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INDUSTRY 5.0: HUMAN-ROBOT INTERACTION, SMART MANUFACTURING, AND AI/ML INTEGRATION—A COMPREHENSIVE REVIEW FOR NEXT-GENERATION MANUFACTURING SYSTEMS

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Abstract
The current development of manufacturing technologies and the ongoing necessity to build sustainable and human-focused production systems are posing a serious threat to the conventional automated manufacturing systems. The Industry 5.0 vision that entails billions of intelligent devices cooperating with human laborers in intelligent manufacturing network must resolve the issue of human-machine synergy and leverage the new technologies of artificial intelligence, machine learning, and cyber-physical systems. Human-centricity is a challenge that has limited human-centricity in the current continuum of Industry 4.0 applications, which drives us to consider human-robot collaboration (HRC) as the solution to the next-generation manufacturing. Industry 5.0 allows pigmenting human capabilities through intelligent robotic systems without compromising the human creativity, flexibility, and ability to make decisions. This paper aims to discuss Industry 5.0 as a paradigm shift in the development of human-centric smart manufacturing and open the way to intelligent production systems of the future to struggle against the sustainability, resilience, and well-being of the working community. We initially point out the transformation of Industry 4.0 into Industry 5.0 and the overall change in manufacturing towards being human centered. Then we explore HRC as an effective intervention to improve the safety and productivity at work place. Next, we discuss the smart manufacturing architecture such as IIoT, cyber-physical systems, and digit twin applications, to exploit the interconnected digital technologies. To learn about data processing and system optimization, we illustrate predictive maintenance and quality control as well as data-based optimization schemes of production that use AI/ML. In addition, we also explain industrial communication standards (OPC UA, MQTT), programming environments (Python, R, MATLAB, Node-RED), and sensor integration methods towards the implementation of Industry 5.0 systems. In a similar manner, to meet the workforce development demands, sufficient extended reality (XR) training solutions and human-machine interface designs are discussed, as well as the aspects of sustainability and the integration of the circular economy. Lastly, we point out the Industry 5.0 applications with current research issues and future perspectives of the next-generation smart manufacturing systems.

INTRODUCTION

Based on the industry estimates, the market of smart manufacturing will continue to grow to $384.8 billion by 2025, as more manufacturers advance AI, IoT, and robotics solutions in a bid to improve the efficiency of their operations [1]. Equally, 78 percent of manufacturers, according to Deloitte 2025 Smart Manufacturing and Operations Survey, have adopted or are planning to adopt AI-driven automation technologies [2]. This massive implementation of smart technologies in the production process, the accentuation on human-robot cooperation systems, and the combination of IIoT with smart-physical systems enables manufacturing processes to be attached to ubiquitous digital networks [3]. Nevertheless, the issue of traditional Industry 4.0 implementations is the smaller emphasis on the human-centricity and well-being of the workers. Therefore, numerous effective automated manufacturing systems do not utilize human creativity, adaptability, and decision-making in full [4].

In recent years, the sphere of manufacturing has achieved a lot in terms of technology, such as integration of artificial intelligence and machine learning to predict analytics, connection of smart equipment in IIoT networks, the use of cyber-physical systems to monitor in real-time, and better methods of collaboration between humans and robots [5]. Such technological progress is slowly taking us to one of the most revolutionary stages of production- the next generation of human-centric smart manufacturing- Industry 5.0 that will add value to human ability without removing the advantages of automation in the new intelligent production models [6], [7].

1.1. Limited Human-Centricity: A Challenge

Conventional Industry 4.0 deployments are mainly centered on automation effectiveness and cost-reduction, commonly considering human employees as parts, which could be substituted instead of empowering them [8]. Until the recent past, the manufacturing systems were more concerned with the technological development without fully taking into account the state of the workers, job satisfaction, and the human qualities of creativity and adaptability which are not easily replaceable [9]. Figure 1 shows the evolution from Mechanization to Humanization. Today Industry 5.0 is focused on human-centered solutions that view workers as key sources of innovation and the ability to solve issues. This paradigm shift promotes sustainable production as well as improving workforce participation. In addition to the efforts to maximize the automation, there are a number of suggestions targeting the human-centricity issues in manufacturing[9], [10].

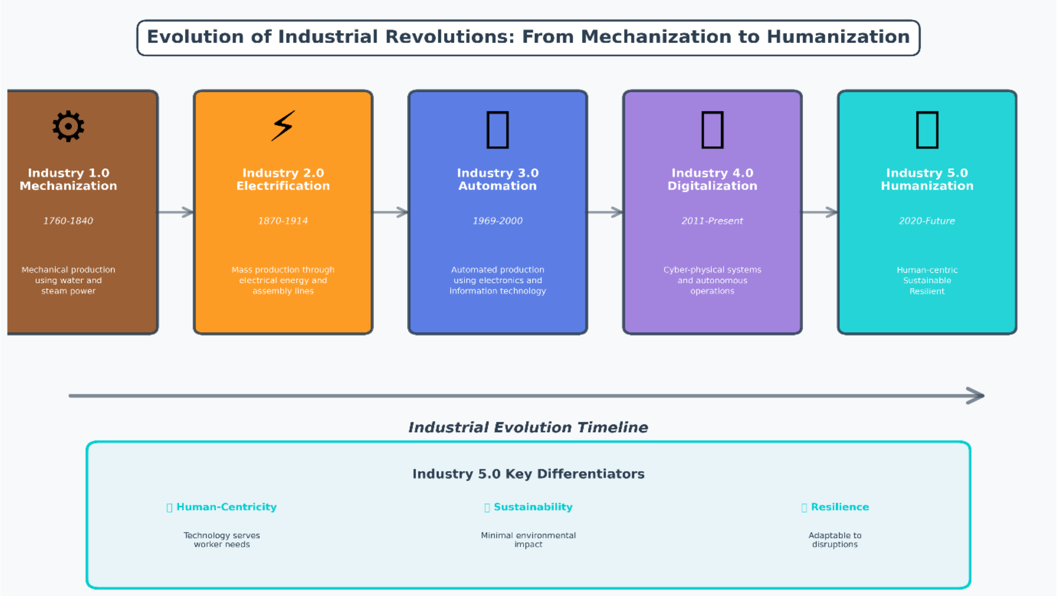

Figure 1: Evolution of Industrial Revolutions from Industry 1.0 to Industry 5.0

These proposals include:

- Human-robot cooperation systems to combine human creativity and robot accuracy with concerns on workplace safety and ergonomics[11];
- Adoption of AI/ ML technologies to support the workings of human decision-making, instead of overtaking human workers[12];
- Virtual work experiences to improve employee competencies and minimize accidents in the workplace [13], [14] ;
- Optimization production plans that are based on data can enable employees with practical knowledge and still maintain human autonomy[15], [16].

Such human-focused solutions improve the interactions and satisfaction of employees without losing the advantages of automation[16], [17]. Nevertheless, the realization of a human-machine synergy is one of the basic challenges that presuppose a wide-scale connection of various technologies[18]. So, what would be the answer to this enduring predicament? This is the issue that encourages us to investigate Industry 5.0 concepts.

1.2. Towards Human-Centric Smart Manufacturing

What would happen to the manufacturing systems should they be able to incorporate human intelligence and efficiency with machine efficiency seamlessly? Human creativity and adaptability would not be lost since we are reaping the gains of automation[19], [20]. The vision would enable manufacturers to prevent the adverse effects of too much automation such as losing employees to jobs that are being automated, lack of innovation and job satisfaction[21], [22]. Industry 5.0 Smart manufacturing systems would enable human workers to have smart tools. The concept of human-centric manufacturing allows employees to add value to the work and have the support of sophisticated technologies. Industry 5.0 has positive aspects as outlined below:

- Robot accuracy can be used in manufacturing processes as well as human ingenuity.
- Employees enjoy increased job satisfaction and significant involvement.
- The production systems are in a better position of sustainability and resilience.

These characteristics would transform the existing idea of automating the manufacturing process. Besides, such features would allow genuinely intelligent production systems that would take sustainability concerns into account and respect human dignity. The manufacturing plants would be very efficient and at the same time keep both the workers as well as the environment[23]. The most recent studies by the European Commission have presented the Industry 5.0 paradigm, which focuses on human-centricity, sustainability, and resilience as the complementary policies to the efficiency-centered approach of Industry 4.0[24]. This model gives a good guideline to the manufacturers that are moving towards Industry 5.0 implementations.

1.3. Human-Robot Collaboration: A Solution to Limited Human-Centricity

Conventional industrial robots are used in secluded cells where they are not in contact with the human workers to avoid accidents. Human-robot collaboration (HRC) is a form of robotics, unlike traditional industrial robotics, which enables human and robot to establish their mutual workspaces, enabling the two parties to utilize their complementary abilities[25], [26]. Nevertheless, HRC discusses the benefit of collaborative robots (cobots) that will have enhanced safety (e.g., force limiting, collision detection, adaptive control), and in this way will transform manufacturing processes[27]. Nowadays, the development of HRC systems with the improvement of productivity, as well as safety, is of great interest among the researchers who want to overcome the human-centricity issues in smart manufacturing[27].

The benefits of Industry 5.0 are AI-based robotic systems that can learn by watching people, as well as adaptive control algorithms with multi-modal sensing capabilities[28]. Cobots can learn by responding to human intentions with these technologies and changing their behavior. Therefore, we examine HRC systems that facilitate human-centric production in the new smart production settings[27], [29]. The current literature has provided comprehensive reviews of the most recent advances in collaborative robotics and safety standards of the HRC applications.

Our survey adds to these works by considering HRC through the lens of Industry 5.0 as an approach that incorporates human-centricity with new technologies, such as AI/ML, IoT, cyber-physical systems, and extended reality. Moreover, our direction closes the gap between past studies of Industry 4.0 orientation and current trends in Industry 5.0 in that we include integrated smart manufacturing ecosystems that prioritize human work and take advantage of advanced automation.

