benefits is predictive maintenance, which minimises equipment downtime and reduces maintenance costs by continuously monitoring equipment and predicting potential failures. DTs also enable process optimisation by simulating different scenarios, allowing manufacturers to evaluate and determine the most effective process. DTs provide actionable insights by integrating real-time data and analytics, allowing quicker and more informed decision-making.

Additionally, DTs create a safe environment for simulating processes and training personnel without the risk of disrupting real-world operations (Qazi et al., 2022). Subsequently, the real-time data integration from IoT makes dynamic simulation possible with machine learning and AI to predict failures, optimise processes, and learn from past data. Improved modelling techniques, enhanced computational power, and sophisticated algorithms make models more accurate and detailed (Zhou et al.,2021). In addition, advancements in communication technologies ensure seamless interaction between the physical system and their digital twin models. At the same time, it is scalable to model entire production lines, facilities, or even entire supply chains.

DTs have revolutionised product design by supporting virtual prototyping and testing. This approach drastically reduces the time and cost associated with physical prototypes. By simulating the product lifecycle and its performance in various conditions, DTs allow for the early identification of design flaws, optimising the product before it enters production. This leads to shorter development cycles, faster time-to-market, and significant cost savings. The ability to virtually test multiple product iterations enhances innovation, allowing companies to explore more complex designs without the financial burden of creating numerous physical prototypes (Kober et al.,2024).

Several advantages are associated with Digital Twin technology (Gong et al., 2024). It offers cost efficiency by minimising downtime, lowering maintenance and prototyping costs, and optimising processes. Increased productivity is correlated with constant monitoring and optimisation. Predictive analytics and virtual simulations make identifying and mitigating potential problems at an early stage easier, reducing risks (Jeremiah et al., 2024). Better design and optimisation lead to improved product and process quality. DTs also contribute to sustainability because they show how to use resources efficiently.

Compared to traditional robotics, DTs offer distinct advantages in predictability, adaptability, and holistic system integration (Liu et al., 2024). DTs enable real-time failure prediction and process optimisation, which conventional robots lack. Extensive virtual testing in a DT environment reduces the traditional trial-and-error approach required by conventional robotics, speeding up the development process. DTs also fuse several sources of information into a holistic view of the system, unlike traditional robots, which generally operate independently. Additionally, the adaptability of DTs allows them to improve continuously using real-time data, unlike conventional robots that need manual reprogramming to handle changes.

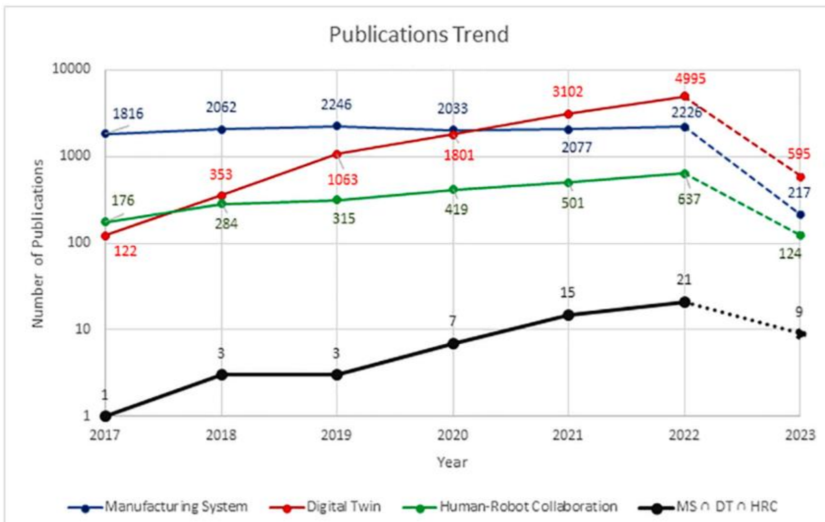

Figure 6: Publication trends. Reprint with permission (Baratta et al., 2024).

Cobots enhance productivity and safety by performing repetitive tasks, assisting with complex operations, and adapting to dynamic manufacturing environments. Their design includes features such as advanced sensors and safety mechanisms that allow them to operate safely in close proximity to humans (Ferraguti et al., 2019; Sara Bragança et al., 2019; Song et al., 2023). The deployment of cobots addresses several critical challenges, including the need for flexibility in production lines and the reduction of physical strain on human workers.

Collaborative robots and other peripheral devices improving the safety of robotic workplaces are not designed to replace current technologies fully. Robotic assistants widen the portfolio of robotic applications in the industry and bring several crucial advantages (Vysocky & Novak, 2016, Fig. 7). The safety of the robot is closely related to the safety of the technology placed on the end of it. Everything that is fastened to the robot can decrease its safety. Manufacturers have chosen different strategies to ensure the safety of their products. The fundamental idea of this strategy is to extend a spectrum of robotic applications to industries that are not automated nowadays. Robots are used as robotic assistants to improve the quality of work of human labourers (Vysocky & Novak, 2016).

