The Industry of the Future: From Industry 4.0 to Industry 5.0 – Integration of Humans and Technology: New Technologies

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ACADEMY OF SCIENCES AND ARTS OF BOSNIA AND HERZEGOVINA

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INDUSTRY OF THE FUTURE: FROM INDUSTRY 4.0 TO INDUSTRY 5.0 – Integration of Humans and Technology

Editor
Isak Karabegović

SARAJEVO - BIHAĆ, 2025

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Integration of Technology and People

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FOREWORD

The Proceedings of the International Scientific Conference The Industry of the Future: From Industry 4.0 to Industry 5.0 – Integration of Humans and Technology, organized by the Academy of Sciences and Arts of Bosnia and Herzegovina – Department of Technical Sciences, with co-organizers the Robotics Society in Bosnia and Herzegovina and the Foreign Trade Chamber of Bosnia and Herzegovina, represent the result of joint efforts to bring together in a single volume current research, experiences, and ideas in the field of industrial transformation.

The conference brought together distinguished scholars, researchers, industry representatives, and policymakers, thereby creating an interdisciplinary framework for the exchange of views and results. The particular importance of the conference lies in its ability to connect theoretical achievements with practical applications, offering answers to the question of how contemporary technologies—such as automation, robotics, artificial intelligence, the Internet of Things, and data-driven systems—can be integrated into industrial practice.

The transition from Industry 4.0 to Industry 5.0 entails profound changes in the way we understand the role of technology and humans in production processes. While Industry 4.0 emphasized digitalization, smart factories, and interconnected systems, Industry 5.0 places a special focus on the humanization of technology. Humans are not perceived merely as users, but as active participants and partners in collaboration with intelligent systems, thereby opening new opportunities for creativity, sustainability, and socially responsible development.

The papers included in this Proceedings volume cover a wide range of topics, including innovations in production processes, the development of advanced robotic systems, the application of artificial intelligence in data analysis and decision-making, safety and ethical issues in the digital era, as well as the role of technology in shaping a sustainable industrial future. Through these contributions, readers will be able to recognize global trends, but also the specific challenges faced by developing countries, including Bosnia and Herzegovina.

The international dimension of the conference has provided particular value, as participants came from diverse academic and industrial backgrounds, enabling the comparison of experiences and the creation of new opportunities for collaboration. Knowledge exchange at events of this kind not only contributes to the advancement of scientific thought but also strengthens the bridges between *academia and industry, between local needs and global trends. In this way, the conference assumes an additional dimension—it is not only a scientific forum but also a strategic platform for planning the future development of industry in a broader social and economic context.*

We extend our sincere gratitude to all authors, reviewers, and participants of the conference for their contributions, which have enriched the content of this Proceedings volume. Their research, ideas, and experiences give this edition its interdisciplinary character and make it a valuable source of information and inspiration for all those engaged in issues of industrial transformation. Special thanks are owed to the institutions and organizers who supported the realization of the conference and the publication of this volume, thereby contributing to the strengthening of the scientific and research capacities of Bosnia and Herzegovina.

We are confident that this Proceedings will serve as a valuable source of knowledge for researchers, students, industry professionals, and policymakers, and that it will further encourage reflection, innovation, and cooperation in shaping a sustainable, innovative, and human-centered industrial future in line with the vision of Industry 5.0.

Sarajevo, October 2025

Corresponding member Isak Karabegović, editor
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Integration of Robotic Technology and Human Creativity: from Automation to Humanization

Isak Karabegović*[1], Ermin Husak[2], Samir Vojić[2], Edina Karabegović[2], Mehmed Mahmić[2]

Abstract: *It is well known that with the emergence of Industry 4.0, the focus was placed on the digitalization and automation of industrial processes through technologies such as the Internet of Things (IoT), Big Data, artificial intelligence (AI) and robotics, which led us in the direction of smart production processes with the goal of ''smart factories''. Unlike Industry 4.0, Industry 5.0 emphasizes the importance of humanization of technology, where people and robots work together in a harmonious environment. The paper examines whether advanced robotic technology can be synergistically integrated with human creativity to create more efficient, innovative and sustainable production practices. The paper explores the key elements that enable the integration of robotic technology and human creativity, including collaborative robots (cobots), artificial intelligence that supports creative processes and advanced sensor systems. Collaborative robots, designed to work safely alongside humans, take over routine and physically demanding tasks, freeing up time for workers to focus on creative and strategic activities. AI technologies analytically support human decisions, enabling faster and more informed innovation. Ethical and safety aspects of robotic technology integration are discussed, emphasizing the need for a transparent and responsible approach. The application of robotic technology in industry brings significant benefits, including increased productivity, cost reduction, improved worker safety and more sustainable development. The key to the success of Industry 5.0 is in creating a balanced synergy between technology and human creativity. By harmonizing automation with humanization, industry can achieve new levels of innovation and efficiency, adapting to the dynamic needs of the global marketplace. This approach ensures not only technological progress, but also social responsibility, thus laying the foundations for a sustainable and prosperous future for the industry.*

Keywords: *Industry 4.0, Industry 5.0, automation, humanization, human creativity.*

1. Introduction

The fourth industrial revolution ''Industry 4.0'' brought a revolution in industrial processes, with the introduction of automation, digitization and smart

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technologies. This concept is based on the use of the Internet of Things (IoT), artificial intelligence (AI), Big Data analytics, virtual and augmented reality (AR), cloud computing, advanced sensors and advanced robotics to optimize production activities [1,2]. However, with the growing advancement of technology and increasing awareness of the importance of human resources, a new concept is emerging - Industry 5.0, which focuses on the synergy between technology and human creativity. The integration of robotic technology and human creativity represents a key step in the evolution of industrial practices. While automation and digitization have enabled a significant increase in efficiency and cost reduction, Industry 5.0 introduces an element of humanization, where humans and robots work together in a harmonious environment [3]. The goal is not only to optimize production processes, but also to create an environment where human workers can use their creative and intellectual abilities to innovate and improve product quality. Collaborative robots, known as cobots, are at the heart of this integration [4]. Designed to work alongside humans, collaborative robots take over routine and physically demanding tasks, freeing workers for more creative and strategic activities. Equipped with advanced sensor systems and artificial intelligence (AI), collaborative robots can collaborate with humans in real time, adapting to their needs and ensuring workplace safety [5]. Artificial intelligence also plays a key role in this integration. AI systems enable the analysis of large amounts of data, prediction of failures and optimization of processes, providing support to workers in making informed decisions. AI can also support creative processes, enabling faster research and development of new products and the adaptation of existing production lines to market demands. However, the integration of robotic technology and human creativity also brings certain challenges. It is necessary to ensure ethics and safety in the application of these technologies, as well as providing continuous education and training for workers to adapt to new technological requirements. It is also important to ensure transparency in the use of data and the protection of workers' privacy. In this paper, we will explore various aspects of the integration of robotic technology and human creativity, including the application of collaborative robots, AI systems, and advanced sensor technologies in industrial processes [6, 7]. We will analyze case studies from various industries that demonstrate successful examples of the implementation of these technologies. We will also consider ethical and safety aspects, as well as the challenges and opportunities that Industry 5.0 brings. The paper provides a comprehensive overview of how the synergy between technology and human creativity can improve industrial practices, increase productivity and innovation, and create a more sustainable and safer working environment [8, 9]. Industry 5.0 represents a step forward in the transformation of industrial processes, combining the benefits of automation with the unique capabilities of human creativity to achieve new levels of success.

2. Industrial Development from the First to the Fifth Industrial Revolution

The first industrial revolution began in Britain with the introduction of the steam engine (end of the 18^{th} and beginning of the 19^{th} century). This period is characterized by the transition from manual production to machine production, which led to mass production and urbanization. The second industrial revolution focused on the introduction of electricity, chemical processes and line production (late 19^{th} and early 20^{th} century). This phase enabled a further increase in productivity and efficiency, along with the emergence of new industries such as steel, oil and automotive. The third industrial revolution, also known as the digital revolution, brought the development of computers, electronics and information technology (mid-20^{th} century). The automation of production processes using computers and robotics has enabled further efficiency gains and cost reductions. Industry 4.0 marks the fourth industrial revolution based on digitization and the application of smart technologies (beginning of the 21^{st} century), as shown in Figure 1.[1,2,10] Key technologies include the Internet of Things (IoT), advanced sensors, additive technologies (3D Printing), artificial intelligence (AI), Big Data analytics, virtual and augmented reality (AR), cloud computing and advanced robotics, digital twins, etc. This phase enables real-time monitoring and optimization of production processes and predictive maintenance.

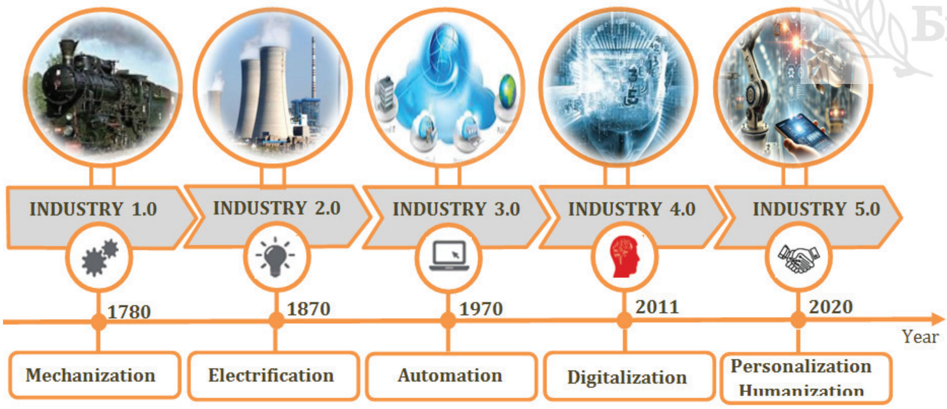

Figure 1. Industrial development from Industry 1.0 to Industry 5.0

Industry 5.0 builds on Industry 4.0, but emphasizes cooperation between people and smart systems (present and future) [11, 12]. Collaborative robots (Cobots) enable safe collaboration between humans and robots, by taking on repetitive and physically demanding tasks. Industry 5.0 also emphasizes the humanization of technology, sustainable development, product personalization, and ethical application of technology. From the steam engine to smart systems, industrial revolutions have enabled enormous leaps in productivity, efficiency, and innovation. Industry 5.0 represents the latest step in this evolution, combining technological advances with human creativity and ethics to create a more sustainable and prosperous future. Now, with the advent of Industry 5.0, we are witnessing a new era that emphasizes the synergy between people and smart systems [13].