This paper will attempt to provide a comprehensive survey on Industry 5.0 as a new paradigm towards attaining human-centric smart manufacturing in next generation production systems. To be specific, the following points are addressed in this paper:

- We talk about Industry 4.0 to Industry 5.0 and introduce HRC as the one of the possible solutions to human-centric manufacturing.
- Our offerings are intelligent manufacturing systems such as IIoT architecture, cyber-physical systems, and Industry 5.0 implementation of digital twins.
- We show AI/ML solutions such as predictive maintenance, quality control and data-driven production optimization schemes.
- We emphasize the industrial communication standards, programming platforms, and sensor integration methods to apply the Industry 5.0 systems.
- We demonstrate workforce training applications, future approaches to research publication, and sustainability issues and work directions.

The remainder of the article will be structured in the following way. Part 2 is dedicated to the Industry 5.0 paradigm shift of technology-driven to human-centric manufacturing. Section 3 addresses human-robot collaboration systems and safety issues. Section 4 discusses intelligent manufacturing technologies such as IIoT, communication protocols and cyber-physical systems. In Section 5, AI/ML uses in predictive maintenance, quality control, and optimization of production are described. Section 6 thinks about the programming tools and sensor integration with Industry 5.0 implementation. Section 7 represents examples of extended reality technologies to develop the workforce. Section 8 refers to the future trends, sustainability and outlook. Lastly, there is a conclusion to the article in Section 9.

2. The Industry 5.0 Paradigm: From Technology-Driven to Human-Centric Manufacturing

The shift, which occurred between the Industry 4.0 and Industry 5.0, is not just an incremental advancement in technology, but it is a complete re-imagination of how humans and the manufacturing technologies relate to one another[4], [7]. The concept of Industry 5.0 was a result of the realization of the shortcomings of the fully automation-oriented strategy and invaluable role of human imagination, flexibility, and moral judgment in the manufacturing environment[7], [12].

2.1. Defining Industry 5.0

European Commission officially introduced the Industry 5.0 concept, which is seen as a continuation of Industry 4.0, making research and innovation its drivers towards a sustainable, human-centered, and resilient European industry[30], [31]. Within this definition, three pillars form its basics as shown in

Figure 2:

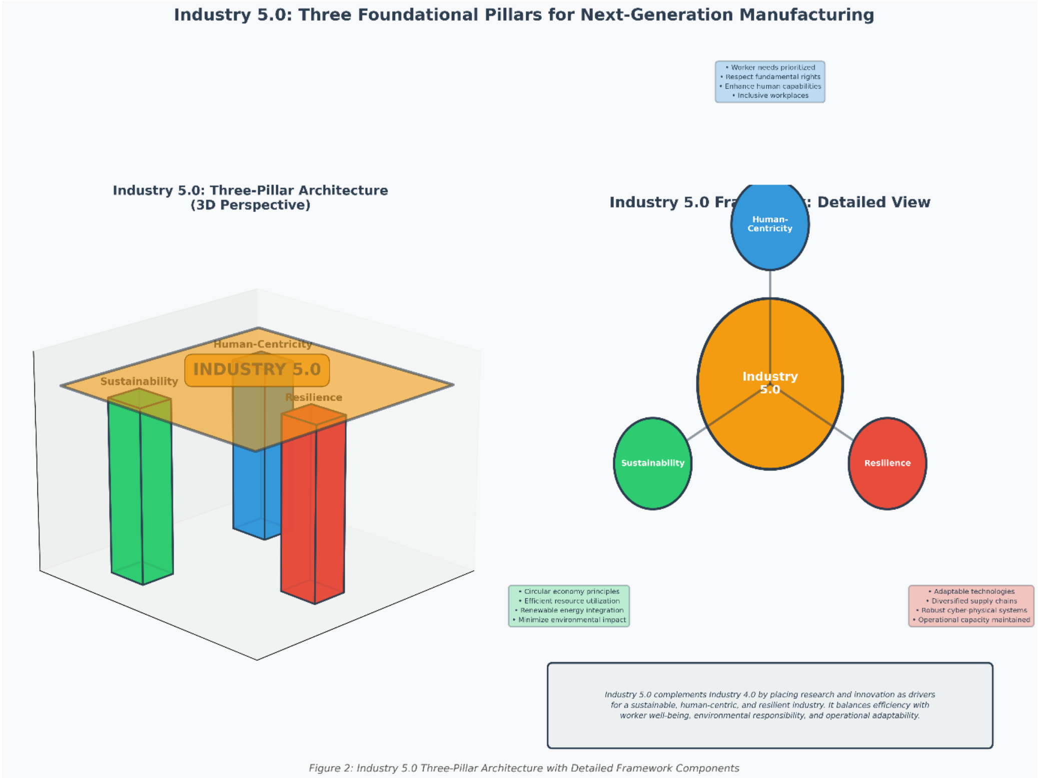

Figure 2: Industry 5.0 Three-Pillar Architecture with Detailed Framework Components

Human-centricity: The manufacturing systems shall be geared to meet the needs of the workers, as well as consider the basic rights of humanity, autonomy, and privacy in the workplace, in addition to establishing inclusive workplaces. This pillar will make sure that the implementation of technologies can boost the human capabilities and job satisfaction but not reduce them.

Sustainability: The production processes are environmentally friendly by considering the concept of the circular economy, efficient use of resources, and the use of renewable energy. Industry 5.0 acknowledges planetary boundaries as restriction limits within which manufacturing has to operate.

Resilience: The manufacturing systems are resilient to disruptive attacks by having flexible technologies, diversified supply chain, and strong cyber-physical infrastructures. Strong structures adapt well to the market variations, supply chain disruptions, and unforeseen difficulties.

2.2. Evolution from Industry 4.0

Table 1 Shows the complete evolution. The initial industrial revolution entailed the mechanical production with the aid of water and steam . Mass production became a reality in the second revolution with the help of electrical energy and assembly lines. The third revolution allowed automated production by the means of electronics and information technology. The fourth revolution involved the introduction of the cyber-physical systems and self-directed functioning with availability of interrelated smart technologies[32].

Table 1: Complete Evolution from Industry 1.0 to 5.0

Industrial Revolution	Era	Key Technologies	Focus	Worker Role
Industry 1.0	1760s–1840s	Water/steam power	Mechanization	Labor replacement
Industry 2.0	1870s–	Electrical power, assembly lines	Mass production	Mass labor

	1970s			
Industry 3.0	1970s–2010s	Electronics, IT, computers	Automation	System monitoring
Industry 4.0	2010s–present	IoT, AI, cyber-physical systems	Autonomous operations	Limited involvement
Industry 5.0	2020s–future	Human-AI synergy, resilience, sustainability	Human-machine collaboration	Active partnership

Industry 5.0 takes the Industry 4.0 as the basis and tackles the urgent gaps. Where Industry 4.0 focused on the ability to substitute human labor with automation, Industry 5.0 focuses on expanding human abilities by using collaborative technologies[6], [30], [33]. Where Industry 4.0 focused on efficiency and productivity, Industry 5.0 strikes a balance between the two and sustainability and human well-being of the workers. Industry 4.0 focused on creating autonomous systems, whereas Industry 5.0 focuses on developing symbiotic human-machine relationships, which use complementary advantages[30].

2.3. Human-Centric Manufacturing Principles

Human centric production appreciates that human beings possess special attributes to production setups which cannot be imitated by machines. The power of creativity allows innovation and finding solutions to new circumstances[20], [21]. It would enable proper cooperation and leadership. Flexibility enables quick reaction to the changing conditions. Moral judgment determines the responsible decisions that are in accordance with the values of society.

The manufacturing systems that are built in line with the Industry 5.0 principles make technology an empowerment of human potential instead of displacing human workers[4]. There is collaboration between robots and humans where the former perform the physically demanding, repetitive or hazardous work but the latter are involved in solving problems creatively, making quality judgments and initiating constant improvement projects [12]. AI systems can be used to support decision-making by studying massive amounts of data and detecting patterns in this data, whereas humans apply their insights to the larger context and decide taking into account ethical consequences[34].

2.4. Discussion

This part is a summary of the Industry 5.0 paradigm and how it differs with the past industrial paradigms. The significant contributions are as follows:

1. In its definition, the European Commission sets three cornerstone pillars, namely human-centricity, sustainability, and resilience, as additional objectives to the efficiency of Industry 4.0. Such a framework gives a definite roadmap to manufacturers who move towards Industry 5.0 implementations by making the articulation that the success of technology depends on striking a balance between human needs and its efficiency in operations[4].
2. The 5.0 industry supports the most severe shortcomings of totally automation-oriented strategies, such as acknowledging the invaluable role of human creativity, flexibility, and moral judgment. This realization makes manufacturing philosophy more of human ability enhancement than the replacement of human labor, thus workforce engagement and not displacement[21].
3. Human-centric manufacturing values make technology an enabler and not a substitute to allow the system to be able to take advantage of the complementary human and machine strengths. This can be used to increase productivity and worker satisfaction by developing meaningful work environments where technology helps to supplement human contribution, as opposed to reducing it.[21]
4. The shift to Industry 5.0 calls manufacturers to rethink the approaches to the application of technologies so that the new systems would create more opportunities to humans without violating their basic rights and encouraging sustainable use. The strategic change impacts the system design, training of workers and the organizational culture[35].

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3. Human-Robot Collaboration: An Effective Solution

Human-robot collaboration is the technology that is the foundation of the human-focused vision of Industry 5.0[4], [36]. HRC systems enable human beings to collaborate with robots on the same working areas and integrate human thinking with robot accuracy and consistency[27]. This chapter examines HRC systems, safety standards, communication strategies, and AI integration to work together in the manufacturing. Figure 3 shows the Human-Robot Collaboration: System Architecture and Safety Standards.