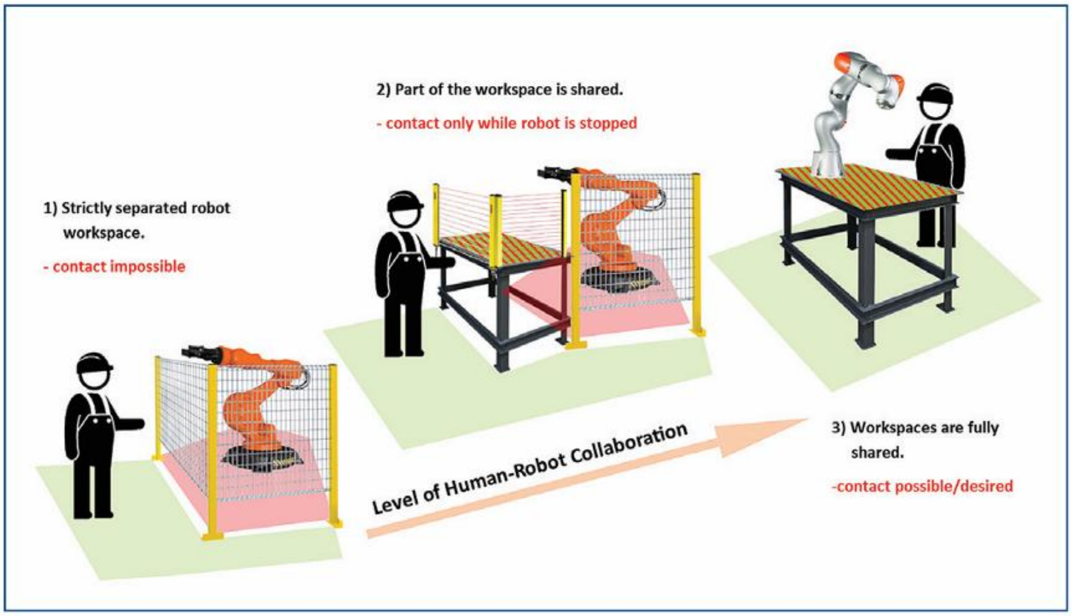

Figure 7: Shared workspace of a human and a robot. It is reprinted with permission (Vysocky & Novak, 2016).

Materials

Robots have been successfully used in manufacturing for many years. However, the capability of aerial robots to navigate agilely in the often sparse and static upper part of factories makes them suitable for performing tasks of interest in many industrial sectors (Perez-Grau et al., 2021). For these applications, soft robotic materials play a critical role. Polymers are employed in soft robotic body development, including conductive, biodegradable, shape memory types, and elastomers like dielectric, liquid crystal, and magnetoactive materials. These materials are highly compatible with human skin, thus enhancing their potential for human-robot interaction (Ju et al., 2021; Hann et al., 2020; Venkiteswaran et al., 2020, Fig. 8).

In pursuing energy efficiency and enhanced productivity, lightweight robotic arms are becoming increasingly prevalent in industrial applications. Various materials, each with distinct advantages and limitations, are currently used in designing these arms. Hollow sphere composites (HSC) are highly effective, but their high-cost limits widespread use (Hagenah et al., 2013b). While more effective, carbon fibre-reinforced plastic (CFRP) has poor processing properties (Ammar et al., 2021). Aluminium alloy (AA), although easy to process, is relatively dense (Yin et al., 2017). A hybrid structure combining CFRP and AA, through parameterisation of structural dimensions and layer configurations, has been proposed to optimise these materials' benefits and improve lightweight robotic arm performance (Quintanar-Guzmán et al., 2017b; Yin et al., 2019b).