3. Integration of Technologies and People, from Automation to Humanization

Industry 4.0 and Industry 5.0 are two concepts that represent different stages of industrial transformation, each with its own specific focus, advantages and disadvantages. To date, it is known that there are over 200 definitions of Industry 4.0 in the world, and we will single out one that says: *''Industry 4.0, also known as the fourth industrial revolution, focuses on the digitization and automation of production processes using technologies such as the Internet of Things (IoT), artificial intelligence (AI), Big Data analytics, robotics and cloud computing''* [1,2].
Industry 4.0 itself includes automation and digitalization through elements of connecting devices for data collection and exchange (IoT-internet of things), data analysis and decision-making (AI-artificial intelligence), processing of large amounts of data for process optimization (Big Data Analytics), storage and access data via the Internet (Cloud Computing) as well as automatic machines that increase precision and productivity (Robotics), as shown in Figure 2 [1, 14].

Figure 2. Schematically presented vision of Industry 4.0 through elements of advanced technologies

The implementation of Industry 4.0 in the company and its production processes brings a number of advantages, of which we will list a few:

- *Increased precision and accuracy of product manufacturing:* advanced sensors and AI enable precise control and reduce the risk of human error.
- *Flexibility:* Quick adaptation of production lines according to market needs and individualization of products.
- *Increased productivity:* Automation reduces production time and increases efficiency.
- *Predictive maintenance:* IoT and Big Data analytics make it possible to predict failures and plan maintenance before problems occur.
- *Reduced costs:* In the long term, automation reduces operational costs.

We are aware that every industrial revolution, in addition to its advantages, also has its disadvantages, so we will list only the most important ones:

- *Cyber security:* Connecting devices via IoT networks increases the risk of cyber-attacks.
- *High initial costs:* The very implementation of Industry 4.0 technologies requires significant initial investments.
- *Management completeness:* Advanced infrastructure and expertise are required to manage complex systems.
- *Social impact:* Automation can lead to job losses due to the replacement of people by robots.

The implementation of Industry 4.0 technologies (of which there are currently over forty-nine) is leading us towards smart production processes or ''smart factories'', which causes early job losses.This is where Industry 5.0 emerges, which builds on Industry 4.0, but emphasizes collaboration between people and smart systems (present and future) [15-18]. Let us highlight one of the definitions of Industry 5.0, which states: *''Industry 5.0 builds on Industry 4.0, emphasizing collaboration between humans and smart systems. It focuses on the humanization of technology, where humans and robots work together in a harmonious environment, using the advantages of both to achieve better results''*.The schematic representation of Industry 5.0 is shown in Figure 3.

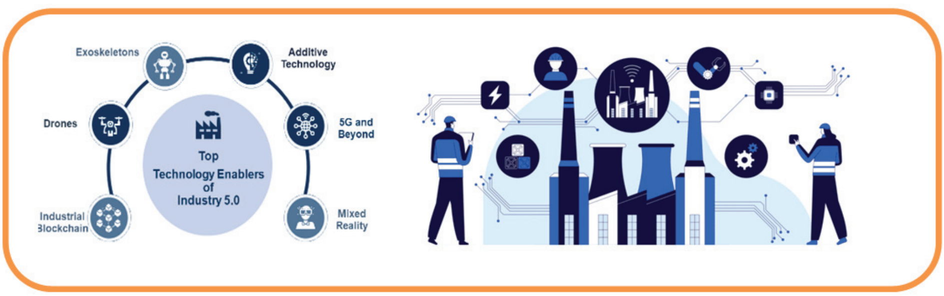

Figure 3. Schematic representation of Industry 5.0

Industry 5.0 is a newer concept that is being developed in response to Industry 4.0, with the aim of fully integrating people into technologically advanced production processes. While Industry 4.0 emphasizes automation and digitalization, Industry 5.0 goes a step further and focuses on collaboration between people and advanced technologies with an emphasis on sustainability, adaptability, and product personalization. One of the main goals of Industry 5.0 is to bring back human creativity and intelligence to production processes that were increasingly automated in previous industrial revolutions [18-20].

In Industry 4.0, robots and machines take over many tasks, while in Industry 5.0, humans and machines work together to create synergy, where technology helps to reduce monotonous tasks, while humans remain responsible for the creative and strategic component of production. Industry 5.0 emphasizes the importance of customizable and personalized solutions, which enable the production of products according to the specific needs of customers. The technology is not only a means to speed up processes, but also to create products that are better adapted to individual desires and market demands. Personalization is becoming essential as it enables rapid adaptation to market trends and end-user needs. Unlike previous industrial revolutions that focused on mass production, Industry 5.0 offers greater flexibility and sustainability. Products can be designed to be more environmentally friendly, using recycled materials or reducing their negative impact on the environment through smart technologies. As consumers become more environmentally conscious, Industry 5.0 also involves the development of sustainable business models that reduce waste and promote a circular economy. From a technical perspective, Industry 5.0 uses advanced tools such as artificial intelligence and data for predictive maintenance, production optimization, and smart product development [21-23]. For example, in the automotive industry, robots and data analysis systems can work together with humans to create vehicles that are fully customized to the needs of end users, while humans contribute creative ideas for design and innovation. An important aspect of Industry 5.0 is also the social dimension. This production model aims to improve the quality of jobs by creating work environments that better support human creativity and health. Automation can take over physically demanding or dangerous tasks, while humans can work on higher-level, intellectual tasks, reducing stress and increasing worker satisfaction. Industry 5.0 also supports the development of intelligent ecosystems in which different industries are connected through smart networks, which leads to increased efficiency and reduced resource consumption. This integrated approach enables better planning, faster response to market changes, and reduced time to develop new products [24-26].

From the very definition of Industry 5.0, we see that it emphasizes collaboration between people and smart systems, which is reflected in the key components:

- *Humanization of Technology:* Industry 5.0 emphasizes the importance of humanizing technology, ensuring that technological advances contribute to human well-being. This includes adapting technology to the needs of workers, improving working conditions, and ensuring the ethical use of technology.
- *Integration of AI and Human Intelligence:* Artificial intelligence supports people in their daily tasks, analyzing large amounts of data, and providing informed recommendations. AI systems can suggest innovative solutions and improvements, while humans make final decisions based on their intuition and experience.
- *Personalization and Adaptability:* Industry 5.0 enables greater personalization of products to specific customer needs. Flexible manufacturing systems allow for rapid adaptation of production lines to respond to changing market demands.
- *Collaborative Robots:*Cobots are designed to work alongside humans in a safe and flexible work environment. Rather than replacing human workers, cobots take on repetitive and physically demanding tasks, allowing workers to focus on creative and strategic activities. This collaboration increases worker productivity and satisfaction.
- *Safety and Ethics:* Industry 5.0 emphasizes the importance of worker safety and the ethical application of technology. Transparency in data use, privacy protection, and the promotion of ethical standards are becoming key aspects of modern industrial practices.
- *Sustainable Development:* The integration of smart systems and human creativity enables more efficient use of resources, waste reduction, and energy consumption optimization. Sustainable approaches to production are becoming a key part of Industry 5.0, reducing the ecological footprint of industrial activities.

Industry 5.0 represents a step forward in the evolution of industrial processes, combining the advantages of digitalization and automation with the unique capabilities of human creativity. Through the synergy of technology and people, Industry 5.0 aims to create more efficient, innovative and sustainable production practices, thus laying the foundation for a prosperous future. Industry 5.0, emphasizing cooperation between people and smart systems, focuses on the humanization of technology, where people and robots work together in a harmonious environment. Its advantages are many, including the following:

- *Human-robot collaboration:* Collaborative robots work together with people, taking over routine tasks and allowing workers to focus on creative activities.
- *Worker safety:* Robots take over dangerous tasks, reducing the risk of injury.

- *Increased creativity:* Collaboration with smart systems encourages innovation and adaptability.
- *Personalization:* Greater ability to adapt products to specific customer needs.
- *Sustainable development:* Industry 5.0 technologies contribute to reducing the ecological footprint and better use of resources.

There are also some weaknesses of the implementation of Industry 5.0, some of which are:

- *Education and training:* Continuous education of workers is required to work with advanced technologies.
- *Complexity of integration:* The integration of people and smart systems requires sophisticated infrastructure and mutual coordination.
- *Ethics and Privacy:* Ethics and privacy issues become more complex with greater integration of technology.
- *High initial costs:* As with Industry 4.0, implementation requires significant investment.

Industry 5.0 brings revolutionary changes in the way we produce, consume and develop technologies. With an emphasis on human-machine collaboration, personalization, sustainability and social responsibility, this model represents an evolution towards a smarter, more sustainable and more flexible industrial future [2,27].

Today's automation includes Industry 4.0 technologies such as artificial intelligence, the Internet of Things (IoT) and smart systems, which enable precise management of production processes and real-time analysis. These technologies improve productivity, reduce costs, improve efficiency and increase product quality.