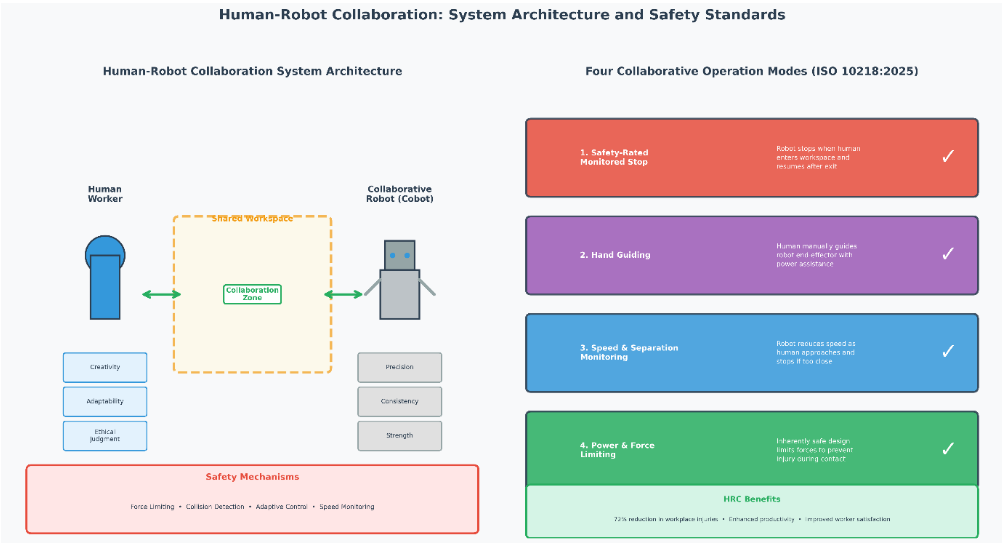

Figure 3: Human-Robot Collaboration System with Safety Mechanisms and Collaborative Operation Modes

3.1. Understanding HRC Systems

Conventional industrial robots work within safety fences since they are very fast, have a big capacity and may be dangerous to other humans near the robots[37]. Cobots (also known as collaborative robots) are specifically developed to operate safely together with human workers using a variety of safety features[38]. Force limiting ensures that the cobot is not able to act with a high amount of force which can hurt someone in case of unplanned contact[38], [39]. The sensors are used in collision detection that instantly halts the movement of the robot in case of human presence. The adaptive control algorithms vary the speed or path of the robot depending on the distance between the robot and the human[40].

The International Federation of Robotics estimated that collaborative robotics was going to expand substantially, with the industry shipment amount projected to be much higher as safety and flexibility advantages are acknowledged by manufacturers[41], [42]. The current generation of cobots is much lighter than the old industrial robots and can be reprogrammed easily to perform new functions, as well as being much more affordable to use and maintain[42], [43].

What are the ways of safe co-operation of manufacturing operators with high-speed robots? The solution is in joint-design of robots that restricts forces and velocities by making innovative mechanical and control systems. Sophisticated sensory arrays can sense the presence of people and surrounding activities which can be used to alter the behavior of the robots in real time[12], [44].

3.2. Safety Standards and Guidelines

The most important issue of HRC implementations is safety. Numerous international standards offer integrated guidelines on safe coexistence of humans and robots. The ISO 10218:2025 standard (which incorporates the previous ISO/TS 15066 to collaboratively operate robots) sets safety standards concerning the industrial robot systems and collaborative robots (in applications)[45], [46]. ANSI/RIA R15.06 in the United States are complementary safety standards, which cover the safety-rated monitoring, collaborative workspace design, and risk assessment[26].

These standards present four ways of collaborative operations:

Stop with safety rating: When a human being enters the collaborative work place, the robot will automatically stop and will resume their work when the human leaves[47].

Hand guiding: A human operator also controls the robot end-effector using his hand, and the robot assists with providing power to the heavy parts[39], [48].

Speed monitoring and separation monitoring: The robot decreases speed when human are near and halts in case minimum separation distances are not met[46], [48].

Restraints of power and force: Naturally designed safe robot designs restrict power to levels that cannot harm the contacting parties even at the point of contact[39], [49].

Studies have shown that well installed HRC systems can minimize the injuries at the workplace by up to 72 percent in comparison with the conventional manufacturing surroundings[37], [50]. These advantages of safety can be attributed to the fact that cobots take on physically challenging and hazardous jobs and put repetitive strain injuries in the background as well as cut down human error in case of fatigue[41], [51].

3.3. Communication in HRC

Successful interaction between human beings and robots needs to be intuitive. The conventional industrial robots need specific programming skills, which puts a barrier between workers and robots[52], [53]. Contemporary HRC systems make use of various modalities of communication to enable natural human-robot interaction[54].

Verbal Communication: Voice commands enable the workers to command robots in natural language. The speech recognition systems comprehend and convert the commands to the actions of the robot. Voice feedback gives state and intention reports on the robot and alerts[55], [56].

Non-verbal Communication: This is through gestures that allow control of the robot intuitively without having to touch it. Computer vision systems are able to identify the hand signals and body movements to detect human intentions. Visual cues such as display screens and lights communicate the aspect of robot position to the nearby employees[57], [58].

Haptic Communication: Force feedback: The force feedback gives feedback on the hand-guiding operations. Robots can respond to physical contact by using touch sensors that identify touch. Vibration patterns or change of pressure can be used to communicate information using tactile displays[59], [60].

The most up-dated research findings have pointed out communication, both verbal and non-verbal, as one of the factors that contributed to effective HRC implementations. Non-verbal cues can play a significant role in updating the robot status in the collaborative work and improve understanding and coordination between the human employees and cobots[29].

3.4. AI Integration in HRC

Current developments in HRC deployments have been more and more focused on the use of artificial intelligence to allow the adaptive operation of robot and learning by human example. Cobots can visually learn responses to human tasks through machine learning algorithms, which acquire ideal motion patterns, grasping methods, and assembly steps after observing human tasks[43], [61]. Reinforcement learning allows robots to become more efficient due to the trial and error interaction with the environments with the supervision of humans[62].

HRC systems based on AI can also be used to assign tasks dynamically, automatically distributing tasks to people and robots according to task demands, human workload, and robot capacity[27], [63]. Deep learning and computer vision help robots perceive complicated scenes and identify objects in a noisy environment, as well as design grasping strategies that suit various constituents[64], [65].

This idea goes beyond physical cooperation to human-AI synergy, merging human mental faculties such as creativity, situational insight, and moral judgment with AI computational capabilities such as fast information processing, pattern identification and optimization[66]. Such synergy enhances the quality of decision making, operations and innovation level in manufacturing settings.

3.5. Discussion

Table 2 summarizes human-robot collaboration technologies and their applications in Industry 5.0 manufacturing. The main contributions are as follows:

# HRC Technology	Mechanism	Key Benefits	Standards
1	Force limiting	Prevents injury through inherent mechanical design	ISO 10218:2025
2	Collision detection	Real-time monitoring and response to human proximity	ANSI/RIA R15.06
3	Adaptive control	Dynamic speed and trajectory adjustment	ISO/TS 15066
4	Verbal communication	Natural language interaction for task specification	ISO 13849-1
5	Gesture recognition	Non-verbal control and status communication	ISO 10218-2
6	Machine learning	Learning from human demonstrations for task adaptation	ISO 10218-1
7	Reinforcement learning	Performance improvement through human feedback	ANSI/RIA R15.06
8	Dynamic task allocation	AI-based distribution of work between humans and robots	ISO 13849-1

Key conclusions include:

- The collaborative robots have various safety features such as force limiting, collision sensors and adaptive control to facilitate safe working conditions with human workers without the use of safety nets. This is a technological innovation that allows flexible manufacturing arrangements, human-robot collaboration in varied assembly operations.

- The ISO 10218:2025 (ANSI/RIA R15.06) is an international standard of safety that offers a detailed set of guidelines that identify four modes of collaboration and safety requirements. Adherence to such standards will make HRC implementations secure the safety of the workers and full productivity benefit by means of standardized risk assessment and risk management[37].

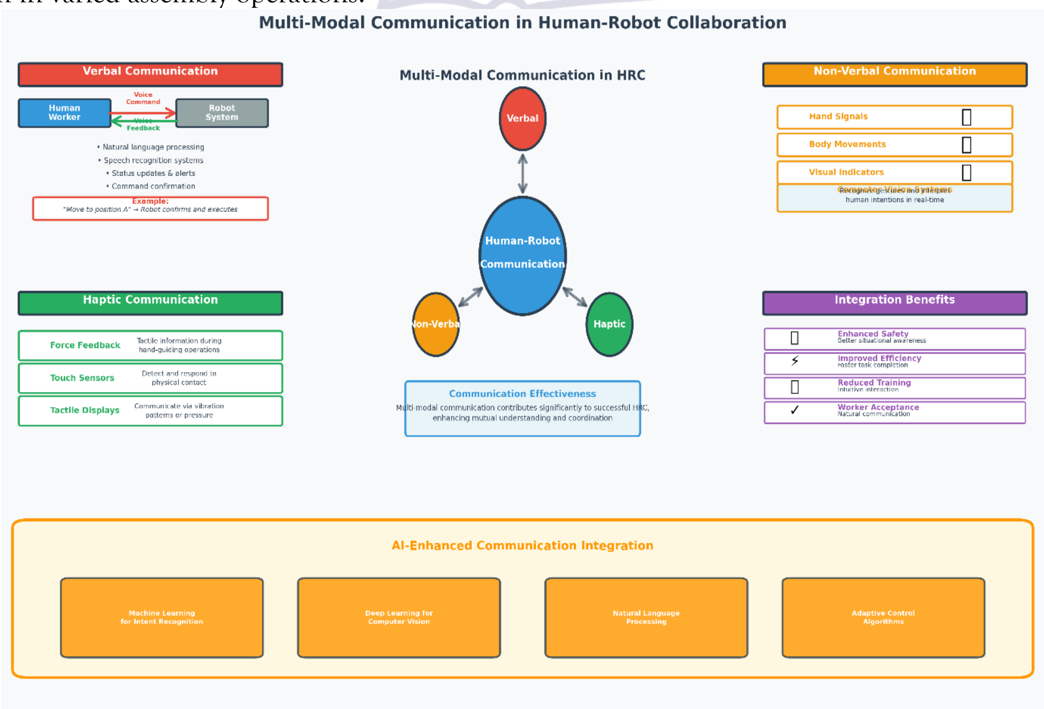

Figure 4: HRC Communication Modalities - Verbal, Non-Verbal, and Haptic Interaction Methods