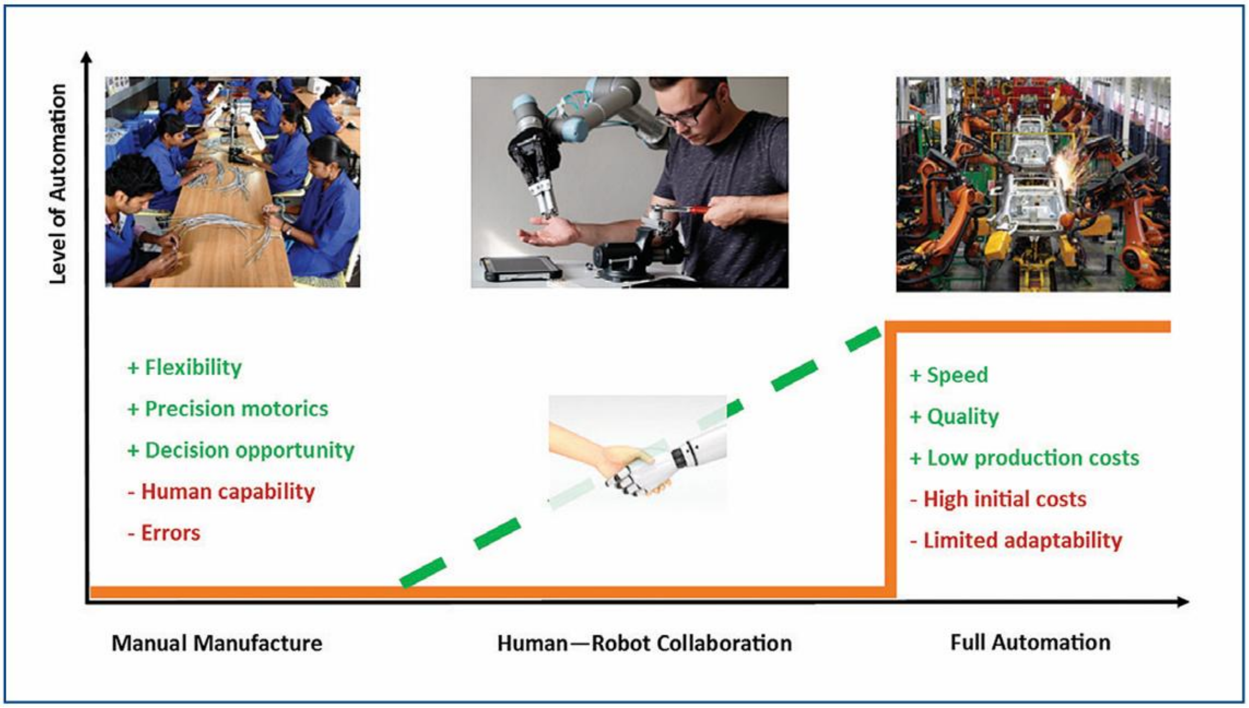

Figure 8: Standing of Human-Robot Collaboration. Reprinted with permission (Vysocky & Novak, 2016).

To create such optimised robotic arms, design variables like drive trains and structural dimensions are parameterised to minimise total mass while meeting strength, stiffness, and dynamic performance requirements. A mapping relationship between the mass and torque of drive trains, utilising power-density curves, helps unify structure and drive train descriptions, combining them with the dynamics of robotic arms (Ivan Virgala et al., 2021). Cellular titanium, manufactured using selective electron beam melting (SEBM), is an advanced material. This process selectively melts titanium powder layer by layer under a high vacuum, producing highly efficient titanium input and output flanges (Hagenah et al., 2013). Another material with great potential is nanocrystalline aluminium sheet metal, which offers enhanced material properties, such as a 70% strength increase after multiple rolling cycles, making it ideal for robot arm outer shells (Kuo et al., 2019).

Because they degrade naturally, polymers—especially biopolymers—have become valuable materials for a variety of industries. Specifically, biopolymers provide a sustainable substitute for traditional plastic packaging, making up one-third of the material in American landfills (Comstock et al., 2006). These materials are now being investigated for robotics applications beyond packaging. Degradable biopolymer-based robots have the potential to lessen their post-use environmental impact. Biopolymers can potentially allow robots to safely decompose within the body after medical procedures, making them perfect for diagnostic applications (Jose & Jagatheeswari, 2019).

Another emerging field where soft materials are essential is bio-inspired robotics. Because they can safely interact with humans, soft robots are increasingly demanding in industries like rehabilitation, medicine, and the military. Comparing soft robots to traditional rigid robots reveals clear benefits. Healthcare and home environments can benefit from their compliant nature, which lowers the risk of injury during human-robot interactions (Niiyama et al., 2015; Tolley et al., 2014; Gariya & Kumar, 2021). These robots can also operate in intricate, unstructured environments and perform precise tasks like manipulating delicate objects and performing surgeries.

Notwithstanding these developments, investigations are ongoing into the difficulties of cleverly incorporating active materials into soft robotic systems. Triboelectric and piezoelectric devices, or their combinations, can potentially improve soft robot performance (Pan et al., 2020). Safe and compliant robots, like soft-bodied robots, are becoming more popular for various uses. Benefits from soft materials include compliance, flexibility, shock absorption, and self-healing properties. Soft robots are more robust and durable than rigid robots because they can change shape and stiffness, absorb impacts, and so on (Gariya & Kumar, 2021).

Soft robotics finds application in minimally invasive medical surgeries, wearable assistive technology, search and rescue, and agricultural tasks requiring careful handling in small areas. Soft robotics is a rapidly expanding field that provides safer, more precise, and adaptable solutions. Despite obstacles like hysteresis and nonlinearity, developing soft materials is still a busy field of study (Lallo et al., 2019; Xing Jin et al., 2020). These materials hold the key to developing soft robots that can fulfil the increasing demands of human-robot interaction, pointing to a future in which robotics will play a more harmonious and integrated role across a range of industries.

Future Trends

The future of robotics in manufacturing revolves around combining cobots with smart tech to boost productivity, flexibility, and effectiveness. Cobots are set to have a significant impact because they can pick up new tasks through easy-to-use software and work with different systems to streamline processes and crunch numbers better. As cobots get more advanced and versatile, they will handle precise and smart jobs, helping to digitise the whole value chain across many industries.

In future, with the help of cobots, there will be open workspaces where robots can work automatically and collaboratively with humans. This will lead to improved flexibility in task scheduling, increased productivity and safer conditions for humans to work with robots, preventing conflicts.

The manufacturing industries will witness the increasing usage of robotics in the automotive industry and other production processes, allowing them to overcome difficulties in integrating with manufacturing tasks such as welding, fabrications, distribution, assembly, and packaging and improving operational versatility. This technological evolution will help take on physically demanding jobs to ensure workers' health and safety.