Digitization of production processes is the process of converting analog information into digital format. In industry, this means using sensors and IoT devices to collect data from production lines and analyze it through software platforms. Digitization enables real-time monitoring of production processes, identification of potential problems and optimization of production lines. Industrial and service robots are key elements of automation in industry. By using advanced robots, production processes become faster, more precise and more efficient. Robots can perform repetitive tasks with high accuracy, reducing the possibility of human error and improving product consistency [28-30]. Automation enables 24/7 work without the need for breaks, which significantly increases production capacity. Robots can work in dangerous or difficult conditions, reducing the risk to workers and allowing people to focus on more complex and creative tasks. Using digital tools and sensors, companies can predict breakdowns and perform timely maintenance, thereby reducing production downtime and extending service life. In the long term, automation reduces operational costs by reducing the need for manual work, optimizing the use of resources and reducing the number of failures. Automated systems can quickly adapt to changes in production requirements, enabling companies to respond to market changes and personalize products according to customer needs. These advances enable industries to be more competitive and adaptable in a dynamic global marketplace. Industry 4.0 and Industry 5.0 bring significant advantages for production processes, but also present certain challenges [33]. While Industry 4.0 focuses on digitization and automation, Industry 5.0 strives to harmonize technology and human creativity. A combination of these approaches can lead to more comprehensive progress, enabling industries to be more productive, innovative and sustainable.

4. Integration of Robotic Technology and Human Creativity

In order to talk about the integration of robotic technology and human creativity, we must examine the trend of implementing both industrial and service robots in the world in all segments of society. In order to do so, an analysis was made based on statistical data obtained from the International Federation of Robotics (IFR), the UN Economic Commission for Europe (UNECE) and the Organization for Economic Cooperation and Development (OECD). The annual trend of the implementation of industrial robots in the world is shown in Figure 1 [33, 34, 35-38].

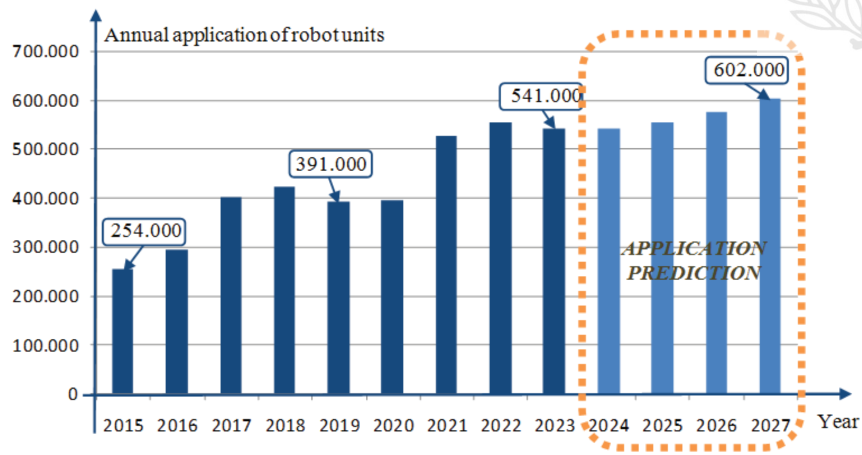

Figure 4. Annual application of industrial robots in the period 2015-2023 and predictions of application until 2027

The diagram shown in Figure 4 gives us an insight into the use of industrial robots in the period 2015-2023, based on which we can see an increase in use on annual basis. 254.000 robots units were used in 2015, while 541.000 robot units were used in 2023, which indicates an increase of 2.1 times in nine years. We notice that the decline in use occurred during the CORONA virus in the period 2019-2020, where the use was around 391.000 robot units. It is predicted that the use of industrial robots will continue to increase in the period 2024-2027, so that the use of about 602.000 robots is expected in 2027. This trend in the application of industrial robots can be attributed to the implementation of Industry 4.0, and robotic technology as one of its basic technologies without which it would be unthinkable to implement Industry 4.0 [33, 34, 35-38].

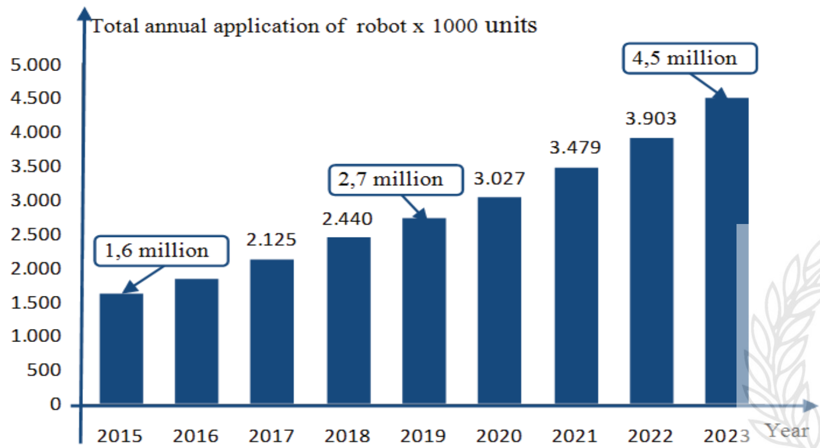

Figure 5. Total annual application of industrial robots in the period 2015-2023

The trend of total annual application of industrial robots in the world for the period 2015-2023 is growing annually, from a total of 1.6 million robot units implemented in the world in 2015 to 4.5 million robot units implemented in 2023. The increase was 2.8 times in just nine years. It is predicted that the total annual application of both industrial and service robots will increase in the coming years, as companies around the world are in the process of complete automation of processes in all industrial branches. The development and implementation of advanced technologies such as: advanced materials, advanced sensors, AI-artificial intelligence, Internet of Things (IoT), Big Data analytics, and cloud computing leads to the development and implementation of the second-generation industrial robots – collaborative robots whose application increases every year, as shown in Figure 6 [36,37]. Figure 6 shows the trend of the use of collaborative industrial robots in the world and in China for the period 2017-2022. In 2017, 11.000 units of collaborative robots were used. With the numbers constantly rising every year, in 2022 this amount increased to around 55.000 units of collaborative robots used in the world.

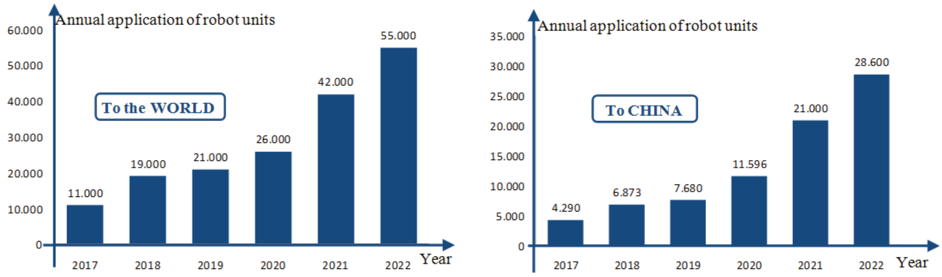

Figure 6. Annual application of the second-generation industrial robots ''Cobot'' in the period 2017-2022 in the world and in the country of China

In six years, the increase in the use of collaborative robots in the world was five times greater.The largest use was recorded in China, which in recent years has become the leader in the use of robots in the world. In 2017, of the total use of collaborative robots in the world, 4.290 units were used in China, which represents about 39% of the use worldwide, while in 2022, this amount increased to 28.600 units of collaborative robots, which is 52% of the total world use of collaborative robots. The comparative analysis of the implementation ofthefirst-generation industrial robots and the second-generation industrial robots – collaborative robots in the world for the period 2015-2022 is shown in Figure 7 [33,34,35-38].

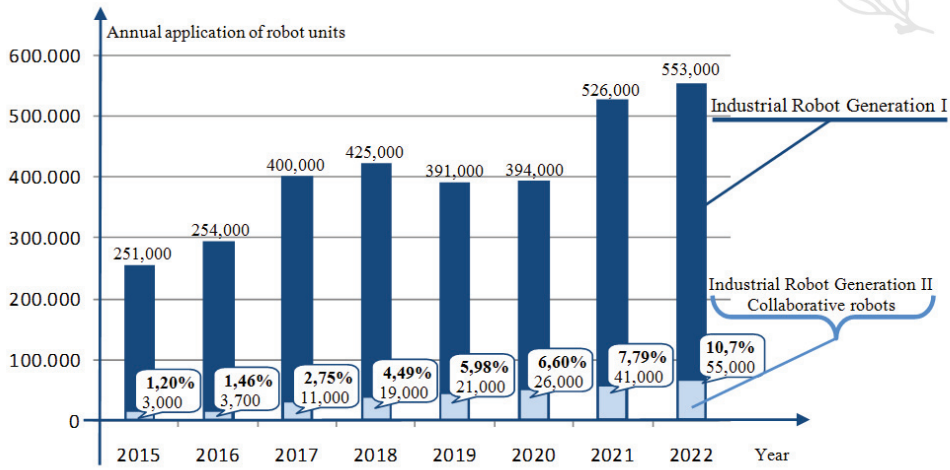

Figure 7. Application ratio of the first-generation industrial robots andsecond-generation industrial robots ''COBOT'' in the world for the period 2015-2023

We will present the comparative difference in the application of first-generation industrial robots and second-generation industrial robots – collaborative robots for the period 2015-2022. Out of the total percentage of industrial robot usein 2015, 1.2% goes to collaborative robots. In the following years, the percentage of the use of the second-generation of industrial – collaborative robots increased annually, so that in 2022 their use has increased to 10.7%. In just seven years, the increase in the use of collaborative robots was 8.9 times. It is expected that the use of collaborative robots in all industrial branches in the world will increase in the coming years. Collaborative robots in the robotics industry are currently the main topic of research in the world. The goal is for workers to work safely with robots, which will assist them in carrying out their daily tasks without any risk. It must be noted that collaborative robots are not intended to completely replace workers, but to work together with the worker and to remove the barriers in production processes that currently exist and confine first-generation industrial robots [39-41]. During work, a human can operate in different fields of work, and perform very complex operations and analytical tasks, while a collaborative robot is simple to operate, performs monotonous repetitive operations, can handle hazardous materials, as well as lift heavy objects. The differences between workers and robots are shown in Figure 8.