- Multi-modal communication, such as through verbal commands, gesture recognition and haptic feedback, allows human- robot communication to be intuitive without the need to have specific knowledge of programming skills. Figure 4 shows the multi model communication in Human-Robot Collaboration. Natural communication interfaces decrease training and increase the acceptance of collaborative robotics to workers in manufacturing facilities[67].
- Due to AI integration, cobots can learn human demonstrations, change behaviors according to the environmental factors, and make decisions in the dynamic allocation of tasks. These intelligent features contribute to the flexibility of the HRC systems, as well as the possibility of continuing the improvement of collaborative activities because of the continuous learning[29], [53].
- The studies show that effectively deployed HRC systems can lessen injuries at the workplace by as much as 72 percent and enhance productivity by distributing human and robot tasks optimally. These two advantages of increased safety and effectiveness confirm the humanistic nature of Industry 5.0 to transform the manufacturing process[33], [68].

4. Smart Manufacturing Technologies

Smart manufacturing is the technological basis that allows Industry 5.0 to operate via connected digital systems that allow real-time monitoring, data-driven decision-making and adaptive production[30], [69]. IIoT architectures, communication protocols, cyber-physical systems, digital twins, and extended reality applications are discussed in this section[68], [70]. Figure 5 shows the IIoT Architecture for Smart Manufacturing.

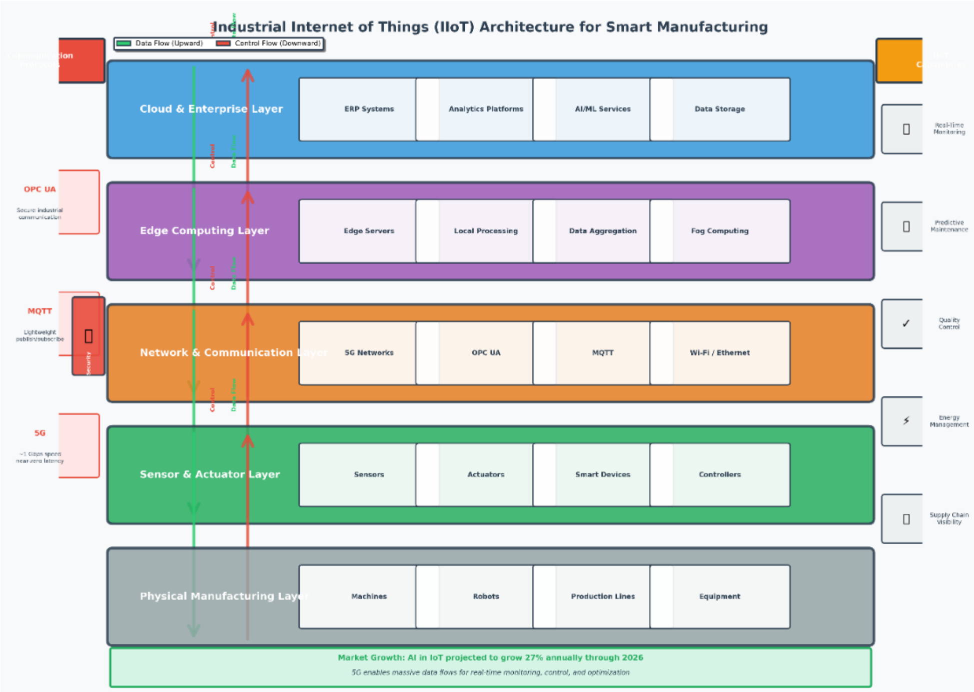

Figure 5: Industrial Internet of Things (IIoT) Architecture - Layered Approach for Smart Manufacturing

4.1. Industrial Internet of Things

The Industrial Internet of Things is the nervous system of the modern smart factories, which links machines, sensors, actuators, and devices into elaborate networks that allow data gathering, data analysis, and control[71]. The IIoTs are systems that incorporate conventional manufacturing devices to include smart sensors, wireless communication units, and edge computing units to form intelligent and responsive production systems[72].

The world AI in IoT market shows speedy growth and it is expected to grow at 27 percent/year till 2026 as manufacturers are becoming more aware of the benefits of the IIoT [73]. Efficient connectivity devices, especially 5G networks, revolutionize IIoT features by offering up to about 1 gigabyte per second download rates and negligible latency[74], [75]. This improves bandwidth to allow huge data flows needed to monitor, control and optimize complex manufacturing processes in real time.

The application of IIoT allows a number of essential functions:

1. Real time equipment monitoring monitors the operational parameters such as temperature, vibration, pressure and energy consumption[76].
2. Predictive maintenance uses sensor data to predict possible failures in equipment prior to them happening[77], [78].
3. Vision sensors and measurement gadgets allow quality control systems to detect defects during production[79], [80].
4. Energy management tracks the consumption patterns and manages them in the most efficient way possible in order to save on costs and impact on the environment[81], [82].
5. Supply chain visibility is a monitoring tool that monitors materials, parts, and completed goods along the manufacturing and distribution chains[83], [84].

4.2. Industrial Communication Protocols

Modern industrial systems need a standard communication protocol that will guarantee communication interoperability among various equipment of different vendors. There are two protocols that prevail in Industry 5.0 implementations: OPC UA (Open Platform Communications Unified Architecture) and MQTT (Message Queuing Telemetry Transport[85], [86]).

OPC UA is a complete framework that is a secure and platform-independent industrial communication. The protocol is compatible with hierarchical data model of complicated machine structures, process parameters and production information[87]. Inbuilt security systems comprise encryption, authentication, authorization and audit logging to counter the cyber threats. OPC UA also allows both client-server designs around conventional request-response designs and publish-subscribe designs to provide an efficient event-driven communication design[88].

MQTT is a simple publish/subscribe protocol that is optimized to run on a small device with a low-quality network[89]. The low overhead of the protocol is suitable to the devices in the IoT that have low processing power and battery capacity. The quality-of-service levels of MQTT provide delivery of messages depending on its application needs of the best-effort delivery as well as guaranteed exactly-once delivery[90], [91].

More and more manufacturers are using hybrid communication structures that combine the two protocols. OPC UA is used to implement structured industrial communication to secure factory networks, and it offers machine-to-machine interactions with semantic richness and security. MQTT supports cloud-connectivity and off-secure-network data-transmission, which allows analytics platforms and remote-monitoring systems to access the production data[91], [92], [93].

4.3. Cyber-Physical Systems

Cyber-physical systems are the combination of computer algorithms with physical manufacturing systems by means of embedded computers, sensors, actuators, and networks[94]. CPS implementations watch physical systems in real-time, process sensor information with embedded algorithms and it controls actuators by decisions computed, to form closed-loop feedback systems[95].

In world, CPS market size stood at 118.20 billion in 2024 and it is expected to grow at 13.7 percent per annum to 2030. This high rate of market expansion indicates growing awareness in the benefits of CPS such as high operational efficiency, quality products, lessening downtime, and increasing resource utilization[96], [97].

Figure 6 shows the cyber-physical systems: five layer architecture for for Industry 5.0. CPS architectures usually consist of two or more layers:

Physical layer: Production machinery, sensors, and actuators.

Network layer: Physical infrastructure that links physical components.

Computing layer: Data processing devices and cloud-based computing.

Application layer: Software systems which offer monitoring, control and optimization capabilities.

Business layer: Enterprise system is a system that links business processes to manufacturing operations.

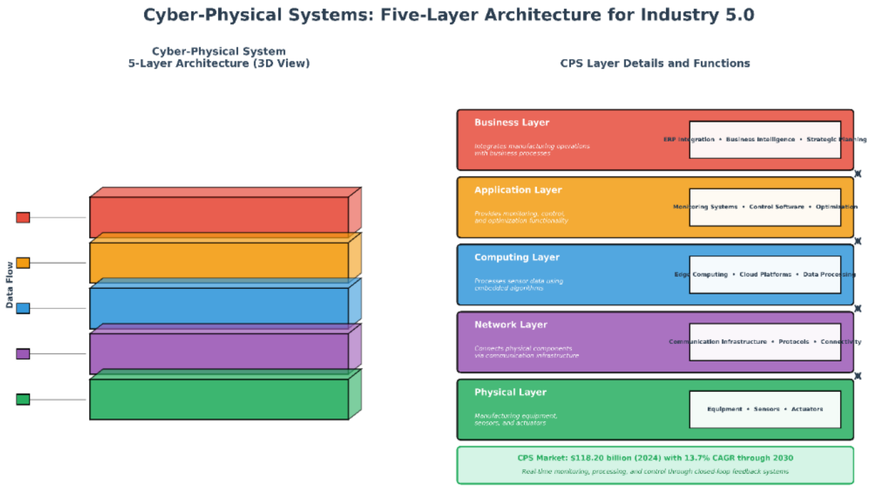

Figure 6: Cyber-Physical System Layers - Integration of Computational Algorithms with Physical Manufacturing

What are the ways of manufacturing systems to be real-time responsive and yet be secure and reliable? The solution is the closely designed cyber-physical systems where physical devices transfer data between physical systems and computational layers and decision systems in closely integrated feedback loops[98].