Factories of the future will learn new tasks quickly and efficiently to prevent production slowdowns. Future workplaces will tackle issues like getting workers to accept robots, building trust between humans and robots working together, changing how workplaces are set up, and providing the proper education and training. People will even develop natural ways to talk to machines, which will help everyone understand each other better and make workers happier in the long run.

Manufacturing industries can use robots to boost productivity, work more efficiently, and be eco-friendly. At the same time, this approach can keep human workers safe and healthy by focusing on these future goals.

Conclusion

Robotic systems and other technologies have made industrial processes more productive and efficient. Trends such as collaborative robots and digital twin technology have brought out new ways of development. Collaborative robots are designed to work alongside humans, enhancing efficiency. They combine robotic accuracy and human dexterity to optimise processes and ensure safety in the workspace. Businesses like DHL and Amazon already use these technologies to improve their warehousing and logistics processes. However, DT technology provides a virtualised version of physical systems, enabling predictive maintenance and real-time monitoring, reducing downtime and increasing productivity. Despite the advancements in the field, some challenges still need to be addressed. One major challenge is teaching robotic systems to handle complex objects, where solving this problem involves a trial-and-error method.

On the other hand, balancing the assembly line to optimise the performance is a key consideration. Additionally, robots have technical limitations, such as difficulty in multitasking, and some social and ethical considerations. Similarly, digital twin technology also consists of a few challenges, such as intensive data gathering throughout the lifetime of the digital twin, possible data breaches, and latency problems. Future workspaces will witness robots and humans working together seamlessly, with improved performance and increased safety. Furthermore, the integration of collaborative robotics in the manufacturing industries will continue to grow, which will help mitigate physically demanding tasks, enhancing the health and safety of workers.

Future factories will quickly adapt to new tasks, preventing production slowdowns. Implementing natural communication methods between humans and machines will improve understanding and job satisfaction. Not only will robots boost productivity, efficiency, and sustainability, but they also prioritise the safety and well-being of workers.

References

Aivaliotis, P., Georgoulias, K., Arkouli, Z., & Makris, S. (2019). Methodology for enabling Digital Twin using advanced physics-based modelling in predictive maintenance. *Procedia CIRP*, *81*, 417–422. https://doi.org/10.1016/j.procir.2019.03.072

Al-Yacoub, A., Zhao, Y., Eaton, W., Goh, Y., & Lohse, N. (2021). Improving human-robot collaboration through Force/Torque based learning for object manipulation. *Robotics and Computer-Integrated Manufacturing*, p. *69*, 102111. https://doi.org/10.1016/j.rcim.2020.102111

Ammar, M. M., Shirinzadeh, B., Zhao, P., & Shi, Y. (2021). An approach for damage initiation and propagation in metal and carbon fiber hybrid composites manufactured by robotic fiber placement. *Composite Structures*, p. *268*, 113976. https://doi.org/10.1016/j.compstruct.2021.113976

Ariansyah, D., Isnan, M., Rahutomo, R., & Pardamean, B. (2023). Digital Twin (DT) Smart City for air quality management. *Procedia Computer Science*, *227*, 524–533. https://doi.org/10.1016/j.procs.2023.10.554

Arkouli, Z., Kokotinis, G., Michalos, G., Dimitropoulos, N., & Makris, S. (2021). AI-enhanced cooperating robots for reconfigurable manufacturing of large parts. *IFAC-PapersOnLine*, *54*(1), 617–622. https://doi.org/10.1016/j.ifacol.2021.08.072

Baratta, A., Cimino, A., Longo, F., & Nicoletti, L. (2024). Digital twin for human-robot collaboration enhancement in manufacturing systems: Literature review and direction for future developments. *Computers & Industrial Engineering*, 187, 109764. https://doi.org/10.1016/j.cie.2023.109764

Berx, N., Decré, W., & Pintelon, L. (2024). A tool to evaluate industrial cobot safety readiness from a system-wide perspective: An empirical validation. *Safety Science*, *170*, 106380. https://doi.org/10.1016/j.ssci.2023.106380

Boschetti, G., Faccio, M., Granata, I., & Minto, R. (2023). 3D collision avoidance strategy and performance evaluation for human-robot collaborative systems. *Computers & Industrial Engineering*, *179*, 109225. https://doi.org/10.1016/j.cie.2023.109225

Boysen, N., Schulze, P., & Scholl, A. (2022). Assembly line balancing: What happened in the last fifteen years? *European Journal of Operational Research*, *301*(3), 797–814. https://doi.org/10.1016/j.ejor.2021.11.043

Bragança, S., Costa, E., Castellucci, I., & Arezes, P. M. (2019). A brief overview of the use of collaborative robots in industry 4.0: human role and safety. In *Studies in systems, decision and control* (pp. 641–650). https://doi.org/10.1007/978-3-030-14730-3_68

Brennan, R. W., & Lyu, G. (2024). Towards sustainable Cyber-Physical manufacturing systems. *IFAC-PapersOnLine*, *58*(3), 345–350. https://doi.org/10.1016/j.ifacol.2024.07.175

Buerkle, A., Bamber, T., Lohse, N., & Ferreira, P. (2021). Feasibility of Detecting Potential Emergencies in Symbiotic Human-Robot Collaboration with a mobile EEG. *Robotics and Computer-Integrated Manufacturing*, *72*, 102179. https://doi.org/10.1016/j.rcim.2021.102179