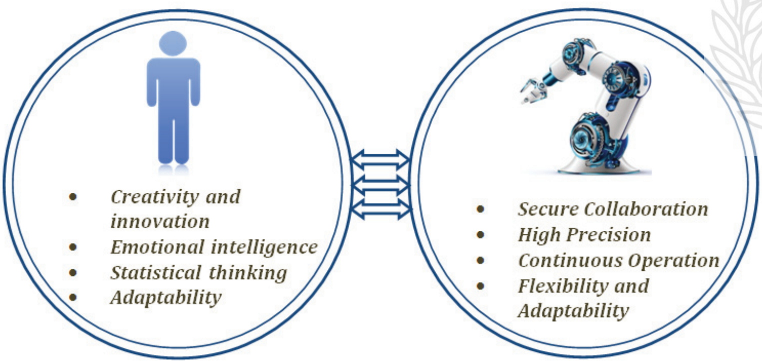

Figure 8. Advantages of humans and second-generation industrial robots - collaborative robots ''Cobots'' [47-48]

Humans possess creativity and innovation, emotional intelligence, strategic thinking and adaptability. The human ability to generate new ideas and innovative solutions is unparalleled. Creativity enables adaptation and improvement of existing processes and products. People can understand and respond to the emotions of others, which is essential for cooperation, teamwork and conflict resolution. Empathy and communication skills play an important role in the work environment. They can analyze complex situations, make long-term decisions and develop strategies to achieve goals. This ability allows companies to adapt to changing market conditions. People can quickly adapt to new situations and working conditions. Flexibility and the ability to learn new skills isthekey to success in a dynamic environment. In relation to humans, collaborative robots ‘’Cobots’’ have the following advantages: safe cooperation, high precision, continuous operation, flexibility and adaptability. Second-generation industrial robots ‘’Cobots’’ are designed to work alongside people, with advanced sensor systems that recognize the presence of people and prevent collisions. This ensures a safe working environment and reduces the risk of injuries. They can perform tasks with a high level of precision and repeatability [42-44]. This capability reduces the possibility of errors and improves product quality. Second-generation industrial robots can operate 24/7 without the need for breaks, thus increasing production capacity and efficiency. This capability enables continuous production and reducing downtime. Another advantage is that they can be quickly programmed to perform different tasks, thus enabling rapid adaptation of production lines to changing market demands. The synergy between humans and cobots creates an optimal working environment in which the advantages of both sides are combined. Humans bring creativity, emotional intelligence and strategic thinking, while cobots ensure safe collaboration, precision, continuous operation and flexibility. This combination allows industries to achieve greater productivity, innovation and adaptability, thus creating a more sustainable and competitive business model. The human ability to generate new ideas and innovative solutions is unmatched. Creativity enables the adaptation and improvement of existing processes and products [45,46]. The advantages of collaborative robots over workers and first-generation industrial robots include: *heavy lifting*– collaborative robots can lift loads weighing more than 20 kilograms, which reduces physical effort and the risk of injury to workers;*handling hazardous materials*– they can work with dangerous chemicals and high-temperature objects, which protects workers’health;*injury reduction*– the use of collaborative robots reduces the risk of injuries at work;*flexibility of application*– collaborative robots do not require fences, which reduces the required work surface to perform tasks;*high sensitivity*– they are equipped with advanced force, torque and visual sensors, which ensures a safe work space and protective zones (as shown in Figure 8 and Figure 9);they can recognize collisions, safely identify tools and monitor forces;*easy programming*– they are easily programmed for various tasks, which increases their flexibility; *adaptable work cycle*– the automatic work cycle of collaborative robots is flexible and easily adapted to specific tasks;*worker safety*– work safety is ensured in accordance with ISO 10218 and ISO 13849 standards, including functional safety and safe zones. Safe zones are maintained by monitoring the speed of the robot in relation to the distance from the worker.

Collaborative robots combine power, precision and sensitivity, thus enabling a safer and more efficient work environment for workers.

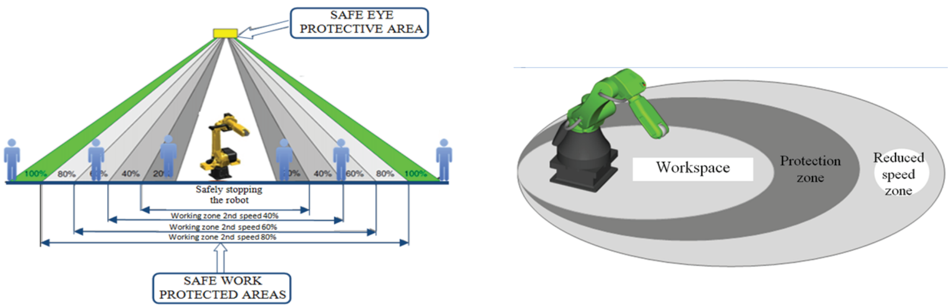

Figure 9.Worker safety is ensured by reducing the robot's speed based on the worker's proximity, using FANUC's DSC – Double Safety System [48-52]

The collaborative robot equipped with sensors is intended for direct interaction with human workers within a shared and predefined workspace. To ensure safety during such interaction, the company FANUC developed a Dual Check Safety (DSC) system, illustrated in Figure 9 [47–52]. This system utilizes laser sensors to provide an additional safety layer and regulate robot behavior accordingly.When the worker is outside the designated zones, the robot operates at its maximum programmed speed. Upon entering the speed reduction zone, the sensor sends data to the PLC, which then issues a command to decrease the robot's velocity. As the worker approaches further into the safety zone, the speed continues to drop, eventually triggering the “Contact Stop” mechanism.If the worker steps into the collaborative working area, the robot transitions into collaborative mode with limited speed, and the “Contact Stop” status remains active. In the event of physical contact—whether with the robot, the end-effector, or the workpiece—the system halts all operations immediately.Once the worker moves away, the robot resumes operation, adjusting its speed based on the current zone the worker occupies. These collaborative robots are covered with a soft, sensitive layer that ensures the machine stops whenever the applied contact force exceeds 150 N. This threshold can be modified via software settings to suit different application requirements. A visual example of this type of interaction is presented in Figure 10.

Figure 10. The sensitivity of the collaborative robot for the safe work of workers [47-52]

To prevent operational interruptions, the system allows the robot to automatically resume movement after a stop, adjusting its speed based on the worker's position within the workspace. Additionally, safety measures are in place to prevent hand injuries by ensuring that the space between the robot's axes does not pose a risk of pinching [49].

The implementation of collaborative robots offers a wide range of significant benefits, making them an increasingly attractive solution in modern manufacturing environments:

- *Safe human-robot interaction:* These robots are specifically designed to operate safely alongside humans within a shared workspace, ensuring a high level of occupational safety.
- *User-friendly operation:* Their intuitive programming and adaptability to various tasks make collaborative robots easy to set up and reconfigure as needed.
- *Enhanced productivity:* Task sharing between human workers and robots enables more efficient workflows, leading to a notable boost in overall productivity.
- *Scalable automation:* In situations where full automation is impractical or too costly, collaborative robots provide a flexible solution by allowing for partial automation within the production process.
- *Ergonomic improvements:* They can be deployed to assist in physically demanding or ergonomically unfavorable tasks, contributing to a safer and more comfortable working environment.
- *Integration with Industry 4.0:* Collaborative robots are a core component of Industry 4.0 initiatives, helping bridge the gap between physical manufacturing and digital technologies.

- *Adaptability to production changes:* Due to their ability to quickly adapt to new product designs and shorter product lifecycles, these robots are ideal for manufacturers who require versatile and responsive automation solutions. This flexibility has led to widespread adoption, especially among small and medium-sized enterprises.

These benefits show how collaborative robots can revolutionize industrial processes, and improve efficiency, safety and adaptability. The basis of the implementation of ''Industry 4.0'' is robotic technology, that is, the implementation of collaborative robots in production processes. In order for the company to be competitive on the global market, it is inevitable that it must move towards the implementation of ''Industry 4.0'', which will result in an increase in the use of collaborative robots. When applying collaborative robots, companies have the following motives: reduction of operating costs, reduction of capital costs, improvement of product quality and consistency, improvement of work quality for workers, respecting health and safety rules, increase of production rate, increase of flexibility in product production, saving of space, etc. It is to be expected that in the future the trend of use of collaborative robots will be growing. Collaborative robots, representing a key component of Industry 5.0, which focuses on the synergy between people and smart systems, brings a new approach, putting human creativity at the center of technological progress. The integration of technology and people has evolved through several phases, from basic automation to today's humanization of technology. Each step of this evolution has brought significant changes in the way we work, increasing productivity and efficiency while improving working conditions. With the advent of Industry 4.0, technologies such as IoT, Artificial intelligence (AI) and Big Data analytics have transformed manufacturing processes. These technologies enable real-time monitoring, analysis, and optimization of operations, thereby increasing efficiency and reducing downtime. Automated systems can operate 24/7, increasing production capacity. Industry 5.0 introduces the concept of humanizing technology, where the emphasis is on collaboration between people and smart systems. Collaborative robots (cobots) enable safe collaboration with humans, taking over repetitive and dangerous tasks, while workers can focus on creative and strategic activities. This synergy increases productivity and worker satisfaction. The evolution from automation to humanization of technology shows how technological progress can be successfully integrated with human creativity and ethics. The synergy between people and technology not only improves efficiency and productivity, but also creates a more sustainable and safer work environment, laying the foundation for future industry development.

