Asia Pacific Academy of Science Pte. Ltd.

Metaverse 2024, 5(2), 2731.
https://doi.org/10.54517/m.v5i2.2731

Review

Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions

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CITATION

Akhtar ZB. Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions. Metaverse. 2024; 5(2): 2731. https://doi.org/10.54517/m.v5i2.2731

ARTICLE INFO

Received: 17 May 2024
Accepted: 29 May 2024
Available online: 4 July 2024

Abstract: Artificial intelligence (AI) stands as a potent catalyst for revolutionizing manufacturing, promising unprecedented efficiency, agility, and resilience. This research embarks on an investigative journey to dissect the multifaceted landscape of AI in manufacturing, aiming to unravel its current status, intrinsic challenges, and prospective pathways. This research unveils the intricate relationship between AI technologies and manufacturing processes across diverse domains. Examining various domains, including system-level analysis, human-robot collaboration, process monitoring, diagnostics, prognostics, and material-property modeling. The research also reveals AI's transformative potential in optimizing manufacturing operations, enhancing decision-making, and fostering innovation. By dissecting each domain, the research illuminates how AI empowers manufacturers to adapt to dynamic market demands and technological advancements, ultimately driving sustainable growth and competitiveness. Moreover, it also examines the evolving dynamics of human-robot collaboration within manufacturing settings, recognizing AI's pivotal role in facilitating seamless communication, shared understanding, and dynamic adaptation between humans and machines. Through an exploration of AI-enabled human-robot collaboration, this research underscores the transformative power of symbiotic relationships in reshaping the future of manufacturing. While highlighting opportunities, it acknowledges the myriad challenges accompanying AI integration in manufacturing, such as data quality issues, interpretability of AI models, and knowledge transfer across domains. By addressing these challenges, the research aims to pave the way for more resilient AI-driven manufacturing systems capable of navigating complex market landscapes and technological disruptions. This research sheds light on AI's transformative potential in manufacturing, inspiring collaborative efforts and innovative solutions that will propel the industry forward into a new era of possibility and prosperity.

Keywords: advanced manufacturing; artificial intelligence (AI); autonomous robotics; computer vision; deep learning; digital transformation technologies; industrial AI; manufacturing applications; manufacturing process; machine learning

1. Introduction

Artificial intelligence (AI) stands at the forefront of transformative technologies, reshaping industries and revolutionizing traditional manufacturing processes. In the landscape of modern manufacturing, the integration of AI promises unparalleled opportunities for agility, efficiency, and resilience. As industries navigate the complexities of global competition, evolving customer demands, and the imperative for sustainable practices, AI emerges as a critical enabler for navigating these challenges effectively [1]. The evolution of AI and machine learning (ML) has ushered in a new era for manufacturing, where data-driven insights and intelligent automation drive optimization and innovation across the production ecosystem [2]. From material design to advanced production systems, AI is permeating every facet of manufacturing, offering novel solutions to age-old problems and unlocking new realms of possibility.

The investigative exploration sets the stage for a comprehensive exploration of the intersection between artificial intelligence (AI) and modern manufacturing, driven by the transformative forces of smart manufacturing and Industry 4.0. It highlights the profound impact of technological advancements, such as IoT, robotics, and data availability, in reshaping the manufacturing landscape, prompting a critical examination of how AI can catalyze this evolution. By tracing the evolutionary trajectory of AI from its inception in the 1950s to its recent resurgence fueled by machine learning (ML) and deep learning (DL), the research exploration underscores the paradigm shift towards AI as a complementary tool for augmenting human expertise in manufacturing contexts. Moreover, the pressing challenges facing contemporary manufacturing operations, including the need to meet throughput, quality, and cost objectives amidst increasing complexity and variability. It underscores AI's potential to address these challenges by leveraging vast amounts of data generated by machines, sensors, and production processes, thereby enabling pattern discovery and insightful decision-making. The pivotal role of AI in transforming manufacturing data into actionable intelligence, offering a pathway towards enhanced productivity, quality, and efficiency. Central to the investigation is the hierarchical approach to manufacturing systems, which serves as a guiding framework for organizing and synthesizing the vast available knowledge on AI applications in manufacturing. Drawing parallels from the ISA-95 framework, the hierarchical view enables a systematic examination of AI's impact across different levels of manufacturing operations, from system-level optimization to process monitoring and material characterization. This hierarchical perspective underscores the importance of understanding data and process dependencies at multiple levels, ensuring alignment with global manufacturing goals and objectives.

Industrial artificial intelligence (AI) and machine learning (ML) represent a significant paradigm shift in the manufacturing sector, aiming to leverage data and advanced technologies to address various industrial challenges and enhance productivity, efficiency, and cost-effectiveness. Unlike general AI research, industrial AI focuses on practical applications tailored to industry-specific needs, such as customer value creation, predictive analysis, and insight discovery. This application-oriented approach has gained momentum in recent years, driven by several factors including the proliferation of affordable sensors, advancements in computational capabilities, and the availability of cloud-based services for data management and computing power outsourcing [3]. In the realm of industrial AI, applications span across different domains within production, including market and trend analysis, machinery and equipment, intralogistics, production processes, supply chain management, building operations, and product development [4]. Each of these application areas can be further subdivided into specific scenarios where AI and ML techniques are deployed to address concrete challenges and optimize operations. For instance, in the application scenario of process design & innovation, collaborative robots exemplify how AI can enable machines to learn and mimic human actions, enhancing flexibility and efficiency in manufacturing processes [5,6].

However, the adoption of AI in real-world production settings poses significant challenges due to the inherent complexity and dynamism of industrial processes. Unlike purely virtual systems, production processes involve the interaction between the physical and virtual worlds, necessitating robust solutions that can handle uncertainties and maintain high reliability. Challenges arise from the characteristics of production data, which often exhibit heterogeneity, noise, and uncertainty, making data integration, cleaning, and management challenging tasks [7]. Additionally, the black-box nature of ML models poses transparency and interpretability issues, impacting their acceptance and certification in safety-critical production environments [8,9]. The conservative nature of the manufacturing industry, coupled with high reliability requirements and the lack of expertise in IT and data science, further impedes the widespread adoption of AI technologies. Moreover, the scarcity of domain-specific datasets suitable for training ML models in industrial contexts hinders progress in developing effective AI solutions. While datasets from public institutions and data analysis competitions exist, they often lack industrial focus and may not meet the specific requirements of manufacturing applications [10,11].

To address these challenges, specialized methodologies such as the machine learning pipeline in production have been developed to guide the development and deployment of ML applications in engineering and production technology [12,13]. This domain-specific methodology emphasizes use-case assessment, data integration, preprocessing of real-world production data, and deployment and certification of ML applications, aiming to bridge the gap between AI research and industrial practice.

Industrial AI holds immense potential to revolutionize manufacturing processes and drive innovation across various domains. However, overcoming the challenges associated with data characteristics, industry dynamics, and model complexity is crucial for realizing the full benefits of AI in industrial settings. Collaboration between researchers, practitioners, and policymakers is essential to advance the field and unlock the transformative power of AI in production engineering. The integration of artificial intelligence (AI) and machine learning (ML) into manufacturing processes marks a significant evolution in the industry, driven by advancements in sensor technology, the Internet of Things (IoT), and robotics. With the aim of meeting throughput, quality, and cost objectives while ensuring a safe working environment, manufacturers are increasingly turning to AI as a solution. This transition is essential in light of growing product and process complexity, variability in customer demand, and competitive pressures. AI's ability to automate activities associated with human thinking, such as planning, decision-making, and problem-solving, has garnered significant attention in academia and industry alike. The exponential growth in AI-related publications and the projected trillion-dollar impact by 2030 underscore its transformative potential [14,15].

One of AI's primary strengths lies in its capability to identify and classify multivariate, nonlinear patterns in operational and performance data, which may dodge traditional analysis methods. Manufacturing environments generate vast amounts of data from machines, sensors, controllers, and labor records, reflecting the physical characteristics of the machinery [16]. AI techniques have revolutionized monitoring, diagnosis, and prognosis in manufacturing, enabling applications such as predictive maintenance and quality control. By harnessing AI, manufacturers can achieve real-time defect detection, predict maintenance needs, optimize processes, manage supply chains efficiently, deploy autonomous robotics, and streamline product design. However, alongside the adoption of AI in manufacturing, there arises a pressing need to prepare the workforce for the digitalization shift and equip them with the requisite skills to navigate technological disruptions. Addressing this need is the digital transformation technologies (DTAM) project, aimed at educating and training the younger generation in digital transformation. The primary objective of the DTAM project is to prepare students to tackle challenges in digitalization by providing them with relevant skills and knowledge.