4.4. Digital Twin Technology

Digital twin technology is an almost real-time and historical-based method of creating virtual versions of a physical object, system or full factory that resembles its real-life equivalent. Digital twins permit manufacturers to track the equipment performance, simulate the working conditions, optimize the processes, and predict the future activities without interference with the real production[99], [100]. Figure 7 shows the Digital Twin Frame work for Industry 5.0.

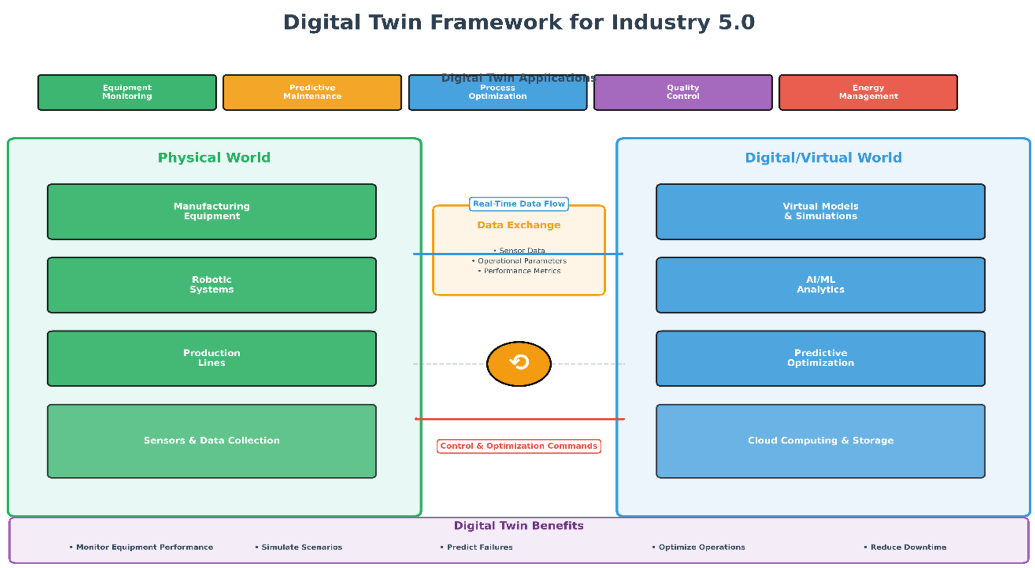

Figure 7: Digital Twin Framework - Virtual Representation and Real-Time Synchronization with Physical Assets

The segment that exhibits the best growth rate in CPS markets is the digital twin one because the capabilities are revolutionizing predictive analysis, simulation, and optimization. Companies that use digital twins have noticed high positive results such as 20-50% reduction of equipment downtime, 10-30% productivity increase, and 5-15% costs of maintenance reduction[101], [102].

Applications of digital twins lie on a maturity scale:

- Descriptive twins: Visualize sensor-based current asset state.
- Informative twins: Report on historical performance and analytics.
- Predictive twins: Predict the future with models of machine learning.
- Prescriptive twins: Advise the best actions by prediction.
- Independent twins: Auto-implement optimization decisions.

Digital twins can be used to provide augmented reality and add strong visualization capacities. AR headset-wearing technicians can observe maintenance processes, equipment diagrams, and real-time operational information superimposed on the real machinery, increasing the level of comprehension and decreasing the number of mistakes in the maintenance processes[103], [104].

4.5. Extended Reality for Manufacturing

Extended reality (XR) technology that includes virtual reality (VR), augmented reality (AR), and mixed reality (MR) technologies is changing the manufacturing training, operations, and quality control. The technologies strike upon important issues in the development of the work forces, especially a severe lack of skilled labor in the manufacturing industry[105], [106].

VR will allow workers to learn how to work the machinery, how to do maintenance, or how to react to an emergency in fully simulated, risk-free virtual conditions, and then apply these skills to real equipment[107], [108]. Literature shows that workers who received training through VR take up to 40 percent shorter time to accomplish tasks with compared to traditional training methods, and training through VR in a large group is up to 52 percent more affordable compared to traditional training[109], [110].

AR applications are digital tools that superimpose data onto the physical environment, offering real-time visual instructions to an assembly process, maintenance, and quality inspection procedure[111], [112]. Holographic instructions, equipment schematics, and operational procedures can be provided to workers individually in their field of view and hands free to allow them to get down to work. This strategy accelerates the process of learning, decreases the use of physical training resources, and improves the effectiveness of knowledge retention due to interactive and practical experiences[113], [114].

4.6. Discussion

Table 3 summarizes smart manufacturing technologies and their roles in Industry 5.0 implementations. The main conclusions include:

# Technology	Function	Market Size/Growth	Key Advantages	Integration
1	IIoT	Real-time data collection	27% CAGR to 2026	5G connectivity
2	OPC UA	Semantic industrial communication	Industry standard	Machine-to-machine
3	MQTT	Cloud connectivity	Lightweight protocol	Edge to cloud
4	Cyber-physical systems	Integrated computing and control	$118.2B in 2024	Multi-layer architecture
5	Digital twins	Virtual representation	13.7% CAGR to 2030	Simulation and prediction
6	VR training	Risk-free skill development	40% faster task completion	Immersive learning
7	AR guidance	Real-time on-site assistance	52% cost reduction vs. traditional	Point-of-need information

8	Augmented analytics	Data-driven insights	Increasing adoption	AI-powered analysis

Key conclusions include:

1. IIoT is the basic layer of connectivity that allows real-time data retrieval of the manufacturing equipment and 5G networks can offer bandwidth and latency properties that ensure responsive control systems[115], [116]. This infrastructural support is what allows the high volumes of sensors needed to monitor the entire production process in a complex structure[117], [118].
2. OPC UA and MQTT are two complementary communication protocols, as OPC UA offers semantic richness and security to intra-factory communications, whereas MQTT allows developing an efficient cloud connection. Based on a combination of both protocols, hybrid architectures are able to maximise the capabilities of Industry 5.0 systems, whilst ensuring the security and scalability of the network[92], [119], [120].
3. Cyber-physical systems combine the process of computational intelligence with physical manufacturing by using embedded computing, which produces a closed-loop system, continually tracking and optimising processes. The projected growth of CPS market at 13.7 percent indicates growing usage in manufacturing industries[94], [97].
4. Digital twins allow virtualizing and simulating real-world assets, assisting predictive maintenance, process optimization, and the what-if analysis, without interfering with production. Organizations that use digital twins realize significant gains in equipment maintenance (20-50 percent downtime savings), productivity (10-30 percent productivity gains) and maintenance efficiencies (5-15 percent savings)[102], [121].
5. Extended reality technologies (VR and AR) transform the training and on-site work processes as they allow to create an immersive learning setting and provide real-time instructions, respectively. The proven advantages are 40 percent faster task completion using VR training and 52-percent lower cost of training than traditional training methods[122], [123].

5. Artificial Intelligence and Machine Learning in Smart Manufacturing

The implementation of AI and ML technologies is transforming the manufacturing process through the ability to predict analytics and optimize processes and make decisions in real time[124], [125]. These technologies enable manufacturers to predict the availability of equipment to failure, plan production time, minimal amounts of waste, and operational efficiency.

5.1. Predictive Maintenance and Process Optimization

Predictive maintenance systems IoT-based predictive maintenance systems introduce sensors that can continuously detect the equipment parameters, like vibration, temperature, pressure, and energy consumptions[77]. This sensor data is processed using advanced analytics and machine learning algorithms to detect subtle changes and trends that indicate some problematic occurrences and therefore perform proactive maintenance before any breakdowns[79], [126]. This maintenance based on data is a great advancement over the conventional preventive maintenance schemes. Whereas preventive maintenance is operated according to a fixed timetable irrespective of the actual equipment state, predictive maintenance is operated according to a timetable and undertakes repairs accordingly depending on the real time equipment health data. It has been shown that predictive maintenance with the use of IoT can help save unplanned downtime by huge percentages and maximize Overall Equipment Effectiveness (OEE[127], [128]). During production optimization, AI analyses large volumes of manufacturing data to determine bottlenecks, optimise the distribution of resources, and enhance production planning. Data analytics will help manufacturers to enhance productivity by an average of 25 percent with improved workflows and efficiency. Modern AI systems predict demand and maintain inventory, optimizing inventory and reacting to market trends in a better way than conventional methods[73], [129], [130]. Figure 8

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shows the AI/ML predictive maintenance workflow from data collection through to decision-making.