5. Integration of the Balance Between Technology and Human Creativity

Integrative cooperation of humans and robots in industrial processes can significantly increase innovation and efficiency. The key way in which this can be achieved is through implementation in production processes: collaborative robots, advanced artificial intelligence, the Internet of Things (IoT), learning and discovery, adaptability and personalization, security and ethics. Collaborative robots are designed to work alongside humans in a safe and flexible environment. They take over repetitive and physically demanding tasks, allowing workers to focus on creative and strategic activities. This collaboration increases productivity and reduces the possibility of errors. AI systems can analyze large amounts of data in real time, providing valuable insights that support informed decision making. AI can recognize patterns and trends that human workers might not notice, enabling faster and more accurate innovation. IoT connects devices and systems within production lines, enabling real-time data collection and analysis. This connection enables better process monitoring and optimization, reducing downtime and improving overall efficiency. Continuous education and training of workers to work with advanced technologies is the key to successful integration. Workers must understand how to use technology to support their daily tasks and how to collaborate with robots in a safe and efficient manner. Flexible production systems enable rapid adaptation to changing market demands and product personalization. The combination of human creativity and robotic precision enables the creation of innovative products tailored to specific customer needs. Safety measures such as advanced sensors and automatic stops ensure a safe working environment. In addition, the ethical application of technology and transparency in the use of data is the key to building trust between workers and consumers. The synergistic integration of humans and robots allows industries to leverage the best of both worlds: robotic precision and efficiency, and human creativity and adaptability [49-52]. This collaboration not only improves productivity, but also fosters innovation, creating more sustainable and dynamic industrial processes.

Balancing technology and human creativity is the key to creating more efficient and sustainable industrial processes. Here are some steps to achieve this:

- *Collaborative work:* Collaborative robots work alongside humans, taking on repetitive and physically demanding tasks. This frees workers to focus on creative and strategic activities.
- *Support for creative processes:* AI can analyze large amounts of data, provide insights, and suggest new ideas. AI supports creative processes, enabling people to make better-informed decisions and develop innovative solutions faster.

- *Flexible production systems:* Introducing flexible production lines that can quickly adapt to changing market demands allows for greater product personalization. The combination of technology and human creativity allows for the creation of products tailored to specific customer needs.
- *Investing in workers:* Ensuring continuous education and training for workers to adapt to new technologies is a key to successful integration. Workers who understand technology can better use it to support their creative tasks.
- *Resource optimization:* By using smart systems to optimize resource and energy consumption, industrial processes become more sustainable. Technology can help reduce waste and make better use of materials, while human creativity can lead to innovations that further reduce the environmental footprint.
- *Ethics in technology:* Ensuring that technology is used ethically and that data is protected is essential for building trust among workers and consumers. Transparency in the use of technology and protecting privacy are key elements of a safe work environment.
- *Encouraging collaboration:* Creating a culture that encourages collaboration between people and technology. Workers need to feel that technology is not a threat, but a tool that helps them do their job. Open communication and involving workers in the decision-making process increases their engagement and innovation.

Achieving a balance between technology and human creativity is essential for creating more efficient and sustainable industrial processes. Synergistic integration allows industries to leverage the best of both worlds - technological efficiency and human innovation - thereby creating more competitive and sustainable business practices.

The vision of the future integration of technology and people in industrial processes aims to create a harmonious, productive and sustainable work environment. Here are some key elements of this vision:

- *Collaborative work:* Smart systems and collaborative robots (cobots) will enable people to work with technology in a safe and efficient way. Robots will take over repetitive and dangerous tasks, while people will focus on creative and strategic activities. This symbiosis will increase productivity and worker satisfaction.
- *Adaptability and personalization:* The future of technology and people integration will enable greater personalization of products and adaptability of production processes. Technologies such as 3D printing, flexible production lines and AI systems will enable rapid adaptation to changing market demands and specific customer needs.

- *Sustainable development:* The integration of smart systems will enable more efficient use of resources, waste reduction and energy consumption optimization. Smart sensors and IoT technologies will enable real-time monitoring of the ecological footprint and process adaptation to achieve sustainable goals.
- *Continuous education:* Investing in education and training of workers will be a key factor for successful integration. Workers will need to continuously learn to adapt to new technologies and make the most of their capabilities. Education will also ensure that workers are safe and effective in their tasks.
- *Safety and ethics:* Worker safety will be a priority. The integration of smart systems will ensure that the work environment is safe and healthy. Ethics in the use of technology, data privacy protection and transparency will be key aspects that will build trust among workers and consumers.
- *Innovation and creativity:* Technology will support worker creativity, enabling faster and more efficient generation of new ideas and solutions. AI systems will analyze large amounts of data, providing valuable insights and encouraging innovations that will improve products and services.
- *Global collaboration:* Technology will enable better global collaboration among industrial partners. Through digital platforms, companies will be able to share information, collaborate on projects and work together on innovations regardless of geographical boundaries.

The vision of the future integration of technology and people is based on harmonious cooperation that improves the efficiency, innovation and sustainability of industrial processes. The synergy between technology and human creativity will create more competitive and sustainable business practices, ensuring a prosperous future for the industry.

6. Conclusion

The integration of robotic technology and human creativity is bringing about significant changes in industrial processes, moving from basic automation to the humanization of technology. Throughout the history of industrial development, from the first to the fifth industrial revolution, we have witnessed continuous progress that has enabled greater productivity, efficiency and safety in the workplace. Automation began with mechanical machines and first-generation industrial robots, enabling mass production and cost reduction. With the development of Industry 4.0, digitalization and smart systems such as IoT, AI and Big Data analytics have transformed production processes, enabling real-time monitoring and optimization. Industry 5.0 brings a new dimension, emphasizing collaboration between humans and smart systems. Collaborative robots (cobots) enable safe and efficient collaboration, taking over repetitive and dangerous tasks, while humans can use their creativity for more complex and strategic activities. This synergy increases productivity, innovation and worker satisfaction. The combination of robotic technology and human creativity creates flexible and adaptable production processes that respond to specific market needs. Integrating the balance between technology and human creativity ensures that industrial processes are sustainable, ethical and focused on long-term development. This paper highlights the importance of the evolution from automation to humanization of technology, highlighting how the harmonization of these aspects can advance industrial practices and create a more prosperous future. The synergy between people and technology not only improves efficiency and productivity, but also contributes to the creation of a more sustainable and safer work environment.

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Cognitive and Visual-Motor Robotic Manipulation in Industrial Environments: A Puzzle Assembly Paradigm

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Abstract: *The increasing complexity of industrial processes and the shift towards automation demand intelligent, adaptive robotic systems capable of performing cognitive and visuomotor tasks in dynamic environments. This paper presents the puzzle assembly gaming task as an illustrative paradigm for the implementation of such systems in industry. The assembly of puzzles, often considered a cognitive game, mimics many characteristics found in industrial tasks: high variability, unstructured environments, the need for visual recognition, decision-making, trajectory planning and fine manipulation. In the paper it is explored how artificial intelligence (AI), computer vision, machine learning, inference systems, and robot motion planning converge to create systems capable of tackling tasks with similar cognitive and manipulative challenges in industrial settings.*

Keywords: *Industry 4.0, cognitive robots, visual motor manipulation, puzzle game 1.*

1. Introduction

Industrial robotics has evolved from executing repetitive, pre-programmed motions to performing increasingly sophisticated tasks that require perception, adaptability, and decision-making. Traditional industrial automation relied heavily on structured environments and fixed scenarios. However, modern manufacturing settings increasingly resemble dynamic environments where objects may arrive in random orientations and positions, requiring a robot to "understand" the scene before acting. This cognitive capability is paramount for applications such as flexible assembly lines, quality inspection, and adaptive sorting.

Puzzle assembly represents an ideal testbed for these capabilities. In the puzzle paradigm, the robot is exposed to an unstructured set of randomly scattered pieces and a reference image representing the completed puzzle. The robot must use vision to recognize, identify, and classify individual pieces, reason about their placement, and perform delicate manipulation to assemble the

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full picture. This paper explores the conceptual foundation and implementation of such systems in industrial contexts.

The central idea of this research is to develop algorithms and a methodology that can automate the human skill of solving jigsaw puzzles, a didactic game, by leveraging visual perception of the complete image and mapping human cognitive and visuo-manipulative skills onto an industrial robot. This illustrative and educational task serves as a prototype for applications in industrial environments, where the goal is to synthesize a high level of cognitive and manipulative autonomy in robots.

The ultimate objective is to achieve a degree of automation in which a robot can independently execute not only simple, predefined operations but also more complex technological tasks that require advanced cognitive intelligence — such as perception, reasoning, and learning. Solving the robotic jigsaw puzzle problem, therefore, becomes a gateway to generalizing this knowledge and skill set to similar assembly tasks within industrial contexts.

In a review of the literature, it was found only a limited number of references directly addressing robotic puzzle assembly. One particularly interesting example includes the project "Jigsaw Puzzle Robot" [1], accompanied by video demonstrations and a technical report [2, 3], in which a gantry robot and vision system were used to solve a jigsaw puzzle. However, their method focused exclusively on the analysis of contour shapes and mechanical fit, ignoring visual parameters such as color and texture. The puzzle pieces used in their study were monochromatic (white), indicating that neither color nor surface detail was considered.