Currently, the DTAM project is in the process of pilot testing its training course on digital transformation technologies. By facilitating access to comprehensive education and training programs, initiatives like DTAM play a crucial role in ensuring a smooth transition to digitalization in manufacturing. As the project progresses, it promises to equip students with the necessary skills and competencies to thrive in the rapidly evolving landscape of digital manufacturing.

The integration of AI and ML in manufacturing holds immense potential for enhancing productivity, efficiency, and safety. However, realizing these benefits requires a concerted effort to upskill the workforce and prepare them for the digital age. Projects like DTAM are instrumental in bridging the skills gap and empowering the next generation of manufacturing professionals to leverage AI for transformative change. The integration of artificial intelligence (AI) and machine learning (ML) into manufacturing systems represents a significant advancement in the industry, driven by the proliferation of sensors, the Internet of Things (IoT), and robotics. This transformation, often referred to as smart manufacturing or Industry 4.0, is reshaping traditional manufacturing paradigms and challenging enterprises to adapt to new operational and strategic realities [17]. In this context, AI emerges as a powerful tool for addressing the complexities and uncertainties inherent in modern manufacturing environments. This research aims to explore the multifaceted role of AI in manufacturing, encompassing applications ranging from quality optimization and process control to material engineering and characterization [18]. The evolution of AI, from its inception in the 1950s to its current state, reflects a journey marked by periods of enthusiasm and disillusionment. Early AI efforts, such as the development of perceptrons and expert systems, faced challenges in scalability and computational complexity, leading to periods known as “AI winters” [19]. However, recent breakthroughs in ML, particularly deep learning, coupled with advances in computational hardware and sensing technologies, have reignited interest in AI’s potential to revolutionize manufacturing [20,21].

In today’s manufacturing landscape, AI offers unprecedented opportunities to analyze vast amounts of data generated by machines, sensors, and production processes. This data, categorized into environmental, process, production operation, and measurement data, provides valuable insights into system behavior and performance [22]. AI techniques, including ML and DL, enable the identification of complex patterns and correlations within this data, empowering manufacturers to optimize throughput, enhance product quality, and ensure workplace safety [23]. The hierarchical approach adopted in this exploration provides a structured framework for examining AI applications across different levels of manufacturing systems: from overall system optimization to detailed process monitoring and control. Through this lens, building the state-of-the-art AI applications, including quality control, supervisory control in human-robot collaboration, process monitoring, diagnosis, prognosis, and materials engineering [24]. By addressing these diverse application areas, the aim is to offer insights into the potential of AI to address key challenges in modern manufacturing and drive operational excellence. Moreover, identifying the future challenges and opportunities for leveraging AI in manufacturing, emphasizing the need for continued research and development to meet the evolving needs of the industry. Key challenges include ensuring AI systems can comprehend the complex interdependencies within manufacturing processes, addressing issues of data quality and integration, and enhancing the transparency and interpretability of AI models [25].

By addressing these challenges, AI has the potential to usher in a new era of manufacturing innovation, characterized by increased efficiency, flexibility, and competitiveness. The exploration provides a comprehensive overview of the role of AI in manufacturing, highlighting its transformative potential across various domains. By adopting a hierarchical perspective and exploring a wide range of application areas, the research contributes to our understanding of how AI can drive the future of manufacturing. However, realizing this potential requires concerted efforts to address technical challenges and foster collaboration between academia, industry, and policymakers [26].

2. Methods and experimental analysis

The methodology for this research entails a systematic investigation into the opportunities, challenges, and future directions of utilizing artificial intelligence (AI) in manufacturing. To commence, a comprehensive available background knowledge will be conducted, delving into a wide array of scholarly articles, conference papers, industry reports, and relevant books. This extensive investigation aims to establish a robust understanding of the current landscape of AI applications in manufacturing, identifying key research domains and trends within the field. Following the iterative checking, the research will proceed to identify specific research domains within AI in manufacturing, such as system-level analysis, data quality, human-robot collaboration, process monitoring, diagnostics, prognostics, and material-property relationships. Data collection will ensue, encompassing empirical data, case studies, experimental results, and theoretical frameworks pertinent to each research domain. The collected data will be diverse and representative, ensuring a comprehensive basis for analysis. Subsequently, the collected data will undergo rigorous analysis using appropriate analytical methods and tools. This analytical phase may involve statistical analysis, qualitative coding, thematic analysis, or other data analysis techniques, depending on the nature of the data and research questions. Through this process, opportunities and challenges associated with the implementation of AI in manufacturing will be identified across the research domains.

Upon identifying opportunities and challenges, the research will proceed to propose potential future directions for research and development in the field of AI in manufacturing. Consideration will be given to advancements in AI technology, data analytics, robotics, and other relevant areas, with a focus on addressing current challenges and enhancing manufacturing processes. A critical reflection on the methodology employed will be conducted, acknowledging the strengths and limitations of the approach taken. Any biases, assumptions, or constraints that may have influenced the findings and interpretations will be discussed transparently. The conclusion of the research will summarize the key findings, reiterate the significance of the topic, and highlight implications for theory, practice, and future research in the field of AI in manufacturing.

Finally, recommendations will be provided for policymakers, industry practitioners, and researchers based on the findings of the research. These recommendations will aim to promote responsible and effective utilization of AI in manufacturing, thereby contributing to the advancement of the field.

3. Artificial intelligence (AI) within manufacturing: Opportunities, challenges, future developments

The convergence of artificial intelligence (AI) and additive manufacturing is revolutionizing the landscape of modern manufacturing. AI, alongside additive manufacturing technologies like 3D printing, has witnessed a surge in adoption, unlocking unprecedented potential for innovation, quality enhancement, and productivity gains. This synergy between AI and additive manufacturing is reshaping various facets of the manufacturing process, from design innovation to quality assurance and maintenance practices, ultimately leading to substantial improvements in efficiency and profitability.

AI's integration into additive manufacturing begins with its pivotal role in prefabrication design. Through generative design and topology optimization, AI facilitates the creation of efficient and innovative designs, streamlining the design process and accelerating time-to-market. Moreover, AI-powered vision systems enable real-time monitoring of the production process, enhancing quality assurance by detecting defects that may not be visible to the naked eye. This proactive approach to quality monitoring minimizes the production of defective parts, thereby reducing waste and enhancing overall product quality.

Furthermore, AI enables precise control over material usage in additive manufacturing by detecting potential defects and initiating corrective actions in real-time. This proactive approach not only minimizes material wastage but also ensures the production of high-quality components. Additionally, AI-driven predictive maintenance practices are transforming maintenance strategies by enabling early detection of production issues and predicting maintenance needs based on historical data.

This predictive capability, coupled with on-demand production of 3D printed parts, enhances maintenance efficiency and inventory management, ultimately improving overall operational efficiency. The benefits of AI in additive manufacturing are manifold. By ensuring prefabrication quality assurance, AI minimizes wasted time, effort, and materials in the design iteration process, leading to significant cost savings. Moreover, AI streamlines the design and ideation stage, reducing process complexity, manufacturing costs, and time to market.

Additionally, AI-driven optimization of production processes enhances efficiency and quality across the board, resulting in measurable cost savings and operational improvements. These benefits underscore the transformative potential of AI in additive manufacturing, offering manufacturers a competitive edge in today’s dynamic market landscape. The integration of AI into additive manufacturing holds immense promise for manufacturers seeking to enhance efficiency, quality, and profitability. By leveraging AI-driven innovations, manufacturers can streamline processes, optimize designs, and improve product quality, ultimately driving business success. As industry leaders like ATS continue to harness the power of AI and additive manufacturing, the future of manufacturing looks increasingly bright, with opportunities for unprecedented innovation and growth.

The role of artificial intelligence (AI) in manufacturing is experiencing a significant growth trajectory, driven by factors such as increased technology availability, tighter profit margins, and the imperative for manufacturers to maintain competitiveness. This surge in AI adoption is underscored by its ability to enhance productivity and provide a competitive edge in the manufacturing sector. As more manufacturers recognize the accessibility of AI technology and its potential to drive operational efficiency, there’s a notable uptick in its integration across various facets of the manufacturing process. AI’s impact in the manufacturing industry is evident through trends indicating rapid adoption and tangible benefits. The dropping cost of AI implementation coupled with its demonstrated positive return on investment (ROI) is driving its widespread usage. Studies reveal that a considerable percentage of companies are leveraging AI in production, with a significant majority witnessing positive ROI from their AI investments. These statistics underscore AI’s enduring presence in manufacturing, fueled by its ability to deliver substantial cost savings and productivity enhancements.