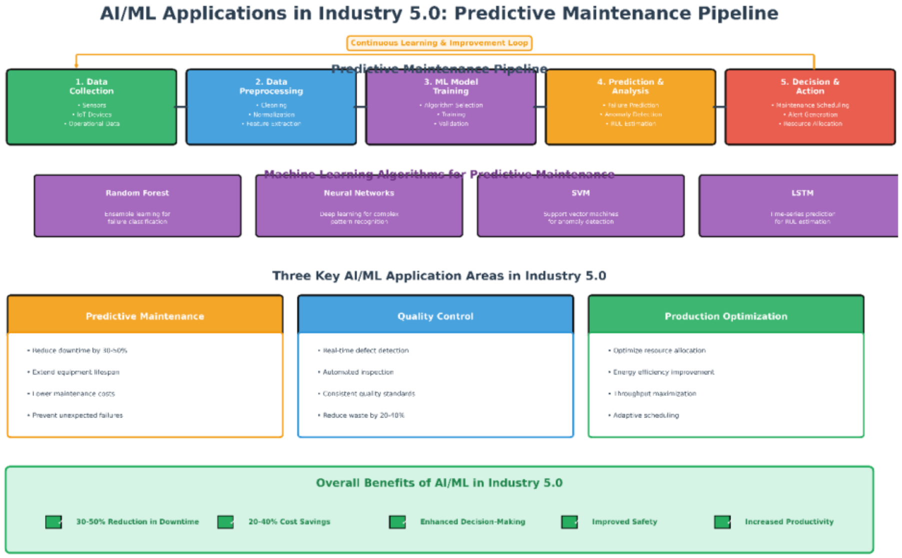

Figure 8: AI/ML Predictive Maintenance Pipeline and Application Areas in Industry 5.0 Manufacturing

5.2. Quality Control and Defect Detection

Deep learning has transformed the field of quality control in production because of the previously uninterested accuracy, speed and flexibility in inspecting defects. The old-fashioned methods of quality control based on the hand-written algorithm is effective but limited in the sense of acquiring knowledge and adjusting to new product defects and variations. The Deep learning does not have these limitations because it uses large volumes of data to train the neural networks that can detect and categorize defects with great accuracy[131], [132].

Research shows that the use of AI has resulted in impressive progress in quality control effectiveness. According to the research findings, deep learning algorithms used in quality control may raise the accuracy of defect detection to 90 percent. According to the reports provided by leading tech firms, manufacturers of deep learning algorithms are able to save up to 80 percent of time spent in quality control, which reflects in the economy of considerable costs[133], [134]. Moreover, AI-based quality control systems allow detecting and fixing defects during the production process but not at the end of the production lines which eliminates the further development of defective products and minimizes waste[135], [136].

Deep learning computer vision systems examine the output of industrial cameras, scanning electron microscopes (SEM), X-ray equipment, and others in order to identify flaws in the surface, dimensional errors, and structural anomalies. These systems are on-duty and ensure consistent accuracy, which manual inspection [137], [138].

5.3. Data-Driven Production Systems

Data-driven manufacturing relies on the use of operational and events data of the shop floor equipment, operators and supply chains to make decisions and optimise operations[139]. This will allow manufacturers to have in-depth understanding of production KPIs like cycle times, downtime, and equipment performance, and realize the opportunities of improvement such as the optimization of machine settings and the efficiency of workflows[100], [140].

The manufacturing analytics systems are manufactured with data incoming across various sources such as databases (SQL, NoSQL), individual file formats, and industrial IoT communication devices (OPC) with manufacturing equipment. Scalability is achieved in data storage and processing through cloud interfaces to Amazon S3, Azure Data Lake, and Google Cloud Storage[141], [142].

Sophisticated analytical methods such as machine learning, multiobjective modeling, and statistical modeling are used on multiple-variate data to apply advanced process control, process monitoring, drift and defect prediction, root cause identification, and manufacturing recipes optimization[143], [144]. Automated Classification and Regression Learner apps based on AutoML technology are interactive applications that can be used to generate optimized machine learning models by automatically selecting, selecting and tuning hyperparameters[145], [146].
Companies that use data-driven manufacturing strategies indicate high levels of improvement in their operations. Studies show that the majority of manufacturers who implemented data-driven strategies (78%), said that operational efficiency had improved, and the average productivity had improved by 25%. The manufacturing industry statistics indicate that manufacturing companies that succeed in exploiting data analytics in their manufacturing processes would be in a position to increase production capacity by up to 20 percent[147], [148].

5.4. Discussion

Table 4 summarizes AI/ML applications in manufacturing and their business impacts. The key contributions are as follows:

# AI/ML Application	Technology	Performance Improvement	Key Metrics	Industry Adoption
1	Predictive maintenance	Early failure detection	Downtime reduction	65% of large manufacturers
2	Demand forecasting	Inventory optimization	25% average productivity increase	Growing adoption
3	Defect detection	Deep learning vision	90% accuracy	72% of quality teams
4	Quality inspection	CNN-based analysis	80% time reduction	Widespread
5	Process optimization	Multiobjective optimization	20% capacity increase	Increasing
6	Root cause analysis	ML pattern recognition	Faster problem resolution	Emerging
7	Anomaly detection	Statistical methods	Early issue identification	Growing
8	Production scheduling	AI optimization	Reduced cycle times	Advanced facilities

Key conclusions include:

1. With the help of IoT sensors and machine learning, predictive maintenance can be implemented, which allows taking some actions in advance before the equipment malfunctions, minimizing any unwanted downtimes and optimizing the usefulness of machines. This is a radical change in terms of reactive to proactive maintenance procedures[128], [149].
2. The quality control systems built with deep learning can identify defects with an accuracy of 90% with the inspection time reduced by 80 percent relative to the manual system. In-line inspection during the manufacturing process avoids advancement of faulty products in the manufacturing stages, and minimizes the expense of rework and scrap at the manufacturing phase[150], [151].
3. Data-driven manufacturing makes use of integrated analytics platforms based on the combination of shop-floor data, enterprise systems and cloud computing to detect optimization opportunities. The observed 25 percent mean productivity boost justifies the usefulness of data-driven decision making in manufacturing processes[139], [152].
4. The most recent machine learning methods such as multiobjective optimization and AutoML allow continuously improving by developing models and tuning hyperparameters automatically. These

capabilities make development effort less and prediction accuracy and system adaptation a lot better[153], [154].

5. Manufacturers that have effectively adopted data-driven strategies also demonstrate and record improvements in several performance dimensions such as productivity (25% average), capacity growth (20% potential), and an operational efficiency growth (78% of adopters)[139].

6.

6. Programming Tools and Technical Implementation

The effective adoption of Industry 5.0 systems will demand an understanding of various programming languages and development platforms depending on various features of smart manufacturing[4], [30]. This chapter discusses Python, R, MATLAB, Node-RED and sensor integration methods towards Industry 5.0.

6.1. Python for Data Science and AI

Python is used very widely in machine learning, artificial intelligence, and data engineering because of its efficiency and a large number of libraries. The language is superb when dealing with large volumes of data and offers extensive structures of deep learning, neural networks, and sophisticated analytics[155], [156], [157]. The ability of Python to integrate with industrial systems with libraries that facilitate connection to OPC UA, MQTT among other industrial protocols makes it useful in IIoT applications[158], [159].

The key benefits of Python in manufacturing include wide machine learning packages (scikit-learn, TensorFlow, PyTorch), good data manipulation (Pandas, NumPy), issues with plenty of visualization (Matplotlib, Plotly) and a large community with widespread industrial automation examples[160], [161], [162].

6.2. R for Statistical Analysis

R is still a better fit to statistical analysis and visualization, with its better abilities to process tabular data and statistical modelling[163], [164]. The storage capacity of R has been found to be better than that of Python Pandas at very specific data scales due to the effective storage of data by R as compared to Python, especially when complex statistical calculations are required without involving large exchanges in databases[165], [166], [167].

R has strong qualities of quality control analysis, process capability studies, and statistical process control (SPC) implementations in manufacturing situations. The language offers sensitive visualization tools to analyze the exploratory data and the full test of statistics to validate the hypothesis[168].

6.3. MATLAB for Manufacturing Analytics

MATLAB is an integrated environment that is especially useful in manufacturing analytics, as it offers data analysis, machine learning, and system modeling with it[169], [170]. The platform allows engineers to get access to operation and test data through databases, dedicated file formats, or industrial IoT communication systems and offers predictive analytics, process optimization, and digital twin development tools[171], [172].

The two-way synchronization of MATLAB and Python enables the teams to utilize the benefits of both languages, and there are functionalities to invoke Python libraries in MATLAB or package MATLAB programs to run in Python programs. This interoperability allows organizations to use the powerful signal processing and control system features of MATLAB with machine learning libraries of Python[170], [173].

6.4. Node-RED for Industrial Automation

Following the release of the Node-RED graphical programming platform, which is now a formidable tool in the design of Industrial IoT applications, the software has become useful in extending platforms pertaining to PLC hardware, networks, and analytics within the same development environment[174], [175], [176]. This is a browser-based platform that operates with functions (also known as nodes) that are linked in flow diagram layouts, and there are also thousands of existing, off-the-shelf nodes that can be used in different industrial applications[177].

The low-code model of Node-RED saves a lot of time spent on the development of the tool because instead of manually writing communication protocols and data processing logic, pre-built functionality is available[178], [179]. The platform is compatible with a large quantity of industrial communication protocols such as MQTT, HTTP, TCP, Modbus,

OPC-UA, and UDP, which allows simplifying communication over the PLC level to cloud applications[180], [181].
According to survey data, Node-RED is finding more significant applications in industrial automation applications such as hosted dashboards, building control, data processing, integration with PLC devices and edge devices logic[175], [182]. This feature of the platform to gather information using the local devices such as PLCs, manipulate it in useful forms, and transmit them to the cloud providers makes it even more valuable in bridging the operational technology and information technology systems.

6.5. Sensor Integration and Data Acquisition

The basis of smart manufacturing today is the use of modern data acquisition systems that transform physical parameters into a series of digital data to be processed and analyzed. Such systems combine different types of sensors such as temperature sensors (thermocouples, thermistors), pressure sensors, accelerator and vibration sensors, flow sensors, displacement sensor and photoelectric sensors[183], [184].
The sensor signals are sampled using data acquisition cards, which facilitate the digitalization of sensor signals and the analysis of the digitalized data using industrial control systems or through cloud platforms. The IoT based data acquisition systems involve sensor networks in remote data collection and wireless transmission that allows real time monitoring and management of equipment, production processes and environmental conditions[185], [186].
With proper sensor integration, it is possible to achieve such critical manufacturing functions as real-time monitoring and quality control, predictive maintenance due to continuous monitoring of the equipment health condition, production optimization due to workflow and layout analysis, and energy management due to consumption monitoring[73], [187]. The combination of AI and machine learning with sensor data will allow more and more accurate prediction and automatic control, where AI will study large volumes of historical data and indicate equipment failures, quality problems, and the most efficient production levels[188], [189].