Buhl, J. F., Grønhøj, R., Jørgensen, J. K., Mateus, G., Pinto, D., Sørensen, J. K., Bøgh, S., & Chrysostomou, D. (2019). A dual-arm collaborative robot system for the smart factories of the future. *Procedia Manufacturing*, *38*, 333–340. https://doi.org/10.1016/j.promfg.2020.01.043

Çalık, A. (2020). A novel Pythagorean fuzzy AHP and fuzzy TOPSIS methodology for green supplier selection in the Industry 4.0 era. *Soft Computing*, 25(3), 2253–2265. https://doi.org/10.1007/s00500-020-05294-9

Chehri, A., Zimmermann, A., Schmidt, R., & Masuda, Y. (2021). Theory and practice of implementing a successful enterprise IoT strategy in the Industry 4.0 era. *Procedia Computer Science*, 192, 4609–4618. https://doi.org/10.1016/j.procs.2021.09.239

Chen, S., Mu, S., He, X., Han, J., & Tan, Z. (2024). Does industrial robot adoption affect green total factor productivity? – Evidence from China. *Ecological Indicators*, *161*, 111958. https://doi.org/10.1016/j.ecolind.2024.111958

Comstock, K., Farrell, D., Godwin, C., & Xi, Y. (2006). From hydrocarbons to carbohydrates: The future of food packaging. *University of Washington, Environmental Management*.

Di Lallo, A., Catalano, M., Garabini, M., Grioli, G., Gabiccini, M., & Bicchi, A. (2019). *Dynamic morphological computation through damping design of soft material robots: application to under-actuated grippers*. https://doi.org/10.1109/icra.2019.8793987

Duan, D., Chen, S., Feng, Z., & Li, J. (2023). Industrial robots and firm productivity. *Structural Change and Economic Dynamics*, 67, 388–406. https://doi.org/10.1016/j.strueco.2023.08.002

Dzedzickis, A., Subačiūtė-Žemaitienė, J., Šutinys, E., Samukaitė-Bubnienė, U., & Bučinskas, V. (2021). Advanced Applications of Industrial Robotics: New trends and possibilities. *Applied Sciences*, 12(1), 135. https://doi.org/10.3390/app12010135

Einabadi, B., Baboli, A., & Ebrahimi, M. (2019). Dynamic Predictive Maintenance in industry 4.0 based on real time information: Case study in automotive industries. *IFAC-PapersOnLine*, *52*(13), 1069–1074. https://doi.org/10.1016/j.ifacol.2019.11.337

Evjemo, L. D., Gjerstad, T., Grøtli, E. I., & Sziebig, G. (n.d.). Trends in smart manufacturing: Role of humans and industrial robots in smart factories. *Current Robotics Reports*, 1(2), 35–41. https://doi.org/10.1007/s43154-020-00006-5

Fathi, M., Sepehri, A., Ghobakhloo, M., Iranmanesh, M., & Tsenge, M. (2024). Balancing assembly lines with industrial and collaborative robots: Current trends and future research directions. *Computers & Industrial Engineering*, 110254. https://doi.org/10.1016/j.cie.2024.110254

Ferraguti, F., Pertosa, A., Secchi, C., Fantuzzi, C., & Bonfe, M. (2019). *A Methodology for Comparative Analysis of Collaborative Robots for Industry 4.0.* https://doi.org/10.23919/date.2019.8714830

Gariya, N., & Kumar, P. (2021). A review of soft materials utilised for the manufacturing of soft robots. *Materials Today Proceedings*, *46*, 11177–11181. https://doi.org/10.1016/j.matpr.2021.02.380

George, A., Ali, M., & Papakostas, N. (2021). Utilising robotic process automation technologies for streamlining the additive manufacturing design workflow. *CIRP Annals*, 70(1), 119–122. https://doi.org/10.1016/j.cirp.2021.04.017

Gong, H., Su, D., Zeng, S., & Chen, X. (2024). Advancements in digital twin modeling for underground spaces and lightweight geometric modeling technologies. *Automation in Construction*, *165*, 105578. https://doi.org/10.1016/j.autcon.2024.105578

Hagenah, H., Böhm, W., Breitsprecher, T., Merklein, M., & Wartzack, S. (2013). Modelling, Construction and manufacture of a lightweight robot arm. *Procedia CIRP*, *12*, 211–216. https://doi.org/10.1016/j.procir.2013.09.037

Hann, S. Y., Cui, H., Nowicki, M., & Zhang, L. G. (2020). 4D printing soft robotics for biomedical applications. *Additive Manufacturing*, p. *36*, 101567. https://doi.org/10.1016/j.addma.2020.101567

Hietanen, A., Pieters, R., Lanz, M., Latokartano, J., & Kämäräinen, J. (2020). AR-based interaction for human-robot collaborative manufacturing. *Robotics and Computer-Integrated Manufacturing*, *63*, 101891. https://doi.org/10.1016/j.rcim.2019.101891

IFR International Federation of Robotics. (n.d.). International Federation of Robotics. https://ifr.org/wr-industrial-robots/

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2021). Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cognitive Robotics*, *pp. 1*, 58–75. https://doi.org/10.1016/j.cogr.2021.06.001