The applications of AI in manufacturing are diverse and multifaceted, encompassing areas such as machine maintenance, quality control, workplace safety, machine vision, inventory management, cybersecurity, robotics, factory automation, and product design. From predictive maintenance leveraging AI-driven condition monitoring to AI-enabled quality control processes, the impact of AI extends across the manufacturing landscape. By optimizing processes, enhancing efficiency, and improving safety, AI is reshaping traditional manufacturing practices and ushering in a new era of innovation and productivity.

The benefits of AI in manufacturing are wide-ranging and impactful. AI facilitates data-driven decision-making by analyzing vast amounts of data collected from industrial sensors, leading to enhanced productivity, uptime, and informed decision-making. Furthermore, AI-driven maintenance practices improve equipment reliability, reduce downtime, and optimize process effectiveness, resulting in cost savings and operational efficiency gains. Moreover, AI enhances workplace safety by enabling automation and robotics to handle hazardous tasks, thereby minimizing safety risks for employees.

Despite the numerous benefits, AI implementation in manufacturing presents challenges, including the cost of adoption, the need for skilled experts, and data quality considerations. However, these challenges can be mitigated through proper planning, strategic partnerships, and a long-term outlook on AI adoption. Establishing realistic expectations and recognizing AI as a transformative, long-term solution can help manufacturers navigate the complexities of AI implementation and unlock its full potential to drive operational excellence.

ATS, as a leading maintenance technology implementation partner, offers expertise in leveraging AI for maintenance solutions, industrial technology, and condition monitoring. With a results-focused strategy, ATS empowers manufacturers to stay ahead of the curve and maximize the benefits of AI in their operations. Through collaborative partnerships and innovative solutions, ATS enables manufacturers to harness the power of AI and achieve reliability excellence in their manufacturing processes.

The adoption of industrial artificial intelligence (AI) in advanced manufacturing is revolutionizing traditional labor forces by augmenting human capabilities with self-learning and self-adapting technology. This integration is not only enhancing production yield and quality but also propelling progress towards sustainability and safety objectives. Despite concerns about AI potentially displacing jobs, studies suggest that AI is forecasted to create millions of new roles, including AI specialists, data analysts, and digital transformation experts. The World Economic Forum (WEF) has recognized the need for robust AI governance frameworks and established the AI Governance Alliance to ensure responsible and inclusive AI systems' design and deployment.

Industrial AI is not replacing humans but rather empowering them by simplifying problem-solving and enhancing productivity. Through AI-driven automation and control algorithms, manufacturing operators can focus on strategic problem-solving rather than routine manipulations, thereby achieving higher levels of efficiency. AI's impact extends beyond the factory floor to training effectiveness, where augmentation technologies significantly enhance learning outcomes, offering gains of up to 80% compared to traditional methods. Moreover, AI facilitates real-time access to instructional materials, maintenance procedures, and videos, streamlining knowledge transfer and operational efficiency.

AI brings next-level computational capabilities to address complex optimization problems in manufacturing, with two predominant strategies: operator-in-the-loop and closed-loop autonomy. These strategies enable AI to analyze processes, recommend optimal changes, and, in closed-loop autonomy, autonomously execute actions with minimal human intervention. Industrial companies are exploring innovative architectures, akin to Tesla's Full Self Driving Version 12, to derive control policies from historical data and enable self-driving production systems.

The shift towards autonomous production systems is poised to revolutionize the global manufacturing economy, leading to increased throughput, product yield, and resource efficiency. This transformation could usher in an era of abundance, where critical goods are effortlessly brought to market to meet consumer needs while also expanding production capacity to emerging markets and remote areas. Importantly, autonomous production systems allow human labor forces to focus on more fulfilling tasks, freeing workers from hazardous and repetitive responsibilities.

The fusion of human ingenuity and AI is reshaping the future of manufacturing, with a focus on empowering individuals to achieve extraordinary results. By leveraging AI as an amplifier, manufacturers can unlock human creativity's full potential and drive unprecedented progress towards a sustainable and productive future.

The integration of digitization and automation, particularly in additive manufacturing (AM), is rapidly transforming the manufacturing landscape. Many companies are leveraging cloud-based solutions and integrated algorithms to maximize 3D printing's potential within Industry 4.0. In this digital realm, the convergence of 3D printing and artificial intelligence (AI), especially machine learning, is proving instrumental in optimizing the entire value chain of manufacturing. Machine learning a subset of AI, involves systems using algorithms to analyze data and identify patterns or solutions, dating back to significant breakthroughs like the Mark I Perceptron in 1957.

AI's role in additive manufacturing spans various aspects, including design innovation, quality control, production efficiency, and facility operations. AI-driven prefabrication design evaluates the viability of AM for specific designs and streamlines the design process through generative design and topology optimization. AI revolutionizes quality assurance by integrating with vision systems for real-time defect detection, enhancing both production and post-production quality monitoring. AI enables proactive defect management by facilitating real-time material usage control and predictive maintenance, which transforms maintenance practices, productivity, and inventory management.

The benefits of AI in additive manufacturing are extensive, ranging from improved quality assurance and streamlined processes to efficient, high-quality production. AI enhances product quality, fosters innovation, drives productivity, and ultimately amplifies companies' profitability. Examples such as Formnext 2023's AMAIZE software and LEAP 71's collaboration with the exploration company illustrate how AI-driven solutions are revolutionizing AM across industries, from energy to aerospace.

While the debate about AI's long-term impact on humanity continues, its role in manufacturing, particularly in conjunction with machine learning, is undeniably offering consistent benefits.

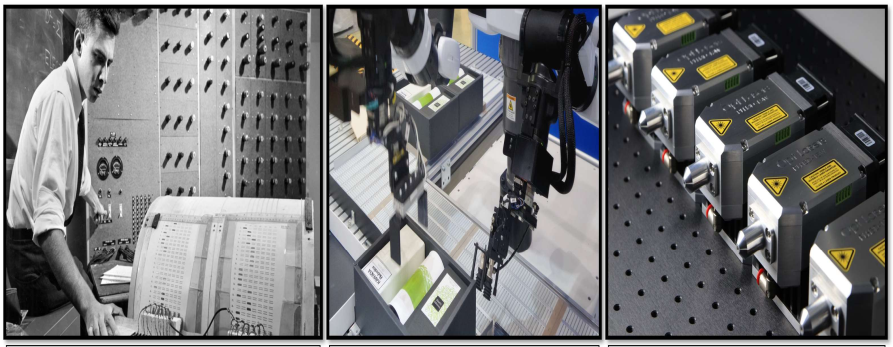


IMAGE 1. Division of Rare and Manuscript Collections
IMAGE 2. Possessed Photography
IMAGE 3. Opt Lasers

Figure 1. AI integration towards additive manufacturing.

Companies like AMFG are actively working with businesses to enhance and accelerate their quoting process, streamline pre-production workflows, and optimize additive manufacturing and CNC machining processes. As AI continues to advance, its synergy with additive manufacturing promises to drive further innovation, efficiency, and competitiveness in the manufacturing sector. To provide an idea **Figures 1** and **2** illustrate the perspective to the matter.

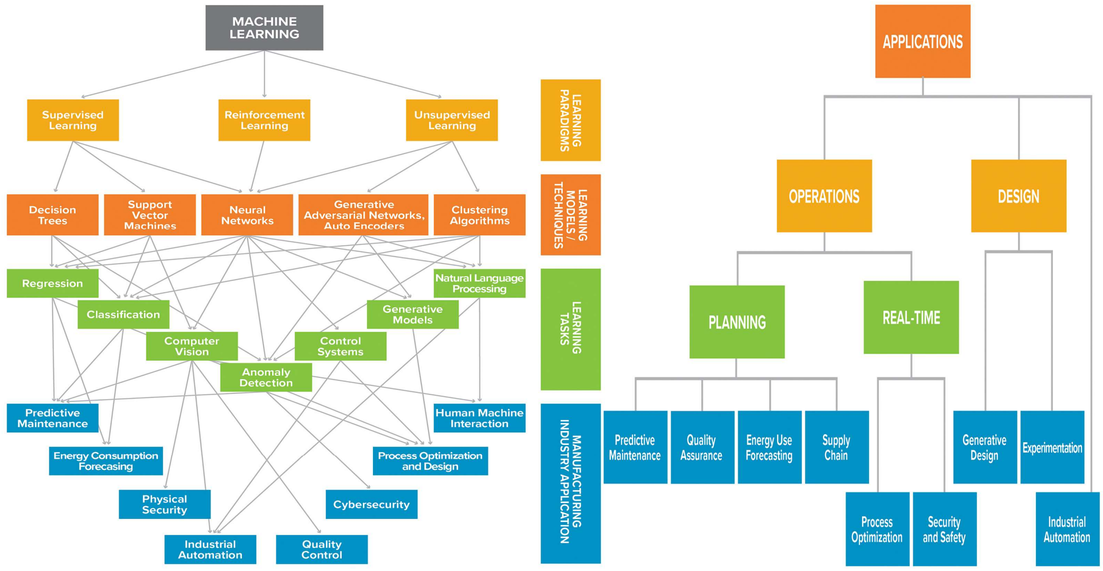


Figure 2. AI/ML integrations towards manufacturing and associated applications.