In contrast, the approach in this paper is inspired by the way humans, as biological systems, solve jigsaw puzzles. Human players rely on a combination of visual cues: color spectra, texture features, and contour shapes to infer the correct positioning of puzzle pieces. Our methodology, therefore, aims to replicate this layered decision-making strategy. We argue that such a biologically inspired, multimodal approach is more comprehensive and meaningful in the context of robotics. It promotes the development of generalizable cognitive and manipulative skills that can be transferred to complex industrial tasks, such as autonomous robotic assembly, where adaptability and perceptual intelligence are essential.

Our intention is not to create a performative or exhibition-level demonstration of robotic skill, but rather to establish a structured framework for understanding and engineering generalizable skills in autonomous robotic systems. This research contributes toward bridging the gap between human cognitive behavior and robotic autonomy in real-world industrial applications.

The project Jigsaw Puzzle Robot [1]-[3] features a gantry-style robot equipped with a vision system designed to assemble jigsaw puzzles.The robot focuses on analyzing the contours of puzzle pieces, using shape-matching algorithms to determine correct placements.Notably, the system does not utilize color or texture information, and the puzzles used are monochromatic.

The CNC Jigsaw Puzzle Building Robot[2] isdeveloped at the University of Pretoria. This project involves a CNC-based robotic system capable of assembling jigsaw puzzles.The system employs computer vision techniques to detect and classify puzzle pieces, followed by a solving algorithm to determine their correct positions.The robot then physically assembles the puzzle using precise movements.

The AI-Powered Jigsaw Puzzle Solving Robot project[3]showcases an AI-driven robotic arm designed to autonomously solve jigsaw puzzles.The system integrates computer vision for piece recognition and deep learning algorithms to predict correct placements, enabling the robot to assemble the puzzle without human intervention.

The academic study [4] presents a method for assembling jigsaw puzzles without relying on pictorial information.Instead, it utilizes integral area invariants for shape matching, allowing the system to solve puzzles based solely on the geometry of the pieces.

Several video demonstrations are available showcasing robotic systems solving jigsaw puzzles [5, 6].

These projects illustrate various approaches to robotic jigsaw puzzle assembly, ranging from contour-based methods to AI-driven solutions.Our research, which emphasizes the integration of color, texture, and shape analysis inspired by human strategies, offers a more holistic approach that could enhance the generalization of robotic assembly skills in industrial applications.

2. Conceptual Framework

The conceptual foundation for applying puzzle assembly logic to industrial robotics rests on the integration of several advanced domains within artificial intelligence and robotics [7]-[16]. These include computer vision [9,11] for perception, machine learning for interpretation and adaptation [7,9], kinematic modeling for motion control [7,8], planning algorithms for sequencing tasks, and cognitive architectures for higher-level reasoning and decision-making. Together, these components enable the robot to simulate human-like problem-solving strategies in a structured, autonomous manner. The process of robotic puzzle assembly can be broken down into a sequence of interrelated cognitive and physical stages:

Perception

The process begins with perception, where the robot acquires visual data from its environment using cameras or other sensors. This includes capturing images of both the puzzle pieces and the reference image of the completed puzzle (if available). Through advanced image processing techniques such as edge detection, segmentation, and keypoint extraction, the system isolates individual pieces and extracts relevant visual features. These may include contours, color distributions, texture patterns, and relative position in space. The output of this phase is a structured digital representation of the observed puzzle elements.

Interpretation
In this phase, the robot interprets the visual data by identifying and classifying puzzle pieces. Shape descriptors (e.g., Fourier descriptors, curvature signatures) are used to characterize the contours of each piece. Texture and color features (e.g., histograms, LBP, color moments) are analyzed to match pieces that likely belong together. Machine learning models or heuristic rules may be applied to infer edge types (e.g., corner, border, or inner piece) and predict the likelihood of a correct match between adjacent pieces. This step mimics human visual reasoning, where a person intuitively evaluates both local details and global patterns when assembling puzzles.

Decision-Making
Based on the interpreted data, the system engages in decision-making to determine the next best piece to place. This involves evaluating all candidate pieces in relation to the current state of the puzzle and estimating where each piece might fit. Scoring functions based on shape compatibility, color continuity, and texture alignment guide this selection. The robot must also consider the evolving context of the puzzle layout, dynamically updating its internal model to reflect changes after each successful placement.

Planning and Execution
Once a piece and its position are selected, the robot plans and executes the physical action needed to grasp and place the piece. This involves calculating collision-free trajectories for its robotic arm and end-effector, using inverse kinematics and motion planning algorithms. Precision is crucial, as misalignment can lead to incorrect placements or physical interference. Gripper control must also be fine-tuned to avoid damaging delicate puzzle pieces while ensuring a firm grip.

Feedback and Adaptation
After each action, the robot evaluates the outcome using sensory feedback. This may include verifying the visual alignment of the piece or detecting tactile feedback from force sensors. If an error is detected—such as a misfit or a placement in the wrong orientation—the robot updates its strategy, either retrying the action with corrections or re-evaluating its previous interpretation

and decisions. This continuous feedback loop enables learning and adaptation, mirroring human trial-and-error behavior.

Ultimately, this structured process serves not only as a foundation for puzzle-solving but also as a model for generalized autonomous assembly tasks in industrial environments, where perception, interpretation, planning, and adaptation are equally critical.

2.1 Visual Reasoning Methodology in Human Puzzle Assembly

When a human player approaches the task of assembling a puzzle based on a reference image, the process begins with a visual decomposition of the integral picture into perceptually salient regions. One of the primary strategies involves segmenting the image into dominant color zones—for example, the sky typically appears in a blue hue, albeit with subtle gradations and variations within the blue spectrum. This chromatic segmentation provides an initial heuristic for narrowing down the potential spatial localization of individual pieces.

Within these color zones, players identify finer perceptual cues—such as small clouds within the sky, a leaf in a green canopy, or architectural details like rooftops or window outlines. These elements correspond to texture, defined in computer vision and perceptual psychology as the spatial variation of intensity or color that forms distinguishable surface patterns. Texture plays a crucial role in differentiating between puzzle pieces that may otherwise share similar color profiles. Thus, the early stages of assembly are heavily reliant on combined color-texture analysis.

However, when the available pieces belong to a visually homogeneous region—e.g., a large portion of sky, ocean, or wall—where both the color and texture offer limited discriminative information, the player shifts cognitive strategy toward analyzing shape and contour geometry. This involves evaluating the external edges of puzzle pieces: convexities, concavities, tabs, and blanks. The geometry of each piece must then be mentally or physically tested against candidate neighbors to find a fit that not only connects mechanically but also aligns with visual continuity in the image.

This layered approach—first utilizing global color segmentation, then localized texture matching, and finally geometric contour reasoning—mirrors human strategies for perceptual disambiguation in uncertain visual contexts. Importantly, this multistage reasoning process is not strictly sequential; rather, it is dynamically adaptive. For example, a player may simultaneously consider edge shape and surface detail when a texture cue alone is ambiguous. The integration of these perceptual modalities allows the human solver to effectively reduce the search space and resolve ambiguities through successive refinement.

This cognitive methodology serves as a powerful metaphor for designing robotic vision systems tasked with visual reasoning under uncertainty. The robotic counterpart must similarly combine global appearance models (e.g., color histograms), local texture descriptors (e.g., Gabor filters, LBP, SIFT), and edge-based shape analysis (e.g., curvature descriptors, contour matching) to infer both semantic and geometric compatibility among parts within an unstructured environment (Fig. 1).

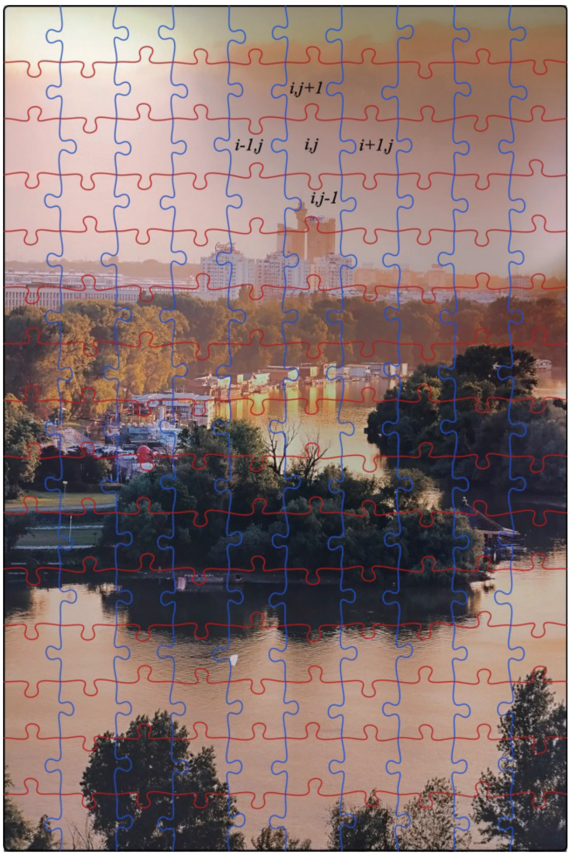

Figure 1. Arranged puzzles into a complete picture. An example of the similarity of neighboring puzzles in the sector $S_{i,j}$, $i \in \{i-1, i, i+1\}$, $j = \{j-1, j, j+1\}$ *with barely noticeable differences in color shade and texture*

2.2 Contour Comparison in Puzzle Assembly

The comparison of puzzle piece contours involves the analysis of the outer edge geometries of each piece to determine potential fits between them. This process is particularly critical in scenarios where color and texture information are insufficient for accurate identification—such as large uniform regions (e.g., sky or sea).