Javaid, M., Haleem, A., Singh, R. P., Rab, S., & Suman, R. (2022). Significant applications of Cobots in the field of manufacturing. *Cognitive Robotics*, *pp. 2*, 222–233. https://doi.org/10.1016/j.cogr.2022.10.001

Jeremiah, S. R., Azzaoui, A. E., Xiong, N. N., & Park, J. H. (2024). A comprehensive survey of digital twins: applications, technologies and security challenges. *Journal of Systems Architecture*, p. *151*, 103120. https://doi.org/10.1016/j.sysarc.2024.103120

Jin, T., & Han, X. (2024). Robotic arms in precision agriculture: A comprehensive review of the technologies, applications, challenges, and future prospects. *Computers and Electronics in Agriculture*, p. *221*, 108938. https://doi.org/10.1016/j.compag.2024.108938

Jin, X., Feng, C., Ponnamma, D., Yi, Z., Parameswaranpillai, J., Thomas, S., & Salim, N. V. (2020). Review on exploration of graphene in the design and engineering of smart sensors, actuators and soft robotics. *Chemical Engineering Journal Advances*, *4*, 100034. https://doi.org/10.1016/j.ceja.2020.100034

Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, 29, 36–52. https://doi.org/10.1016/j.cirpj.2020.02.002

Jose, R. A., & Jagatheeswari, P. (2019). Neutroscopic data synthesis of biodegradable polymer for industrial bio robots. *Cognitive Systems Research*, *56*, 72–81. https://doi.org/10.1016/j.cogsys.2018.11.008

Ju, Y., Hu, R., Xie, Y., Yao, J., Li, X., Lv, Y., Han, X., Cao, Q., & Li, L. (2021). Reconfigurable magnetic soft robots with multimodal locomotion. *Nano Energy*, *87*, 106169. https://doi.org/10.1016/j.nanoen.2021.106169

Kareemullah, H., Najumnissa, D., Shajahan, M., Abhineshjayram, M., Mohan, V., & Sheerin, S. A. (2023). Robotic Arm controlled using IoT application. *Computers & Electrical Engineering*, p. *105*, 108539. https://doi.org/10.1016/j.compeleceng.2022.108539

Kober, C., Medina, F. G., Benfer, M., Wulfsberg, J. P., Martinez, V., & Lanza, G. (2024). Digital twin stakeholder Communication: characteristics, challenges, and best practices. *Computers in Industry*, *161*, 104135. https://doi.org/10.1016/j.compind.2024.104135

Kuo, J. (2019). Multi-objective optimal design of motion precision for fork robot arm in LCD panel manufacturing process system. *Microelectronics Reliability*, *pp. 99*, 19–30. https://doi.org/10.1016/j.microrel.2019.05.003

Lee, D., Lee, S. H., Masoud, N., Krishnan, & Li, V. C. (2021). Integrated digital twin and blockchain framework to support accountable information sharing in construction projects. *Automation in Construction*, p. 127, 103688. https://doi.org/10.1016/j.autcon.2021.103688

Leutert, F., Bohlig, D., Kempf, F., Schilling, K., Mühlbauer, M., Ayan, B., Hulin, T., Stulp, F., Albu-Schäffer, A., Kutscher, V., Plesker, C., Dasbach, T., Damm, S., Anderl, R., & Schleich, B. (2024). AI-enabled Cyber-Physical In-Orbit Factory - AI approaches based on digital twin technology for robotic small satellite production. *Acta Astronautica*, *217*, 1–17. https://doi.org/10.1016/j.actaastro.2024.01.019

Liu, S., Wang, L., & Wang, X. V. (2021). Sensorless haptic control for human-robot collaborative assembly. *CIRP Journal of Manufacturing Science and Technology*, *32*, 132–144. https://doi.org/10.1016/j.cirpj.2020.11.015

Liu, Y., Feng, J., Lu, J., & Zhou, S. (2024). A review of digital twin capabilities, technologies, and applications based on the maturity model. *Advanced Engineering Informatics*, *62*, 102592. https://doi.org/10.1016/j.aei.2024.102592

Lu, Z., Tischer, T., Lutter, C., & Schnake, K. J. (2024). Robotic-Assisted Surgery for adult spinal deformity. A Systematic Review. *Brain and Spine*, 102904. https://doi.org/10.1016/j.bas.2024.102904

Lv, Q., Zhang, R., Sun, X., Lu, Y., & Bao, J. (2021). A digital twin-driven human-robot collaborative assembly approach in the wake of COVID-19. *Journal of Manufacturing Systems*, pp. *60*, 837–851. https://doi.org/10.1016/j.jmsy.2021.02.011

Ma, S., Huang, Y., Cai, W., Leng, J., & Xu, J. (2024). Integrated sustainable benchmark based on edge-cloud cooperation and big data analytics for energy-intensive manufacturing industries. *Journal of Manufacturing Systems*, *74*, 1037–1056. https://doi.org/10.1016/j.jmsy.2024.05.010

Mazumder, A., Sahed, M., Tasneem, Z., Das, P., Badal, Ali, M., Ahamed, M., Abhi, S., Sarker, S., Das, S., Hasan, M., Islam, M., & Islam. (2023). Towards next generation digital twin in robotics: Trends, scopes, challenges, and future. *Heliyon*, *9*(2), e13359. https://doi.org/10.1016/j.heliyon.2023.e13359