The manufacturing sector, already deeply entrenched in the Fourth Industrial Revolution (4IR), is experiencing a further surge in technological innovation, with Artificial Intelligence (AI) and machine learning playing pivotal roles. Amidst the complexity and competitiveness of modern manufacturing, AI offers transformative solutions to enhance efficiency, productivity, and competitiveness. From robots on assembly lines to automated supply chain management, factories are increasingly incorporating cutting-edge technologies to stay ahead of the curve.

One of the key ways AI enhances manufacturing is through deep learning, a subset of machine learning, which unlocks the value hidden in unstructured data. Deep learning algorithms excel at pattern recognition, enabling the extraction of actionable insights from vast datasets generated throughout the manufacturing process. AI-driven simulation and automation, particularly through the Industrial Internet of Things (IIoT) and digital twins, provide real-time monitoring and optimization of production workflows. These technologies enable predictive maintenance, reducing downtime and improving machinery lifespan while facilitating digital experimentation for process optimization. AI and robotics collaborate to streamline traditionally manual tasks, increase production yields, and progress towards fully digitized smart factories. Through AI-enabled platforms, robots can perform intricate tasks with precision, contributing to increased yields and cost savings.

AI enhances supply chain management, logistics, and inventory control through real-time tracking, optimization, and price forecasting. Visual inspection powered by AI-driven computer vision ensures quality control by detecting defects, mitigating risks, and improving overall product quality. AI's impact extends beyond operational efficiency to pivotal business decisions and customer experience optimization. By analyzing customer data and leveraging predictive analytics, AI facilitates product development, buyer journey optimization, and demand forecasting.

This rich data enables manufacturers to build trust, remove friction in customer interactions, and drive long-term sustainability and growth. AI addresses health and safety concerns by proactively monitoring worker safety, preventing accidents, and facilitating rapid incident response through real-time data analysis and predictive modeling.

Looking ahead, the future of AI in manufacturing promises even greater advancements, with automation guided by AI reaching unprecedented levels of productivity and energy efficiency. Despite the uncharted territory, AI applications aim to empower stakeholders at all levels, from decision-makers to factory workers, ensuring efficient, safe, and synergistic operations. Ultimately, AI enables manufacturers to achieve unprecedented control over processes, drive digital transformation, and navigate the evolving landscape of competition and consumer demands while maintaining quality and sustainability.

4. How manufacturers can amplify intelligence with AI: A case report investigation analysis

The adoption of artificial intelligence (AI) in manufacturing is gaining momentum, with the potential for transformative impact becoming increasingly apparent. However, despite the growing recognition of AI's importance, many manufacturing companies still lack comprehensive plans for its implementation. A survey conducted by EY and Microsoft reveals that while 81% of manufacturing companies acknowledge the increasing importance of AI, only 10% have detailed plans with defined initiatives and responsibilities in place. This underscores the urgency for manufacturing leaders to capitalize on AI's potential to drive business outcomes effectively.

Manufacturers are enthusiastic about AI due to its wide-ranging applications, including predictive maintenance, digital twins for simulations, chatbots for customer inquiries, and cybersecurity intrusion detection. These technologies enhance operational efficiency, extend the lifespan of assets, and improve customer engagement. However, realizing the full potential of AI requires more than just implementing new software. It necessitates a strategic approach focused on business outcomes, robust data quality, and governance processes. Challenges such as data silos, manual processes, and organizational culture need to be addressed to harness AI effectively.

To navigate the AI journey successfully, manufacturing companies can follow a roadmap comprising six key steps. Firstly, acknowledging AI's potential requires leadership commitment and engagement across all business units. Secondly, transformational planning, aligned with the organization's strategy and KPIs, is essential. Thirdly, establishing a strong data foundation and structure is crucial for effective AI implementation.

This involves data collection, cleansing, governance, and storage to ensure data quality and effectiveness in AI solutions. Moreover, leveraging external partnerships with startups, academia, and tech leaders can provide valuable insights and expertise in AI implementation. Building in-house AI skills and fostering a culture of continuous learning are also vital. This involves hiring AI experts, data scientists, and engineers while promoting cross-disciplinary collaboration within the organization. Finally, designing a scalable architecture and infrastructure to integrate AI solutions seamlessly is paramount for success.

Despite the challenges, manufacturers that cultivate an AI-friendly culture stand to gain significant competitive advantages. By leveraging AI to enhance customer and employee satisfaction while reducing costs, these companies can position themselves for success in an increasingly complex business landscape. The journey towards AI integration may be challenging, but the opportunities it presents for innovation and efficiency are immense.

Only a mere 10% of surveyed businesses have concrete initiatives and responsibilities outlined in their AI plans, despite acknowledging the pressing need for AI integration. Recognizing that the journey toward leveraging AI's transformative potential extends far beyond mere software implementation, companies must adopt a holistic approach.

A comprehensive six-step roadmap provides a way forward, encompassing crucial elements such as securing buy-in from the C-suite, establishing a solid foundation, and addressing the evolving talent requirements essential for successful AI implementation.

Artificial intelligence (AI) has emerged as a transformative force in the realm of manufacturing technology, heralding a new era of efficiency, quality enhancement, and operational flexibility. One of its pivotal applications lies in predictive maintenance, where AI algorithms harness sensor data from machinery to forecast potential failures, enabling proactive maintenance interventions and minimizing costly downtime.

This proactive approach revolutionizes traditional maintenance practices by offering a glimpse into the future, allowing companies to stay ahead of potential equipment failures. Moreover, AI plays a crucial role in bolstering quality control processes within manufacturing. By leveraging advanced algorithms, AI systems meticulously inspect products for defects and deviations from specifications, enhancing the accuracy and efficiency of quality assurance procedures. This capability ensures that products meet stringent quality standards, fostering customer satisfaction and brand reputation.

Where AI truly shines is in process optimization, offering manufacturers unparalleled insights into their production operations. By analyzing vast amounts of production data, AI identifies bottlenecks and inefficiencies, enabling real-time optimization and performance enhancement. This proactive approach empowers manufacturers to streamline their processes, maximize productivity, and drive operational excellence.

AI facilitates the seamless integration of advanced manufacturing techniques and automation. Through sophisticated algorithms, AI controls robots and automated systems, automating tasks that were once exclusively performed by humans. This convergence of AI and automation revolutionizes production processes, unlocking new levels of efficiency, precision, and scalability.

AI lends invaluable support in the domain of design and development. By harnessing powerful algorithms, AI assists in optimizing product designs for performance, cost-effectiveness, and other critical factors. This capability enables manufacturers to accelerate the product development cycle, drive innovation, and stay ahead of market trends.

AI revolutionizes inventory management practices by enabling predictive demand forecasting and optimizing inventory levels. By leveraging AI-driven insights, manufacturers can anticipate demand fluctuations, minimize inventory holding costs, and reduce waste, thereby enhancing operational efficiency and profitability. To provide visual analytics concerning the matter **Figures 3** and **4** represent the illustration for a better understanding.

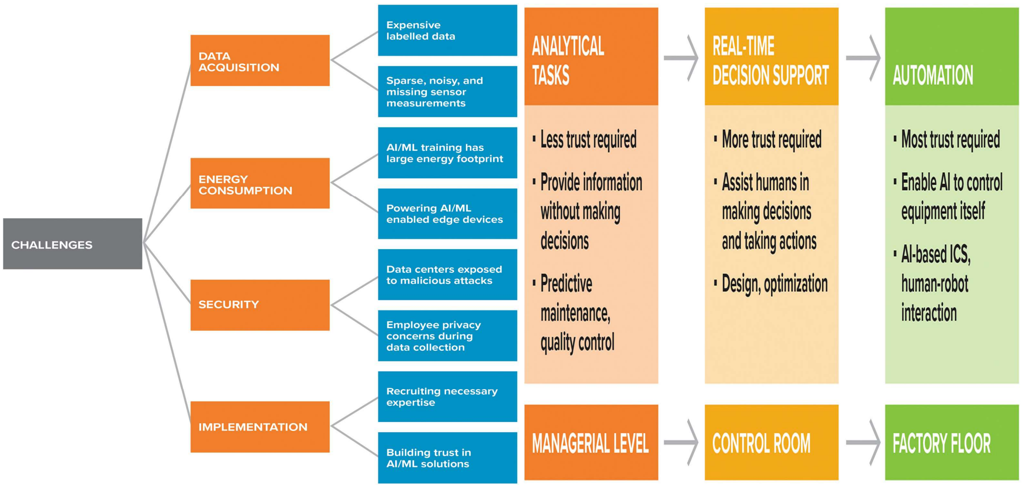


Figure 3. The challenges of AI/ML in terms of advanced manufacturing process.