From a computational perspective, contour comparison is typically approached through several key steps (Fig. 2):

1. **Contour Extraction.** First, the edges of each puzzle piece are detected and extracted using image processing techniques. Algorithms such as Canny edge detection or morphological contour tracing can be applied to obtain a clean representation of the external boundaries of each piece.
2. **Segmentation into Edge Sections.** Each piece is segmented into individual edge elements—usually four in a classic jigsaw puzzle (top, bottom, left, right). Each segment is characterized either as an **inward (concave)** or **outward (convex)** shape, or as a **flat edge** in the case of border pieces.
3. **Shape Representation.** The shape of each edge is encoded using mathematical descriptors. Common representations include:
   - **Curvature descriptors**: Capture the bending of the contour line at various points.
   - **Fourier descriptors**: Transform the contour into the frequency domain for comparison.
   - **Chain codes**: Encode the direction of contour points for compact representation.
   - **Shape context descriptors**: Provide a histogram-based representation of the spatial distribution of contour points.
4. **Matching Criteria.** The goal is to match a convex edge with a corresponding concave edge such that:
   - **Geometric complementarity** is maximized (e.g., the two contours “fit” when aligned).
   - **Distance metrics** such as Hausdorff distance or sum of squared differences between contour points are minimized.
   - **Orientation alignment** is preserved, ensuring rotational consistency (especially important in robotic systems).
   - **Continuity and smoothness** are evaluated, confirming that the joint between two pieces is visually and physically seamless.
5. **Fit Scoring and Ranking**. Each candidate pair is assigned a **fit score** based on the similarity of their contours. A lower score (or higher similarity) indicates a better match. Pairs are ranked, and the top candidate is selected for further visual or mechanical validation.

In human cognition, this process is intuitive and largely subconscious. People visually inspect the "male" (tab) and "female" (blank) shapes of puzzle pieces, rotate them mentally or physically, and judge potential matches based on how

well their profiles interlock. This ability is informed by experience and refined through trial and error.
In robotic systems, this contour matching process must be implemented through algorithmic pipelines that integrate vision-based contour extraction, shape analysis, and probabilistic matching models. It is especially important in unstructured environments where traditional indexing (e.g., part IDs or labels) is not available.

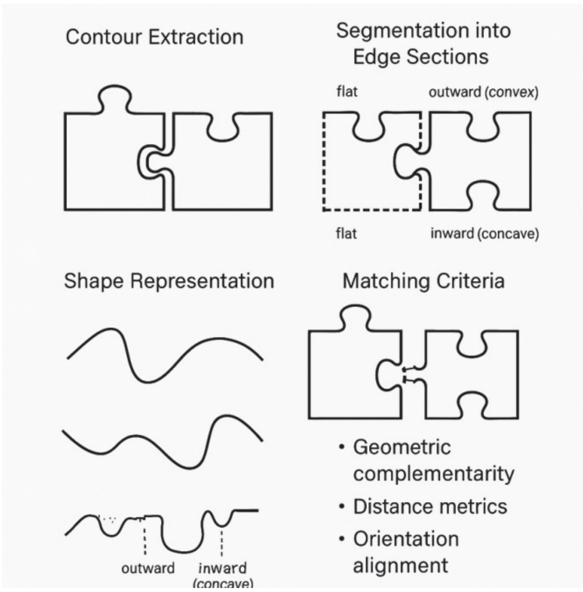

Figure 2. Puzzle contour detection

3. Industrial Analogues to Puzzle Assembly

While jigsaw puzzle assembly may initially appear as a recreational activity, its underlying principles closely mirror numerous industrial tasks that demand advanced perception, reasoning, and manipulation capabilities. By examining these parallels, we can better understand how robotic systems can be designed to handle complex assembly operations in dynamic industrial environments.

Electronic Component Placement
Automated placement of electronic components on printed circuit boards (PCBs) is a prime example (Fig. 3a). This process requires precise identification and positioning of various small components, such as resistors and integrated circuits, onto designated spots on a PCB. The task involves recognizing component types, determining their correct orientation, and placing them

accurately, akin to fitting puzzle pieces based on shape and position. Advanced vision systems and robotic arms are employed to achieve the necessary precision and speed in this application.

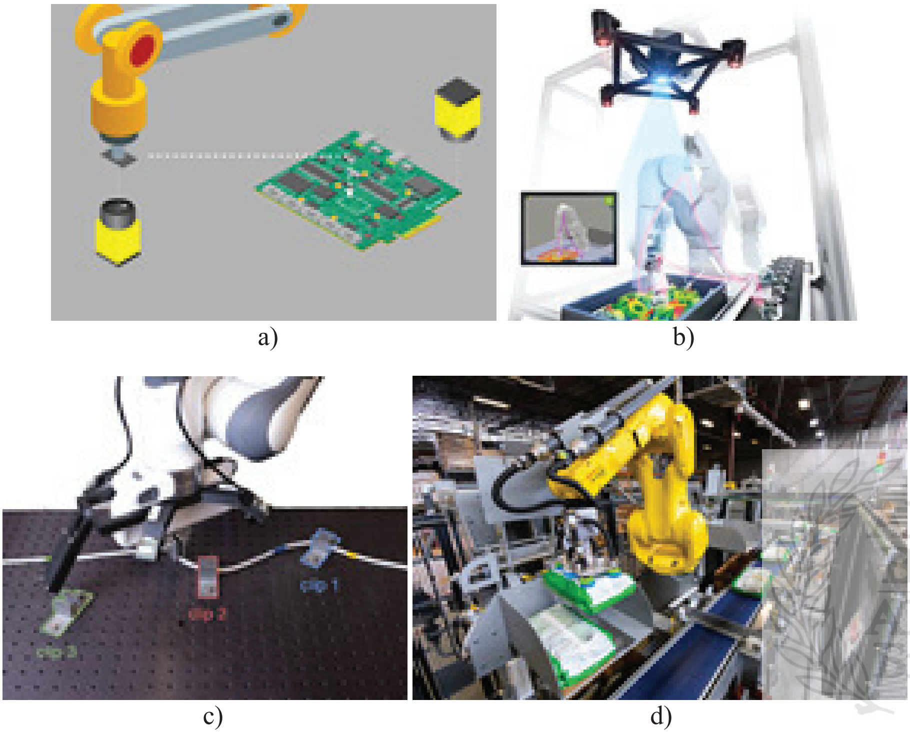

Figure 3. Puzzle inspired scenarios – industrial analogues. a) PCB component placement guidance – semiconductor manufacturing and printed circuit board, b) Bin picking – 3D vision-guided robotics (Keyence), c) Cable routing system, d) Multi-line robotic packing system – Pearson packaging system

Bin Picking and Sorting

In logistics and manufacturing, bin picking involves selecting and sorting items randomly placed in containers (Fig. 3b). Robots must identify objects of varying shapes and sizes, determine their orientation, and grasp them appropriately. This scenario resembles the randomness and variability encountered in jigsaw puzzles, where each piece must be recognized and correctly oriented before placement. Implementing 3D vision systems and machine learning algorithms enables robots to handle such tasks effectively .

Flexible Assembly Tasks

Industries such as aerospace and automotive manufacturing often deal with components that arrive unsorted or require adjustments due to tolerances. Robots must adapt to these variations, making decisions on-the-fly to assemble parts correctly. This flexibility mirrors the cognitive processes involved in puzzle assembly, where each piece's placement depends on its relation to others and the overall picture. Developing robots with adaptive planning and decision-making capabilities is crucial for these applications .

Cable Routing and Hose Assembly
Routing cables and assembling hoses involve handling flexible components that require precise placement along predefined paths (Fig. 3c). Robots must recognize layout patterns, infer routing paths, and manipulate flexible parts without causing damage. This task is analogous to connecting puzzle pieces with intricate shapes and paths, demanding both visual recognition and delicate handling. Advanced control algorithms and tactile sensors are often utilized to achieve the necessary compliance and precision .

Adaptive Packaging Systems
In packaging industries, robots are tasked with arranging items of various shapes and sizes into packages efficiently (Fig. 3d). This process requires recognizing item characteristics, determining optimal placement configurations, and adapting to changing product lines. Similar to assembling a puzzle, robots must analyze visual information and make decisions to achieve the desired arrangement. Incorporating computer vision and real-time planning algorithms enables robots to perform these tasks with high efficiency .

By drawing parallels between jigsaw puzzle assembly and these industrial tasks, we highlight the importance of integrating perception, reasoning, path planing, trajectory generation and manipulation in robotic systems. Developing such capabilities is essential for achieving higher levels of autonomy and flexibility in industrial automation.

4. System Architecture

To enable a robotic system capable of solving complex tasks such as jigsaw puzzle assembly—or analogous industrial operations—a tightly integrated system architecture is required. This architecture must incorporate visual perception, learning algorithms, symbolic reasoning, motion planning, manipulation control, and a human-machine interaction interface.

Visual Perception Subsystem
Visual perception forms the first layer of information acquisition. Typically, a combination of RGB cameras and depth sensors (e.g., stereo vision, LiDAR, or Time-of-Flight sensors) is employed to capture three-dimensional

representations of the environment. These data are used for object detection, contour extraction, and spatial pose estimation. Major challenges in this subsystem include variations in lighting, partial occlusions, and diversity in object appearance regarding shape and color.

Machine Learning Models

Deep learning techniques, especially convolutional neural networks (CNNs), are applied for object classification, scene segmentation, and prediction of optimal actions. These models are trained on datasets comprising images and features of objects similar to those expected in the target scenarios. Transfer learning and fine-tuning allow the adaptation of pre-trained networks to specific real-world applications with relatively limited annotated data.

Cognitive Layer

Building upon perceptual input, the cognitive layer utilizes symbolic reasoning to decide which object to pick, where to place it, and in what sequence actions should be performed. This layer may include an inference engine employing rule-based logic, heuristics, or planning algorithms to simulate human-like decision-making processes. It is particularly crucial for orchestrating multi-step actions that require a global understanding of task objectives—such as completing a puzzle or assembling a component.