6.6. Discussion

Table 5 summarizes programming tools and their applications in Industry 5.0 implementations. Key contributions include:

# Tool/Language	Primary Function	Key Strength	Integration	Use Case
1	Python	Machine learning and AI	Extensive ML libraries	IIoT data analysis
2	R	Statistical analysis	Advanced statistics	Quality control analysis
3	MATLAB	System modeling and control	Signal processing	Digital twins
4	Node-RED	Low-code automation	Pre-built industrial nodes	Real-time control
5	OPC UA	Industrial communication	Semantic data models	Machine integration
6	MQTT	Lightweight communication	Minimal overhead	Cloud connectivity
7	Sensors	Physical data collection	Real-time monitoring	Equipment health
8	Edge computing	Local processing	Low-latency response	Predictive control

Key conclusions include:

1. Python also has extensive machine learning and AI, and features a high level of integration of industrial protocols, which makes it a great choice when creating IIoT applications and has to perform advanced data analysis. The large Industry 5.0 ecosystem of libraries and community support helps develop Industry 5.0 systems quickly[115], [116].

2. R is also used in statistical analysis, quality control applications, which provide process capability studies and statistical process control tools, as needed by manufacturing organizations. The effective data management in R renders it useful in organizations with big historical data to be analyzed[190], [191].

3. MATLAB integrates signal processing, control systems, and machine learning into a single environment and is strong in areas of developing digital twins and optimization on the system level. Hybrid Python integration has been made possible via two-way integration to allow hybrid applications that can exploit the control features of MATLAB with machine learning libraries in Python[192], [193].

4. The low-code graphical interface of Node-RED can cut industrial automation development time dramatically with factory-supported industrial communication protocols and data processing capabilities. The platform helps in rapid prototyping and deployment of IIoT solutions with little knowledge of programming knowledge[177], [178].

5. Integration approaches that involve wide varieties of sensors along with cloud-based data acquisition platforms allow accessibility to real-time, increased maintenance-related predictions, and automated optimization choices. The capabilities of AI analysis of sensor data are growing to offer predictive capabilities that ensure prevention of failures and proactive optimization of operations[34], [194].

7. Extended Reality for Workforce Development

The technologies of the extended reality are revolutionizing the training of the workforce in the manufacturing sector which has a severe lack of the skills and allows transferring knowledge safely and efficiently[106], [195]. This section discusses VR training, AR-assisted operations, and hybrid methods of developing the Industry 5.0 workforce. Figure 9 shows the Extended Reality (XR) technologies for workforce development in Industry 5.0.

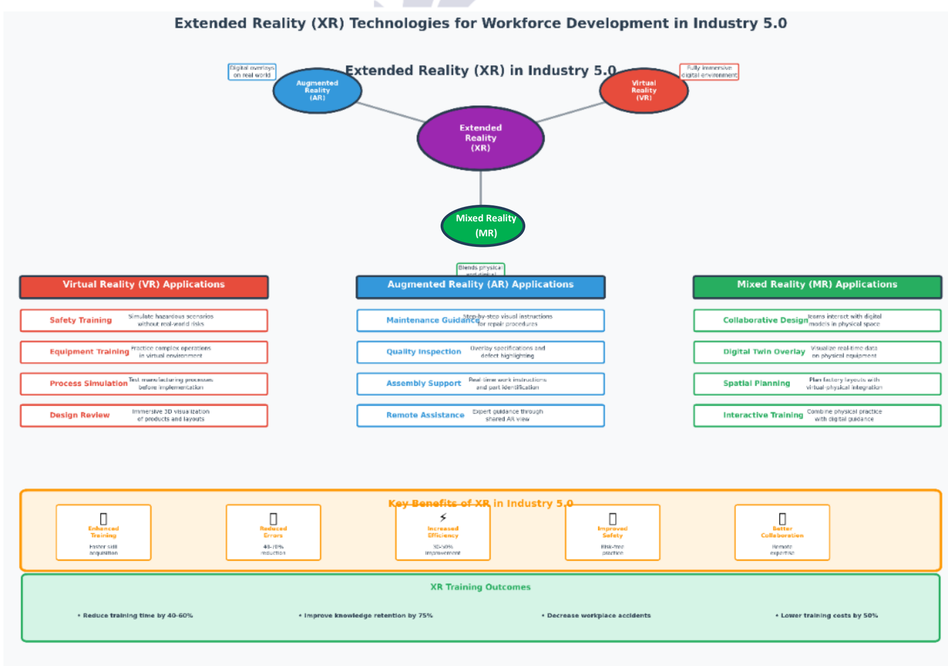

Figure 9: Extended Reality Applications - VR, AR, and MR for Training and Operational Support

7.1. Virtual Reality Training

VR allows employees to train based on how to use the machinery, do maintenance, or react to emergencies in fully simulated, risk-free virtual space before interacting with the real equipment. This ability eliminates a very difficult issue of manufacturing training, the cost and the difficulty of giving practice using costly production equipment[196].

Research shows that VR-trained workers can accomplish their tasks up to 40 times faster than in more conventional methods and that VR-based mass training is sometimes up to 52 times less expensive than more traditional classroom training[107]. These enhancements are due to a number of factors such as the provision of immersive learning experiences that involve the utilization of multiple senses, the capability of practicing endlessly without the risk of damaging equipment and also the ability to learn at a pace of your own that suits various levels of skills[197], [198].

The VR training applications in manufacturing involve:

1. Training of equipment operation CNC machines, injection molding equipment, and assembly equipment[199], [200].
2. Preventive maintenance such as equipment diagnosis, replacement, and troubleshooting[201], [202].
3. Hazardous situation and emergency response safety training[203].
4. Inspection methods of quality control and identification of defects[204].
5. Production changes to new product assembly processes[205].

7.2. Augmented Reality Guidance

The AR applications also superimpose digital information to the physical world that can be used as a guide to assemble, maintain, and perform quality inspections in real-time[206], [207]. The workers are also able to see step-by-step holographic instructions, equipment schematics, and operational procedures that are in their field of view and they are free to carry out their tasks.

This type of information at the point-of-need improves the learning processes and minimizes the dependency on physical training resources and increases the retention of the knowledge through the interactive and hands-on learning[208], [209]. The best manufacturers and leaders have shown impressive improvements in the application of AR. Volvo Group found AR as the best option to be paper based quality assurance that developed digital threads between engineering systems and assembly technicians that allow AR experiences to be created and updated within minutes instead of hours or weeks[206], [210]. Digital twin technology is one of the applications that Siemens deployed at their Amberg electronics factory through AR visualization to streamline the production and maintenance processes, allowing employees to detect possible problems at an early stage and conduct a more efficient predictive maintenance[210], [211].

7.3. Mixed Reality Integration

Mixed reality (MR) is a set of VR and AR features that allow to provide advanced training and operations support. MR can enable trainees to engage with virtual equipment but they can see their physical surroundings and this results in building hybrid training environments which become much more easily transferred to real-world operations[212], [213].

More sophisticated applications of MR devices encompass collaborative training in which numerous workers perceive common virtual objects located in their physical areas, which make it possible to learn together and coordinate team learning. Also, MR can be used in hybrid maintenance in which the technician is physically working on the actual equipment and a virtual overlay is used as a guide, performance history data and predictive maintenance suggestions[214], [215].

7.4. Discussion

Table 6 summarizes extended reality technologies for workforce development. Key findings include:

# XR Technology	Application	Performance Improvement	Cost Benefit	Industry Use
1	VR equipment operation	40% faster task completion	Training cost reduction	Assembly, machining
2	VR maintenance training	Skill acquisition improvement	52% vs. traditional	Troubleshooting, diagnostics
3	VR safety training	Knowledge retention	Risk-free practice	Emergency response

4	AR assembly guidance	Real-time instruction	Error reduction	Complex assemblies
5	AR maintenance support	Faster troubleshooting	Reduced downtime	Predictive maintenance
6	AR quality inspection	Accuracy improvement	Defect detection	Quality assurance
7	MR collaborative training	Team coordination	Knowledge sharing	Multi-worker processes
8	Digital twin visualization	Comprehensive understanding	System optimization	Equipment monitoring

Key conclusions include:

1. VR training is an approach that allows practicing the risk-free environment, and, thus, it is possible to complete the tasks 40 and 52 times faster and save money 52 times more than traditional training techniques. The effects of these improvements are due to limitless repetition of specific practice and customized learning speed[200], [216].
2. The point of need AR guidance is visual support in real-time overlaying the procedures on the physical equipment, schematics, and data to minimize errors and speed up the learning process. Effective commercial applications indicate fast development and integration of AR experiences, which make them quickly adapt to process modification[210], [217].
3. The hybrid training and operational experience through the integration of mixed reality allows virtual practice with virtual equipment and real-world awareness of the physical environment, which enhances the effectiveness of the transfer to real-world manufacturing activities[210], [218].
4. The combination of digital twins and AR and VR can be used to develop multi-dimensional visualization systems that allow workers to perceive complex systems in multiple ways- virtual practice systems, real-time overlays, and predictive analytics[1], [102].

8. Emerging Trends, Sustainability, and Future Directions

There are a number of new trends that are defining the future of Industry 5.0 research, implementation, and manufacturing practice. In this part, the author discussion delves into progressive human-machine interfaces, sustainability integration, and workforce development issues, as well as future research.