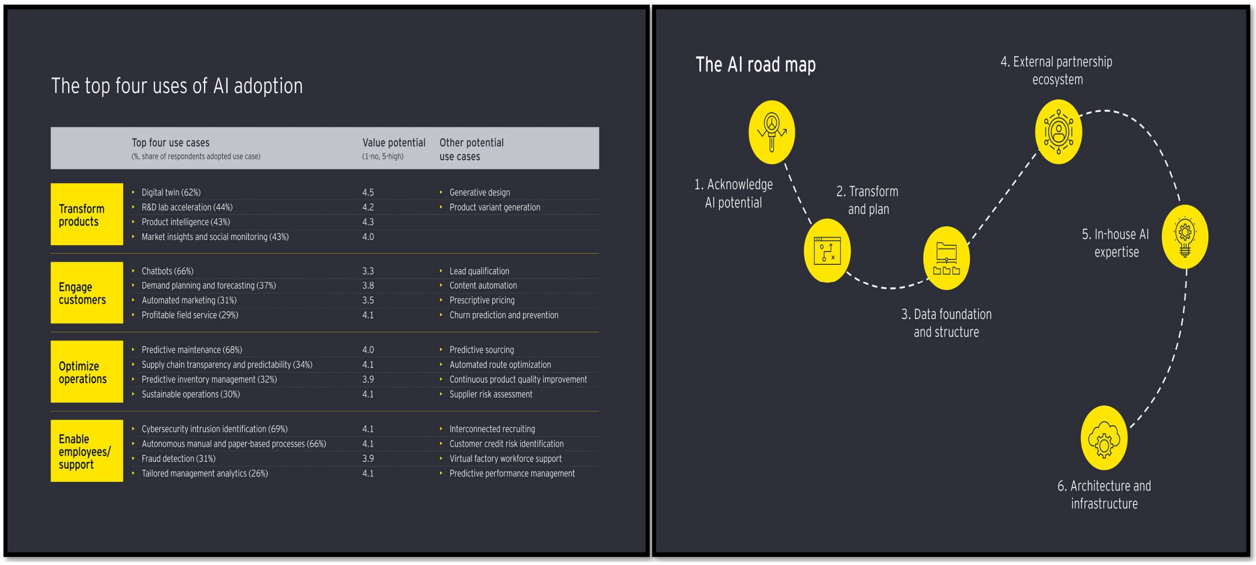


Figure 4. The influence of AI within advanced manufacturing.

The integration of AI into manufacturing processes holds immense promise for the industry, offering a myriad of benefits ranging from enhanced operational efficiency to increased competitiveness. As manufacturers embrace AI-powered solutions, they stand to reap substantial rewards, driving innovation, and reshaping the future of manufacturing.

5. Results and findings

Artificial intelligence (AI) is revolutionizing the manufacturing industry, offering a myriad of potential benefits including increased productivity, reduced expenses, enhanced quality, and decreased downtime. While large factories have already begun leveraging AI technology to optimize their operations, many smaller businesses have yet to realize the accessibility of high-value, low-cost AI solutions. From defect detection using image processing techniques to predictive maintenance and process optimization, AI has emerged as a cornerstone technology in modern manufacturing.

The role of AI in manufacturing spans various key segments, including machine learning, deep learning, and autonomous objects. Machine learning algorithms enable manufacturers to automatically learn from underlying patterns in data, while deep learning neural networks analyze complex data such as images and videos. Autonomous objects, such as collaborative robots, manage tasks independently, further enhancing operational efficiency and flexibility.

This convergence of AI technologies is projected to drive substantial growth in the AI manufacturing market, with estimates indicating a remarkable compound annual growth rate (CAGR) of 57% from 2020 to 2026 [27–30]. The application of AI in manufacturing is diverse and multifaceted. For instance, AI enables the automation of tasks by learning from human demonstrations and crowd-sourced data, ultimately improving operational efficiency and scalability. AI facilitates predictive maintenance by analyzing sensor data to forecast equipment failures, thus optimizing maintenance schedules and minimizing production disruptions. Additionally, AI-driven quality control mechanisms ensure adherence to stringent quality standards, enhancing product reliability and customer satisfaction.

AI empowers manufacturers to enhance various aspects of their operations, including supply chain management, robotics, process improvement, and shop floor performance. By leveraging AI-powered solutions, manufacturers can optimize inventory management, automate warehouse operations, and streamline production processes, thereby improving efficiency and reducing costs. AI facilitates predictive analytics for raw material pricing, enabling informed decision-making and cost optimization. Furthermore, AI-driven innovations such as generative design, connected factories, and cybersecurity solutions are reshaping the manufacturing landscape. Generative design software enables the rapid generation of product designs, while connected factories leverage IoT devices and cloud technology to enhance visibility and efficiency. Additionally, AI-driven cybersecurity systems help safeguard industrial facilities and mitigate the risks associated with cyber threats, ensuring uninterrupted production operations. The integration of AI into manufacturing processes holds immense potential for driving innovation, efficiency, and competitiveness in the industry.

As AI continues to evolve and proliferate, investing in AI talent and technology becomes increasingly imperative for manufacturers seeking to thrive in the digital age. By embracing AI-powered solutions, manufacturers can unlock new opportunities for growth, agility, and sustainability in the ever-evolving landscape of modern manufacturing.

The future of advanced manufacturing is intricately intertwined with the utilization of artificial intelligence (AI) systems, poised to deliver unprecedented levels of agility, efficiency, and resilience. Across various sectors, AI and machine learning (ML) are driving transformational changes, and the realm of material design and advanced manufacturing is no exception. In an increasingly complex landscape, where competition is fierce, customer demands evolve rapidly, and product and process intricacies continue to grow, the necessity for targeted AI and ML platforms becomes ever more evident.

Envisioning the trajectory of advanced manufacturing, it becomes clear that foundational AI systems will play a pivotal role in several key areas. Firstly, these AI systems will provide resilience across product design, production, and distribution processes.

By minimizing waste and enhancing the uptake of recycled raw materials through compositional flexibility, manufacturers can adapt more effectively to changing market dynamics and supply chain fluctuations. Moreover, the ability to facilitate rapid product design iterations enables manufacturers to meet evolving specifications with agility, ensuring alignment with market demands. Furthermore, AI-driven systems will enable personalized product design in collaboration with human experts, catering to the growing demand for customized solutions in various industries.

This fusion of AI capabilities with human expertise not only enhances creativity and innovation but also ensures that products are tailored to meet individualized customer preferences. Additionally, AI will play a crucial role in optimizing manufacturing processes, driving efficiencies, and maximizing productivity across the production line.

The integration of AI into advanced manufacturing holds the promise of revolutionizing the industry by unlocking new levels of adaptability, efficiency, and sustainability. By harnessing the power of AI-driven solutions, manufacturers can navigate the complexities of modern production environments with greater agility and resilience, ultimately driving competitiveness and driving innovation in the global marketplace. To provide a better understanding the results and findings are illustrated within **Figures 5–8** concerning the perspective of the matters.