Morrell, B. J., Da Silva, M. S., Kaufmann, M., Moon, S., Kim, T., Lei, X., Patterson, C., Uribe, J., Vaquero, T. S., Correa, G. J., Clark, L. M., Agha, A., & Blank, J. G. (2024). Robotic exploration of Martian caves: Evaluating operational concepts through analog experiments in lava tubes. *Acta Astronautica*. https://doi.org/10.1016/j.actaastro.2024.07.041

Mukherjee, A., Divya, A., Sivvani, M., & Pal, S. K. (2024). Cognitive intelligence in industrial robots and manufacturing. *Computers & Industrial Engineering*, p. 191, 110106. https://doi.org/10.1016/j.cie.2024.110106

Mukherjee, D., Gupta, K., Chang, L. H., & Najjaran, H. (2022). A survey of Robot Learning Strategies for Human-Robot Collaboration in Industrial Settings. *Robotics and Computer-Integrated Manufacturing*, p. *73*, 102231. https://doi.org/10.1016/j.rcim.2021.102231

Niiyama, R., Sun, X., Sung, C., An, B., Rus, D., & Kim, S. (2015). Pouch Motors: Printable Soft Actuators Integrated with Computational Design. *Soft Robotics*, *2*(2), 59–70. https://doi.org/10.1089/soro.2014.0023

Nourmohammadi, A., Fathi, M., Arbaoui, T., & Slama, I. (2024). Multi-objective cycle time optimisation and robot energy expenditure in human-robot collaborated assembly lines. *Procedia Computer Science*, 232, 1279–1288. https://doi.org/10.1016/j.procs.2024.01.126

Ozer, T., Agir, I., & Henry, C. S. (2022). Rapid prototyping of ion-selective electrodes using a low-cost 3D printed internet-of-things (IoT) controlled robot. *Talanta*, *247*, 123544. https://doi.org/10.1016/j.talanta.2022.123544

Pan, M., Yuan, C., Liang, X., Zou, J., Zhang, Y., & Bowen, C. (2020). Triboelectric and piezoelectric nanogenerators for future soft robots and machines. *iScience*, *23*(11), 101682. https://doi.org/10.1016/j.isci.2020.101682

Patrício, L., De Sousa Costa, C. R., Varela, L., & Cruz-Cunha, M. M. (2024). Literature review on the sustainable implementation of Robotic Process Automation (RPA) in medical and healthcare administrative services. *Procedia Computer Science*, *239*, 166–176. https://doi.org/10.1016/j.procs.2024.06.159

Pedone, G., Váncza, J., & Szaller, Á. (2024). Exploring hidden pathways to sustainable manufacturing for cyber-physical production systems. *Heliyon*, *10*(8), e29004. https://doi.org/10.1016/j.heliyon.2024.e29004

Perez-Grau, F. J., Dios, J. R. M., Paneque, J. L., Acevedo, J. J., Torres-González, A., Viguria, A., Astorga, J. R., & Ollero, A. (2021). Introducing autonomous aerial robots in industrial manufacturing. *Journal of Manufacturing Systems*, *60*, 312–324. https://doi.org/10.1016/j.jmsy.2021.06.008

Qazi, A. M., Mahmood, S. H., Haleem, A., Bahl, S., Javaid, M., & Gopal, K. (2022). The impact of smart materials, digital twins (DTs) and Internet of things (IoT) in an industry 4.0 integrated automation industry. *Materials Today Proceedings*, pp. *62*, 18–25. https://doi.org/10.1016/j.matpr.2022.01.387

Quintanar-Guzmán, S., Kannan, S., Aguilera-González, A., Olivares-Mendez, M. A., & Voos, H. (2017). Operational space control of a lightweight robotic arm actuated by shape memory alloy wires: A comparative study. *Journal of Intelligent Material Systems and Structures*, *30*(9), 1368–1384. https://doi.org/10.1177/1045389x17721050

Rahman, M. S., Ghosh, T., Aurna, N. F., Kaiser, M. S., Anannya, M., & Hosen, A. S. (2023). Machine learning and Internet of things in industry 4.0: A review. *Measurement Sensors*, *28*, 100822. https://doi.org/10.1016/j.measen.2023.100822

Rus, D., & Tolley, M. T. (2015). Design, fabrication and control of soft robots. *Nature*, *521*(7553), 467–475. https://doi.org/10.1038/nature14543

Russo, M., Raimondi, L., Dong, X., Axinte, D., & Kell, J. (2021). Task-oriented optimal dimensional synthesis of robotic manipulators with limited mobility. *Robotics and Computer-Integrated Manufacturing*, *69*, 102096. https://doi.org/10.1016/j.rcim.2020.102096

Song, X., Sun, P., Song, S., & Stojanovic, V. (2023). Quantised neural adaptive finite-time preassigned performance control for interconnected nonlinear systems. *Neural Computing and Applications*, *35*(21), 15429–15446. https://doi.org/10.1007/s00521-023-08361-y