8.1. Advanced Human-Machine Interfaces

The future will focus on human-friendly AI that will guarantee transparency, flexibility, and confidence in the decision-making systems. Highly developed cobots that can sense and learn better will allow greater collaboration in common work areas. To address very complex problems of the industrial nature, hybrid decision-making will combine human intuition and reasoning in the conditions of uncertainty with the computational capabilities of AI and huge quantities of data to effectively resolve the problems[34], [219], [220].

ER technologies actively develop to enable human-machine co-operation, and AR-assisted robot programming tries to overcome the drawbacks of traditional programming-by-demonstration technologies, by increasing the modality of the input[221], [222], [223]. There is a growing development of virtual and augmented reality applications of digital management of work places and human-robot collaboration that can aid the interconnected human-robot data transfer to optimize the task assignment, motion planning and manipulator coordination[222].

8.2. Sustainability and Circular Economy

The concept of sustainability and resource efficiency is becoming a priority issue in Industry 5.0. The AI technologies are also used to enhance the energy efficiency, waste minimization, and use of resources to help the manufacturer comply with the environmental regulations and meet the sustainability targets, as well as, increase the cost-efficiency[81], [224], [225].

Circular economy principles are already being developed in connection with Industry 5.0 technologies, and special attention is paid to bio-inspired technologies and smart materials that will enable materials with built-in sensors and other functionalities and be recyclable. Simulation technologies and digital twins can be used to model a complete system to facilitate circular methods of manufacturing and material consumption[226].

Figure 10 shows the Sustainable Manufacturing and Circular Economy Integration in Industry 5.0.

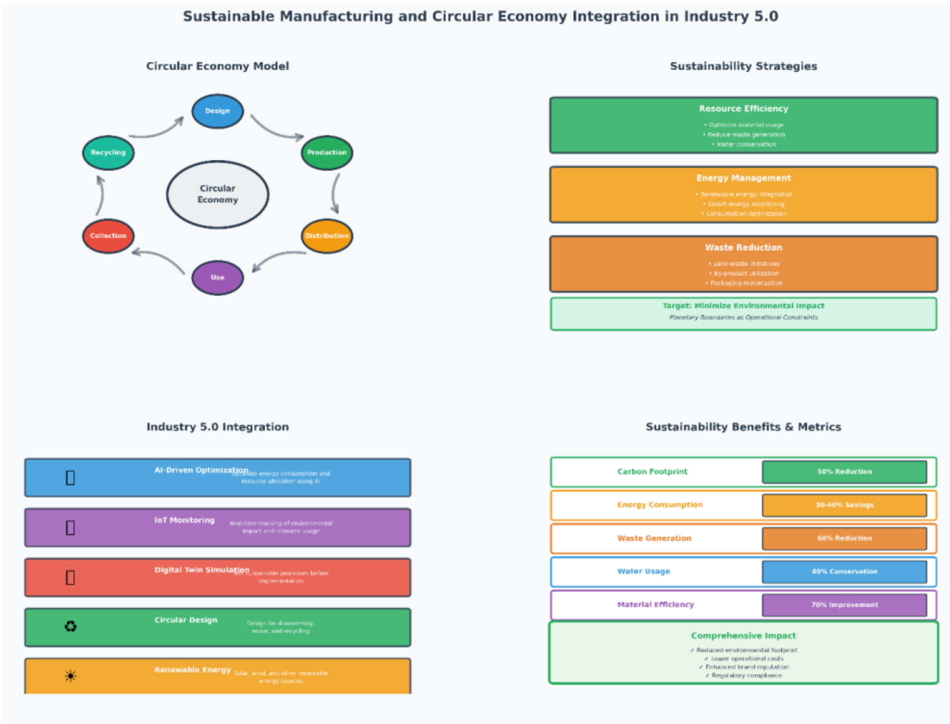

Figure 10: Sustainable Manufacturing Framework with Circular Economy Principles and Environmental Impact Metrics

8.3. Workforce Development and Human-Centricity

Solving human-related conflicts in Industry 5.0 implementation is an important field of research. The main issues are how to incorporate the current human factors into the cooperation with the latest technologies, how to keep the constant industrial and digital projects and introduce human aspects in them, and how to focus on the development of skills of workers and the technological growth[9], [16].

Resolution strategies that have been found in the literature are the intelligent automation of manufacturing processes to minimize redundant tasks, the use of Industry 5.0 maturity models that facilitates human-centricity, re-training of manufacturing personnel on soft skills and academic qualifications, and the creation of new tools to support workers in the virtual realm[4], [9]. Including performance-fatigue balance decision models and the creation of technologies that meet the needs of the workers and enhance human-focused value creation are also perspectives of current research importance[227], [228].

8.4. Research Challenges

There are a number of long-term problems that should be addressed through research:

1. Security of cyberspace in IIoT settings - Safeguarding more and more manufacturing systems with increasing connections to cyber attacks and their effect on operation efficiency[229], [230], [231].
2. Data quality and integration - Providing data flows between various legacy and new manufacturing equipment that is reliable and consistent[232], [233], [234].
3. AI explainability - Building clear machine learning models that are comprehensible and credible to manufacturing workers[235], [236], [237].

4. Skills development - Educating the workforce to handle Industry 5.0 jobs that need technical skills and humanistic skills[4], [69].

5. Standardization - Developing universal standards of industrial protocols, data formats and system interfaces so that they are interoperable[4], [30]

8.5. Future Research Directions

The research opportunities that can be advanced to support Industry 5.0 are:

1. Federated learning - Creation of distributed machine learning models, which allow training AI models on multiple facilities and maintain the privacy of all the data[30], [116], [238].

2. Quantum computing applications - Investigating the application of quantum algorithms in solving complex optimization manufacturing problems that cannot be resolved by classical computational facilities[239], [240].

3. Bio-inspired manufacturing - Biological lessons on resilient, adaptive manufacturing processes[241].

4. Human-AI collaboration models - Designing conceptual frameworks and procedures to assign and interact tasks to humans and machine in the best way achievable[242], [243].

5. Sustainable manufacturing systems - Circular economy focused manufacturing with Industry 5.0s to create zero-waste manufacturing[24].

6. Edge AI systems - Further development of the capabilities of on-device machine learning to enable real-time decision-making without the need to connect to the cloud[69], [244].

8.6. Discussion

This section integrates the new trends and research priorities in developing Industry 5.0. Key conclusions include:

1. In the advanced human-machine interface development is concentrated on transparency, adaptability and trust as it is acknowledged that acceptance of technology relies on the understanding and the trust of the user towards AI-driven systems. Cobots of the future with more advanced sensing and learning will allow more complex scenarios of cooperation[245].

2. Sustainability integration is an ideal change to manufacturing philosophy as a continuation of efficiency optimisation to environmental responsibility and the principles of a circular economy. This shift will need coming up with AI systems that are sustainable and productive[244].

3. The development of the workforce is also one of the significant barriers to implementation, which requires the combination of technical skills development with the development of soft skills and the development of meaningful work that utilizes human individuality[4].

4. Cybersecurity, data integration, AI explainability, and standardization are urgent problems that need to be resolved on an industry-wide level and allow the Industry 5.0 to be used all over the world[4], [246].

5. New research topics such as federated learning, applications of quantum computing, bio-inspired manufacturing, and sustainable system design are expected to give Industry 5.0 its next leap forward. These guidelines imply that there will be a shift towards manufacturing systems that are more and more distributed-intelligence based, more environmentally responsible, and more human friendly[4], [246].

9. Conclusion

Industry 5.0 is a vision statement of how the manufacturing industry should look like in the future where human workers will be at the centre of more and more digitalized and automated manufacturing settings. When humans and robots work together, artificial intelligence and machine learning, Industrial Internet of things, cyber-physical systems, and augmented/virtual reality are all integrated, complete ecosystems are formed, which help improve productivity and human well-being.

This review has captured the complex aspects of Industry 5.0 development and implementation. The human-centric philosophy of Industry 5.0, particularly in comparison to the technology-centric nature of Industry 4.0, is the initial indication of the fact that sustainable manufacturing is successful only when the efficiency is combined with the human dignity, sustainability, and resilience. The collaborative technologies between humans and robots show that technological development can make human workers better contributors, and the manufacturing work is safe, productive, and meaningful.

The infrastructure to support operational excellence and human-centric manufacturing is a set of smart manufacturing technologies such as IIoT, cyber-physical systems, and digital twins, which are used to support real-time monitoring, data-driven decision-making, and adaptive production systems. The application of artificial intelligence and machine learning in predictive maintenance, quality control, and optimization of production are examples of how high-tech technologies can supplement the human decision-making process and speed up the process of innovative development.

Industry 5.0 is based on a large number of programming tools (Python, R, MATLAB, Node-RED), industrial communication standards (OPC UA, MQTT), and overall sensor integration strategies that allow manufacturers to create responsive and intelligent production systems. The ER technologies transform the process of workforce development by providing the ability to train in the immersive environment and guiding the operations on the point-of-need basis.

The publication of research in high-impact journals demands the use of strategic strategies that include quality research, journal selection, as well as effective presentation, whereby researchers will be able to share the advances of Industry 5.0 with the global manufacturing and academic fraternity.

The current developments such as high-tech human-machine interfaces, sustainability, and the principles of the so-called circular economy suggest that future manufacturing systems will be more oriented towards responsible attitudes towards the environment and human well-being in equal ratio. Ongoing research issues such as cybersecurity, data integration, explainability of AI, or workforce development are issues that need to be addressed to achieve the transformative potential of Industry 5.0.

The shift aimed at Industry 5.0 promises high opportunities to develop the manufacturing capacities and provide safer and more satisfying and sustainable working conditions. The vision will require more studies and development of these interrelated areas of technology together with changes within an organization in support of human-centric values to handle the complicated issues of the next generation manufacturing systems.

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