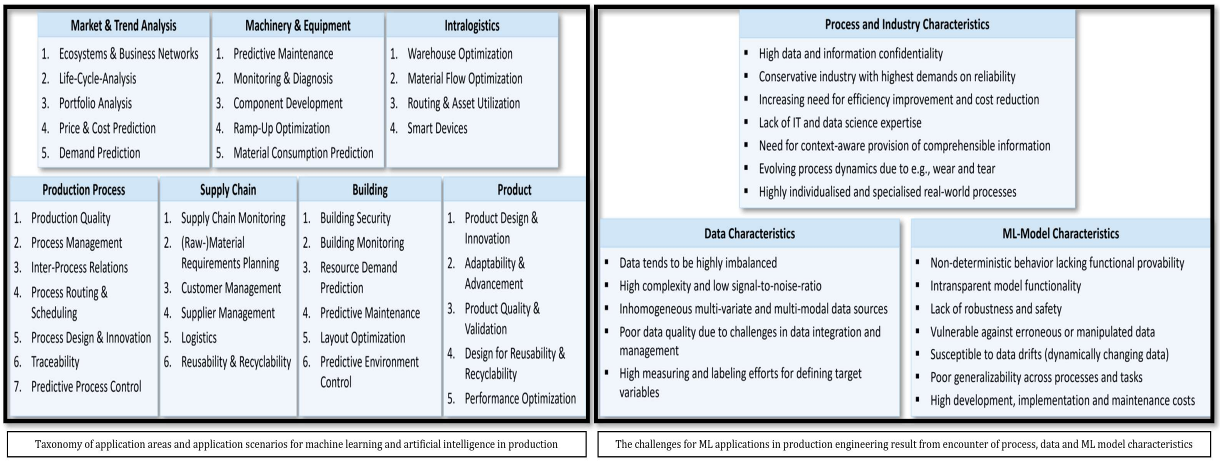
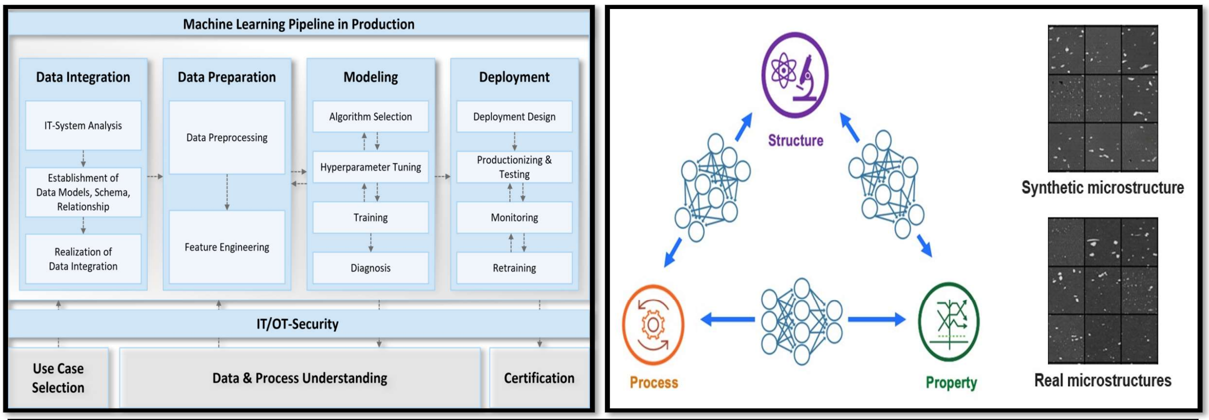


Figure 5. An illustrative representation of the research findings 1.



The Machine Learning Pipeline in terms of Production and Artificial Intelligence (AI) Toolsets for Advanced Manufacturing

Figure 6. An illustrative representation of the research findings 2.

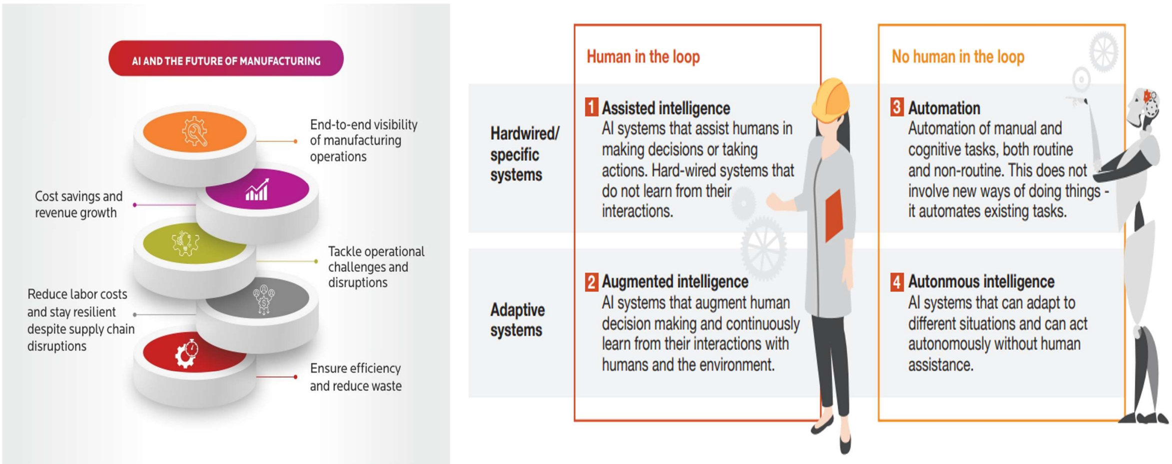
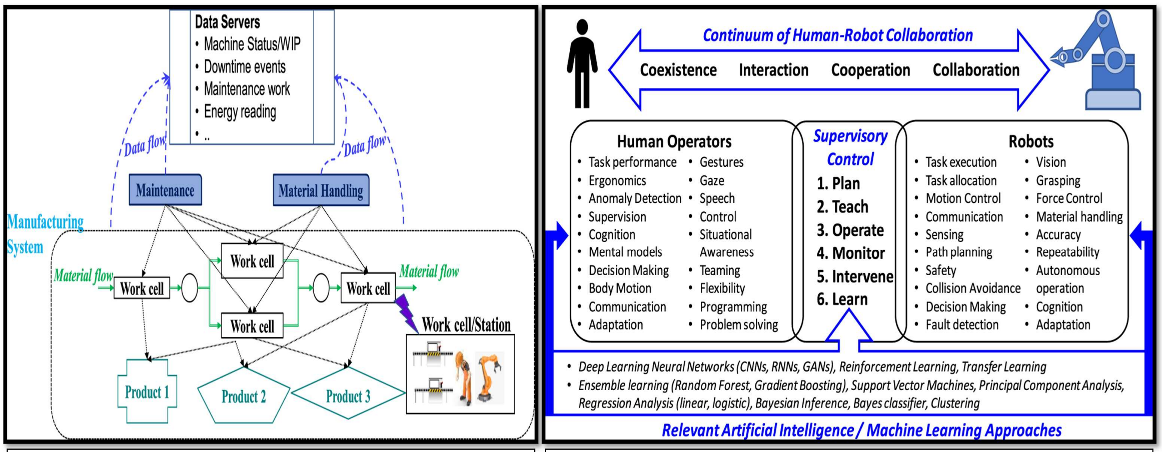


Figure 7. An illustrative representation of the research findings 3.



The Schematic for a modern manufacturing system

The Illustrative sets of actions, functions, requirements, characteristics, behaviors for human operators and robots which are candidates for application of AI/ML approaches

Figure 8. An illustrative representation of the research findings 4.

The integration of artificial intelligence (AI) into human-robot collaboration (HRC) within manufacturing systems represents a significant area of research and development, poised to revolutionize industrial processes. HRC, defined as the simultaneous task execution within a collaborative workspace by both purposedesigned robotic systems and human operators, is undergoing profound transformations due to advancements in AI and machine learning (ML) technologies. Historically, robots were primarily utilized in manufacturing for tasks requiring repeatability, endurance, and strength, while humans focused on cognitive tasks. However, as AI capabilities expand, the traditional boundaries between human and robotic roles are blurring, prompting a reevaluation of the human-robot relationship and the potential for enhanced productivity, flexibility, and adaptability.

The investigative exploration on HRC encompasses a broad array of industrial research areas, each one driving various AI-related technologies applicable to robotic systems [31–57]. To navigate this vast field, a hierarchical framework is proposed illustrated within **Figure 5**, combining human supervisory control theory with a classification scheme for HRC characteristics. This framework aids in categorizing AI-based technologies and identifying key areas of research and application within HRC. It highlights the evolving nature of human-robot interactions, the challenges posed by industrial safety requirements, and the need to address uncertainties in human behavior and intentions within HRC systems. Characterizing the human-robot relationship is crucial for understanding how manufacturing operations are executed jointly by humans and robots. Four types of HRC collaboration, ranging from independence to simultaneous collaboration on common processes and workpieces, provide a comprehensive framework for describing various operational environments. Additionally, the concept of human supervisory control functions, augmented with an operating function explicitly involving both human and robot task execution, offers insights into the roles of AI in HRC systems.

The framework further delves into specific actions and functions within HRC, such as planning, teaching, operation, monitoring, intervention, and learning, each of which presents opportunities for AI/ML application. Examples include using Bayesian decision-making for optimal task allocation, developing machine learning frameworks for transferring tasks from humans to robots, and implementing deep learning architectures for multimodal fusion in monitoring human-robot interactions. Moreover, addressing uncertainties and variability in human task performance, real-time decision-making, and bi-directional learning between humans and robots are key challenges in advancing HRC. Techniques such as dynamic clustering algorithms for real-time performance improvement, integrated teaching-learning-operating strategies, and predictive modeling of human motions using artificial neural networks demonstrate the potential of AI to enhance collaboration and productivity in manufacturing environments.

The integrated perspective provided by the framework facilitates the mapping of AI/ML technologies to existing and potential HRC applications, offering insights into problem types and corresponding solutions. By leveraging AI advancements, HRC holds the promise of transforming manufacturing processes, driving efficiency, flexibility, and innovation in industrial operations.