Tannous, M., Miraglia, M., Inglese, F., Giorgini, L., Ricciardi, F., Pelliccia, R., Milazzo, M., & Stefanini, C. (2020). Haptic-based touch detection for collaborative robots in welding applications. Robotics and Computer-Integrated Manufacturing, 64, 101952. https://doi.org/10.1016/j.rcim.2020.101952

Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-Art. *IEEE Transactions on Industrial Informatics*, *15*(4), 2405–2415. https://doi.org/10.1109/tii.2018.2873186

Tao, F., Zhang, Y., Cheng, Y., Ren, J., Wang, D., Qi, Q., & Li, P. (2022). Digital twin and blockchain enhanced smart manufacturing service collaboration and management. *Journal of Manufacturing Systems*, pp. *62*, 903–914. https://doi.org/10.1016/j.jmsy.2020.11.008

Tavares, P., Silva, J. A., Costa, P., Veiga, G., & Moreira, A. P. (2017). Flexible Work cell Simulator using Digital twin methodology for highly complex systems in industry 4.0. In *Advances in intelligent systems and computing* (pp. 541–552). https://doi.org/10.1007/978-3-319-70833-1_44

Technical Articles Archives - Industrial Robotics. (n.d.). https://marorob.com/category/technical-articles-en/

Tolley, M. T., Shepherd, R. F., Mosadegh, B., Galloway, K. C., Wehner, M., Karpelson, M., Wood, R. J., & Whitesides, G. M. (2014). A resilient, untethered soft robot. *Soft Robotics*, *1*(3), 213–223. https://doi.org/10.1089/soro.2014.0008

Vachalek, J., Bartalsky, L., Rovny, O., Sismisova, D., Morhac, M., & Loksik, M. (2017). *The digital twin of an industrial production line within the industry 4.0 concept*. https://doi.org/10.1109/pc.2017.7976223

Venkiteswaran, V. K., Tan, D. K., & Misra, S. (2020). Tandem actuation of legged locomotion and grasping manipulation in soft robots using magnetic fields. *Extreme Mechanics Letters*, *41*, 101023. https://doi.org/10.1016/j.eml.2020.101023

Vicentini, F. (2020). Terminology in safety of collaborative robotics. *Robotics and Computer-Integrated Manufacturing*, *63*, 101921. https://doi.org/10.1016/j.rcim.2019.101921

Virgala, I., Kelemen, M., Prada, E., Sukop, M., Kot, T., Bobovský, Z., Varga, M., & Ferenčík, P. (2021). A snake robot for locomotion in a pipe using trapezium-like travelling wave. *Mechanism and Machine Theory*, *158*, 104221. https://doi.org/10.1016/j.mechmachtheory.2020.104221

Vysocky, A., & Novak, P. (2016). HUMAN – ROBOT COLLABORATION IN INDUSTRY. *MM Science Journal*, *2016*(02), 903–906. https://doi.org/10.17973/mmsj.2016_06_201611

Wang, R. S., & Ambani, S. N. (2021). Robotic surgery training. *Urologic Clinics of North America*, *48*(1), 137–146. https://doi.org/10.1016/j.ucl.2020.09.014

Xu, W., Yang, H., Ji, Z., & Ba, M. (2024). Cognitive digital twin-enabled multi-robot collaborative manufacturing: Framework and approaches. *Computers & Industrial Engineering*, 110418. https://doi.org/10.1016/j.cie.2024.110418

Yang, Q., Du, X., Wang, Z., Meng, Z., Ma, Z., & Zhang, Q. (2023). A review of core agricultural robot technologies for crop productions. *Computers and Electronics in Agriculture*, *206*, 107701. https://doi.org/10.1016/j.compag.2023.107701

Yin, H., Huang, S., He, M., & Li, J. (2017). A unified design for lightweight robotic arms based on unified description of structure and drive trains. *International Journal of Advanced Robotic Systems*, *14*(4), 172988141771638. https://doi.org/10.1177/1729881417716383

Yin, H., Liu, J., & Yang, F. (2019). Hybrid structure design of lightweight robotic arms based on carbon fiber reinforced plastic and aluminum alloy. *IEEE Access*, *7*, 64932–64945. https://doi.org/10.1109/access.2019.2915363

Zafar, M. H., Langås, E. F., & Sanfilippo, F. (2024). Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review. *Robotics and Computer-Integrated Manufacturing*, *89*, 102769. https://doi.org/10.1016/j.rcim.2024.102769

Zhao, Y., Said, R., Ismail, N. W., & Hamzah, H. Z. (2024). Impact of industrial robot on labour productivity: Empirical study based on industry panel data. *Innovation and Green Development*, *3*(2), 100148. https://doi.org/10.1016/j.igd.2024.100148

Zhou, C., Xu, J., Miller-Hooks, E., Zhou, W., Chen, C., Lee, L. H., Chew, E. P., & Li, H. (2021). Analytics with digital-twinning: A decision support system for maintaining a resilient port. *Decision Support Systems*, *p. 143*, 113496. https://doi.org/10.1016/j.dss.2021.113496

Zhu, C., Yu, T., & Chang, Q. (2021). Applying Task-Oriented safety field calibration in human-robot collaborative systems. *Procedia Manufacturing*, pp. *53*, 673–679. https://doi.org/10.1016/j.promfg.2021.