6. Discussions and future research directions

In the realm of advanced manufacturing, the integration of artificial intelligence (AI) systems presents both challenges and opportunities for future research endeavors. One crucial area for exploration lies in system-level analysis, where the stochastic and non-linear nature of manufacturing systems poses complexities for decision-making processes. While machine learning (ML) has found success in specific applications within manufacturing, such as process monitoring and optimization, its utilization at the system level remains limited. Addressing this challenge requires a deeper understanding of manufacturing processes and the selection of appropriate AI techniques and algorithms.

Data quality emerges as another significant concern in the context of AI integration in manufacturing. The increasing availability of heterogeneous data introduces challenges related to data curation, as irrelevant or redundant information may overshadow crucial data points. Ensuring the quality of manufacturing data is essential for the effectiveness of AI algorithms and the generation of actionable insights. Furthermore, transfer learning and data synthesis techniques offer promising avenues to overcome data scarcity issues and enhance the robustness of AI models.

Modeling material-processing-property relationships represents another area ripe for exploration in future research endeavors. Achieving a comprehensive understanding of these relationships is vital for ensuring the desired performance of manufactured parts. AI techniques hold the potential to streamline the modeling process and improve prediction accuracy, thereby enhancing productivity across various manufacturing processes.

Promoting trust in AI remains a critical challenge in manufacturing, as the interpretation of AI analysis results may be inaccessible to individuals lacking specialized skills in data science. Transparent and explainable AI models is greatly needed to bridge this gap and facilitate the adoption of AI technologies as powerful tools for enabling smart manufacturing. The practical implementation of AI in manufacturing environments requires further attention, as companies seek to adapt and implement state-of-the-art AI solutions to improve production efficiency and reduce costs.

Addressing these challenges and leveraging emerging opportunities in AI research will be essential for advancing the capabilities of advanced manufacturing systems and realizing the full potential of AI-driven innovations in the industry. Through interdisciplinary collaboration and a concerted research effort, the integration of AI into manufacturing holds the promise of revolutionizing production processes and driving continued progress in the field.

7. Conclusions

The comprehensive investigative exploration conducted in this work highlights the current utilization of artificial intelligence (AI) in manufacturing systems and processes across multiple hierarchical levels. It underscores the diverse range of AI tools already deployed to address various challenges within manufacturing, while also recognizing the existing limitations and opportunities for further advancement. One notable observation is the varying degrees of success in implementing these tools, each accompanied by unique challenges. For instance, while supervised learning in manufacturing system control benefits from abundant labeled data, it often grapples with knowledge-sparse problems. Conversely, the simulation of manufacturing systems offers a pathway to knowledge acquisition through the generation of training data, albeit constrained by the model's fidelity to reality.

In the realm of human-robot collaboration (HRC), AI technologies have shown promise in facilitating communication between humans and robots, leveraging inputs such as voice, gesture, gaze, and explicit commands. However, achieving a higher level of cognition in shared workpiece activities remains a subject of ongoing research, necessitating the development of robots with reliable mental models capable of dynamically adapting to human behavior.

The deployment of AI tools for process monitoring, diagnostics, and prognostics has been more extensive due to the abundance of data streams from processes, sensors, and equipment. Conventional machine learning methods rely on high-quality data to extract relevant features, enabling the formulation of classifications and associations with fault types and severity levels. Additionally, the application of AI to enhance understanding of material properties in manufacturing processes has emerged as a promising avenue. AI has expedited the prediction of material properties and experimental results, significantly reducing the time required compared to conventional methods. This predictive capability spans macro and micro levels, encompassing properties like hardness and melting point, thereby informing complex process modeling reliant on time-dependent material properties.

The research also identifies new challenges and opportunities for future research, particularly in the domains of system-level analysis, data quality, model and knowledge transfer, and modeling material-processing-property relationships. Despite these challenges, the overarching trend points towards increased implementation of AI-based analytical tools in manufacturing.

The demonstrated potential of AI to transform manufacturing processes underscores its significance, notwithstanding the need to address existing research gaps and data-related challenges. Ultimately, AI holds immense promise in reshaping the manufacturing landscape, paving the way for enhanced efficiency, productivity, and innovation.

Acknowledgments: The idea representation with the research focusses along with the context concerning the investigative exploration and manuscript writing was done by the author himself. All the datasets, data models, data materials, data information, computing toolsets used and Available online: for the conduction concerning this research are mentioned within the manuscript and acknowledged with its associated references where appropriate.

Availability of data and materials: The various original data models and datasets of which are not all publicly available, because they contain private information. The available platform provided datasets and data models that support the findings and information of the research investigations are referenced where appropriate.

Conflict of interest: The author declares no conflict of interest.

References

1. Tech27. Reducing downtime using AI in Oil and Gas. Available online: https://tech27.com/resources/reducing-downtime-

using-ai-iot-in-oil-gas-exploration-and-production/ (accessed on 30 May 2024).
2. Sallomi P. Artificial Intelligence Goes Mainstream. Available online: https://deloitte.wsj.com/cio/artificial-intelligence-goes-mainstream-1438142473 (accessed on 30 May 2024).
3. Schatsky D, Muraskin C, Gurumurthy R. Cognitive technologies: The real opportunities for business. Available online: https://www2.deloitte.com/tr/en/pages/technology-media-and-telecommunications/articles/cognitive-technologies.html (accessed on 30 May 2024).
4. Krauß J, Hülsmann T, Leyendecker L, Schmitt RH. Application Areas, Use Cases, and Data Sets for Machine Learning and Artificial Intelligence in Production. In: Liewald M, Verl A, Bauernhansl T, et al. (editors). Production at the Leading Edge of Technology. Lecture Notes in Production Engineering. Cham: Springer International Publishing; 2023. pp. 504-513. doi: 10.1007/978-3-031-18318-8_51
5. What Does Collaborative Robot Mean? Available online: https://blog.robotiq.com/what-does-collaborative-robot-mean (accessed on 30 May 2024).
6. Monostori L, Kádár B, Bauernhansl T, et al. Cyber-physical systems in manufacturing. CIRP Annals. 2016; 65(2): 621-641. doi: 10.1016/j.cirp.2016.06.005
7. Wuest T, Weimer D, Irgens C, et al. Machine learning in manufacturing: advantages, challenges, and applications. Production & Manufacturing Research. 2016; 4(1): 23-45. doi: 10.1080/21693277.2016.1192517
8. Lu SCY. Machine learning approaches to knowledge synthesis and integration tasks for advanced engineering automation. Computers in Industry. 1990; 15(1): 105-120. doi: 10.1016/0166-3615(90)90088-7
9. Jourdan N, Longard L, Biegel T, et al. Machine Learning for Intelligent Maintenance and Quality Control: A Review of Existing Datasets and Corresponding Use Cases. Hannover: publishing; 2021. doi: 10.15488/11280
10. Azavedo A. KDD, SEMMA and CRISP-DM: A parallel overview. Available online: https://www.semanticscholar.org/paper/KDD%2C-SEMMA-and-CRISP-DM%3A-a-parallel-overview-Azevedo-Santos/6bc30ac3f23d43ffc2254b0be24ec4217cf8c845 (accessed on 30 May 2024).
11. Krauß J, Dorißen J, Mende H, et al. Machine Learning and Artificial Intelligence in Production: Application Areas and Publicly Available Data Sets. In: Wulfsberg JP, Hintze W, Behrens BA (editors). Production at the leading edge of technology. Berlin, Heidelberg: Springer; 2019. pp. 493-501.
12. Panayotov V, Chen G, Povey D, et al. Librispeech: An ASR corpus based on public domain audio books. In: Proceedings of the 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp. 5206-5210.
13. OpenAI. GPT-4 Technical Report. arXiv. 2023; arXiv:2303.08774.
14. Arinez JF, Chang Q, Gao RX, et al. Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook. Journal of Manufacturing Science and Engineering. 2020; 142(11). doi: 10.1115/1.4047855
15. PWC. Pwc’s Global Artificial Intelligence Study: Sizing the Prize. Available online: https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html (accessed on 30 May 2024).
16. Mozaffar M, Liao S, Xie X, et al. Mechanistic artificial intelligence (mechanistic-AI) for modeling, design, and control of advanced manufacturing processes: Current state and perspectives. Journal of Materials Processing Technology. 2022; 302: 117485. doi: 10.1016/j.jmatprotec.2021.117485
17. Wang L. From Intelligence Science to Intelligent Manufacturing. Engineering. 2019; 5(4): 615-618. doi: 10.1016/j.eng.2019.04.011
18. Chui L, Kamalnath V, McCarthy B. An Executive’s Guide to AI, McKinsey. Available online: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/an-executives-guide-to-ai (accessed on 30 May 2024).
19. Cardon D, Cointet JP, Mazières A. Neurons Spike Back: The Invention of Inductive Machines and the Artificial Intelligence Controversy. Reseaux. 2018; 5(211): 173-220.
20. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015; 521(7553): 436-444. doi: 10.1038/nature14539
21. Lee J, Davari H, Singh J, et al. Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. Manufacturing Letters. 2018; 18: 20-23. doi: 10.1016/j.mfglet.2018.09.002
22. Li B, Hou B, Yu W, et al. Applications of artificial intelligence in intelligent manufacturing: a review. Frontiers of Information Technology & Electronic Engineering. 2017; 18(1): 86-96. doi: 10.1631/fitee.1601885
23. Zhong RY, Xu X, Klotz E, et al. Intelligent Manufacturing in the Context of Industry 4.0: A Review. Engineering. 2017;

3(5): 616-630. doi: 10.1016/j.eng.2017.05.015
24. Sharp M, Ak R, Hedberg T. A survey of the advancing use and development of machine learning in smart manufacturing. Journal of Manufacturing Systems. 2018; 48: 170-179. doi: 10.1016/j.jmsy.2018.02.004
25. Godfrey C, Brown D, Emerson T, et al. On the Symmetries of Deep Learning Models and their Internal Representations. In: Proceedings of the Thirty-fifth Conference on Neural Information Processing Systems; 2022.
26. Courts N, Kvinge H. Bundle Networks: Fiber Bundles, Local Trivializations, and a Generative Approach to Exploring Many-to-one Maps. In: Proceedings of the International Conference on Learning Representations; 2021.
27. Howland S, Kassab L, Kappagantula K, et al. Parameters, Properties, and Process: Conditional Neural Generation of Realistic SEM Imagery Toward ML-Assisted Advanced Manufacturing. Integrating Materials and Manufacturing Innovation. 2023; 12(1): 1-10. doi: 10.1007/s40192-022-00287-y
28. Green SA, Billinghurst M, Chen X, et al. Human-Robot Collaboration: A Literature Review and Augmented Reality Approach in Design. International Journal of Advanced Robotic Systems. 2008; 5(1): 1. doi: 10.5772/5664
29. Verma A, Kumar S. Cognitive robotics in artificial intelligence. In: Proceedings of the 2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence). pp. 65-70.
30. Duan F, Tan JTC, Arai T. A New Human-Robot Collaboration Assembly System for Cellular Manufacturing. In: Proceedings of the Chinese Control Conference; 2011; Yantai, China. pp. 5468-5473.
31. Marvel JA, Falco J, Marstio I. Characterizing Task-Based Human–Robot Collaboration Safety in Manufacturing. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2015; 45(2): 260-275. doi: 10.1109/tsmc.2014.2337275
32. Robla-Gomez S, Becerra VM, Llata JR, et al. Working Together: A Review on Safe Human-Robot Collaboration in Industrial Environments. IEEE Access. 2017; 5: 26754-26773. doi: 10.1109/access.2017.2773127
33. Nikolaidis S, Lasota P, Rossano G, et al. Human-robot collaboration in manufacturing: Quantitative evaluation of predictable, convergent joint action. In: Proceedings of the IEEE ISR 2013. pp. 1-6.
34. Helms E, Schraft RD, Hagele M. rob@ work: Robot assistant in industrial environments. In: Proceedings of the 11th IEEE international workshop on robot and human interactive communication. pp. 399-404.
35. Wang XV, Seira A, Wang L. Classification, Personalised Safety Framework and Strategy for Human-Robot Collaboration. In: Proceedings of the International Conference on Computers and Industrial Engineering; 2018; Auckland, New Zealand.
36. Sheridan TB. Telerobotics, Automation, and Human Supervisory Control. MIT Press; 1992.
37. Sheridan TB. Human-Robot Interaction. Human Factors: The Journal of the Human Factors and Ergonomics Society. 2016; 58(4): 525-532. doi: 10.1177/0018720816644364
38. Rahman SMM, Liao Z, Jiang L, Wang Y. A Regret-Based Autonomy Allocation Scheme for Human-Robot Shared Vision Systems in Collaborative Assembly in Manufacturing. In: Proceedings of the IEEE International Conference on Automation and Science Engineering; 2016. pp. 897-902.
39. Brady M. Artificial intelligence and robotics. Artificial intelligence. 1985; 26(1): 79-121.
40. Roncone A, Mangin O, Scassellati B. Transparent role assignment and task allocation in human robot collaboration. In: Proceedings of the 2017 IEEE International Conference on Robotics and Automation (ICRA). pp. 1014-1021.
41. Huang CM, Mutlu B. Anticipatory robot control for efficient human-robot collaboration. In: Proceedings of the 2016 11th ACM/IEEE international conference on human-robot interaction (HRI). pp. 83-90.
42. Doltsinis S, Krestenitis M, Doulgeri Z. A Machine Learning Framework for Real-Time Identification of Successful Snap-Fit Assemblies. IEEE Transactions on Automation Science and Engineering. 2020; 17(1): 513-523. doi: 10.1109/tase.2019.2932834
43. Akan B, Curuklu B, Spampinato G, et al. Towards Robust Human Robot Collaboration in Industrial Environments. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction; 2010; Osaka, Japan. pp. 71-72.
44. Karoly AI, Kuti J, Galambos P. Unsupervised real-time classification of cycle stages in collaborative robot applications. In: Proceedings of the 2018 IEEE 16th World Symposium on Applied Machine Intelligence and Informatics (SAMI). pp. 000097-000102.
45. Batth RS, Nayyar A, Nagpal A. Internet of robotic things: driving intelligent robotics of future-concept, architecture, applications and technologies. In: Proceedings of the 2018 4th international conference on computing sciences (ICCS). pp. 151-160.
46. Sadrfaridpour B, Wang Y. Collaborative Assembly in Hybrid Manufacturing Cells: An Integrated Framework for Human-Robot Interaction. IEEE Transactions on Automation Science and Engineering. 2018; 15(3): 1178-1192. doi:

10.1109/tase.2017.2748386
47. Liu H, Fang T, Zhou T, et al. Towards Robust Human-Robot Collaborative Manufacturing: Multimodal Fusion. IEEE Access. 2018; 6: 74762-74771. doi: 10.1109/access.2018.2884793
48. Sariel S, Yildiz P, Karapinar S, et al. Robust task execution through experience-based guidance for cognitive robots. In: Proceedings of the 2015 International Conference on Advanced Robotics (ICAR). pp. 663-668.
49. Reimann J, Sziebig G. The Intelligent Factory Space—A Concept for Observing, Learning and Communicating in the Digitalized Factory. IEEE Access. 2019; 7: 70891-70900. doi: 10.1109/access.2019.2919340
50. Ravichandar HC, Dani A. Human intention inference and motion modeling using approximate EM with online learning. In: Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). pp. 1819-1824.
51. Zhang J, Liu H, Chang Q, et al. Recurrent neural network for motion trajectory prediction in human-robot collaborative assembly. CIRP Annals. 2020; 69(1): 9-12. doi: 10.1016/j.cirp.2020.04.077
52. Wang W, Li R, Chen Y, et al. Facilitating Human-Robot Collaborative Tasks by Teaching-Learning-Collaboration from Human Demonstrations. IEEE Transactions on Automation Science and Engineering. 2019; 16(2): 640-653. doi: 10.1109/tase.2018.2840345
53. Zhao R, Yan R, Chen Z, et al. Deep learning and its applications to machine health monitoring. Mechanical Systems and Signal Processing. 2019; 115: 213-237. doi: 10.1016/j.ymssp.2018.05.050
54. Akhtar ZB. The design approach of an artificial intelligent (AI) medical system based on electronical health records (EHR) and priority segmentations. The Journal of Engineering. 2024; 2024(4). doi: 10.1049/tje2.12381
55. Akhtar ZB. Securing Operating Systems (OS): A Comprehensive Approach to Security with Best Practices and Techniques. International Journal of Advanced Network, Monitoring and Controls. 2024; 9(1): 100-111. doi: 10.2478/ijanmc-2024-0010
56. Akhtar ZB, Gupta AD. Integrative Approaches for Advancing Organoid Engineering: From Mechanobiology to Personalized Therapeutics. Journal of Applied Artificial Intelligence. 2024; 5(1): 1-27. doi: 10.48185/jaai.v5i1.974
57. Akhtar ZB. Advancements within Molecular Engineering for Regenerative Medicine and Biomedical Applications an Investigation Analysis towards A Computing Retrospective. Journal of Electronics, Electromedical Engineering, and Medical Informatics. 2024; 6(1). doi: 10.35882/jeeemi.v6i1.351