Motion Planning Engine

The trajectory generation component is responsible for planning collision-free and kinematically feasible paths in constrained environments. Algorithms such as RRT* (Rapidly-exploring Random Tree), A*, and optimization-based methods like CHOMP or STOMP are commonly used. The planner must account for manipulator constraints, task-specific precision requirements, and system dynamics.

Manipulation Controller

Precise object manipulation necessitates low-level control of the end-effector. This subsystem integrates feedback from tactile sensors (e.g., piezoelectric, capacitive) or visual markers (e.g., ArUco) to perform real-time adjustments. The goal is to ensure accurate placement and gentle handling of parts, avoiding damage or misalignment.

Human-Machine Interface (HMI)

To ensure practical deployment in semi-autonomous or supervised industrial environments, the system includes an HMI that allows users to set high-level goals, monitor progress, visualize perception outputs, and intervene when necessary. The interface may consist of a graphical user interface (GUI), command console, or voice control, depending on the application requirements and user expertise.

5. Implementation Using Techman TM7S Cobot

5.1 Experimental Setup

The Techman TM7S collaborative robot offers a practical platform for implementing visuo-motor and cognitive assembly tasks. It combines a 6-DOF collaborative robotic arm with an integrated vision system and user-friendly programming environment.

For puzzle assembly by Techman Cobot TM7S [17] an experimental setup was configured as presented in the Fig. 4. The elements of the testbed system are (Fig. 4):

- Two high-resolution IDS uEye Cameras, Model UI-5240CP-P-HQ, captures the scene.
- Image processing identifies puzzle pieces, their edges, and potential neighbors.
- A deep learning classifier evaluates the most probable placement for each piece.
- The robot plans its movement to pick a selected piece and place it in the identified location using its vision-guided manipulation. The Fig. 5 presents a fragment of robotic puzzle dislocation from the *Staging Area* to the accurate position in the *Solution Area*. Robot controller receives the starting point coordinates A (x1, y1) as well as the end-point coordinates B (x2, y2) from the cameras (left and right one). The end-effector orientation (pneumatic gripper) should be kept always perpendicular to the robot work surface. The robot controller re-calculate coordinates of the points A and B in its' own coordinate system attached to the robot fundament.
- The Techman Cobot TM7S [17] controller does not support built-in path planning or end-effector trajectory generation. Therefore, this task is delegated to an external computer running MATLAB and the Robotics Toolbox for MATLAB/Simulink developed by Peter Corke [18]. The concept in this study involves using installed cameras to detect the location of a specific puzzle piece in the so-called *Staging Area* and the target position where the puzzle should be placed in the *Solution Area(Fig. 5)*. These coordinates are captured by two cameras, CAM-1 (left camera) and CAM-2 (right camera), and transmitted to the auxiliary computer, where they are used in MATLAB to plan the motion of the robot gripper within the task's operational workspace. Within MATLAB, the trajectory from point A to point B is computed based on inverse kinematics algorithms. In this experiment, artificial neural

networks were applied to calculate the internal joint coordinates (angles) of the robot, in order to accelerate the trajectory computation process. To achieve this, a neural network was first trained offline using a large dataset of robot positions within the task workspace, specifically where the end-effector was positioned in both the *Staging* and *Solution* areas for puzzle manipulation. Communication between MATLAB (on the auxiliary computer) and the Techman robot controller is established using the TCP/IP communication protocol.

- The robot performs the task of assembling the puzzle piece by piece in a sequential order, starting with the first piece that corresponds to the bottom-left corner of the final image.

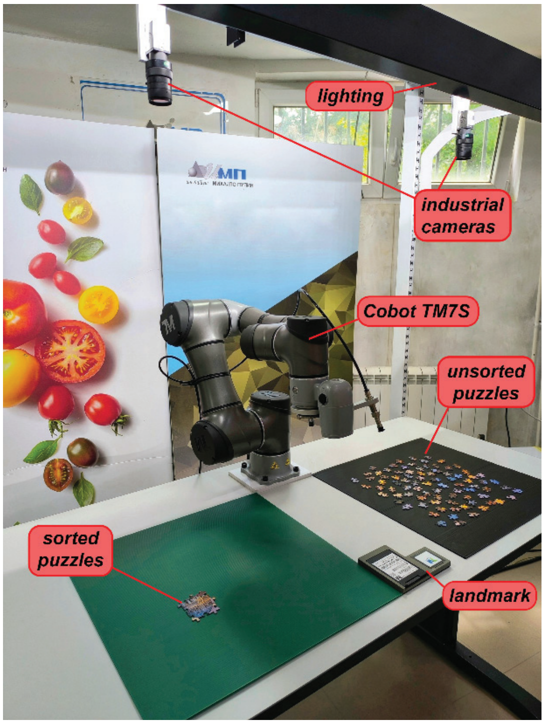

Figure 4. Experimental setup for robotic puzzle assembly with Cobot TM7S, cameras, lightining, landmarks and set of puzzles in the Stage Area (right) and Solution Area (left)

The procedure is repeated according to a predefined sequence: (i) perception, i.e., recognizing the next puzzle piece to be placed, following a left-to-right order, row by row, up to the top of the image; (ii) transmitting the coordinates (x1, y1) of the detected puzzle piece's centroid in the *Staging Area* and the target coordinates (x2, y2) in the *Solution Area* (Fig. 5), where the piece should be placed such that its centroid aligns precisely with this target point; (iii) based on these received coordinates, which represent the start and end points of the robot's trajectory, a nominal path is computed in MATLAB; (iv) the planned trajectory is then exported from MATLAB to the Techman robot controller, where it is executed; (v) the robot follows the calculated trajectory, while at the start point A, the pneumatic gripper receives a command to activate the vacuum and pick up the puzzle piece, and at the end point B, the gripper is commanded to release the vacuum, placing the piece accurately at the designated position.

5.2 Robot perception

The algorithm, implemented in MATLAB, relies on visual information to determine the placement of each puzzle piece in its predicted location(Fig. 4).
The decision-making process is based on the following criteria:

1. the color of each segment/piece;
2. specific visual features present on the segments/pieces;
3. the shape of the puzzle pieces.

Assuming the puzzle consists of *n* individual pieces, the final (target) image is divided into *n* spatially and dimensionally aligned segments, such that each segment corresponds to exactly one puzzle piece and defines its intended location in the assembled image.

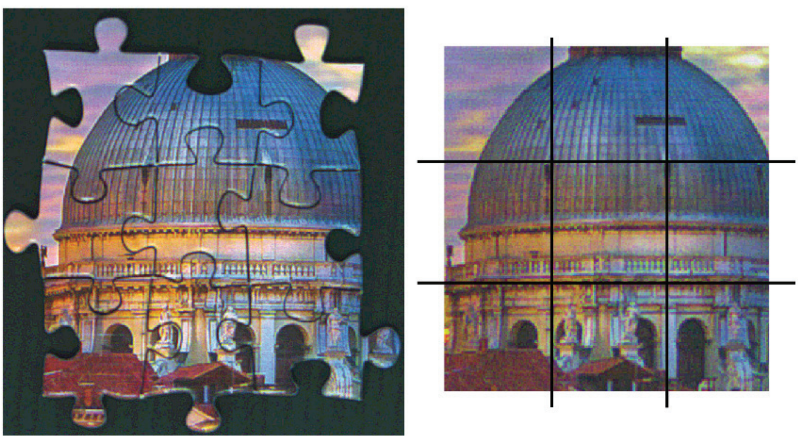

Figure 5. Example showing nine puzzle pieces (left) and their corresponding nine segments of the final (target) image (right)

The primary comparison criterion involves matching the red, green, and blue (RGB) color components between each segment and the corresponding puzzle piece. Another important criterion involves matching distinctive visual features or image patterns present on each segment and its corresponding puzzle piece.

However, these two criteria can often be disrupted by inconsistencies in shape—puzzle pieces are typically irregular, featuring interlocking tabs and slots. Therefore, shape compatibility becomes a crucial additional criterion.For instance, if k out of n puzzle pieces have already been assembled ($k < n$), the algorithm utilizes an overhead camera to scan the pieces and evaluate whether a new candidate piece fits spatially and geometrically as the $(k+1)^{th}$ piece in the puzzle.

5.3 Path Planing and Trajectory Generation

Trajectory planning for the Techman TM7S robot involves computing a smooth and feasible path for the robot's end-effector to move from a given start position to a target position in *Robot Operation Space*, both defined in Cartesian coordinates along with their respective orientations. The process begins by transforming these Cartesian poses into the robot's joint space using inverse kinematics, which provides the joint configurations required at the start and end of the motion. A trajectory is then generated in joint space by interpolating between these configurations over time, ensuring continuous and smooth motion that adheres to the robot's joint limits, velocity, and acceleration constraints. During this planning, collision avoidance with the robot's own structure and surrounding environment is taken into account. The planned trajectory is typically optimized for efficiency, safety, and precision, and is executed through the robot's control system, which ensures that each joint follows the calculated path accurately in real time.

When applying artificial neural networks (ANNs) to solve inverse kinematics for a robot like the Techman TM7S, the approach involves training a neural model to learn the complex, nonlinear relationship between the robot's end-effector pose (position and orientation in Cartesian space) and the corresponding joint angles. First, a large dataset is generated, typically using the robot's forward kinematics equations, which compute the end-effector pose for known joint configurations. This data is used to train the ANN in a supervised learning setup, where the input to the network is the Cartesian pose, and the output is the corresponding set of joint angles. Once trained, the network can rapidly approximate joint configurations for any feasible pose within the robot's workspace, bypassing the need for iterative numerical solvers. This method offers advantages in speed and adaptability, especially in real-time control scenarios or in applications where traditional inverse kinematics struggle due to redundancy or singularities. However, care must be taken to ensure the network generalizes well and that outputs remain within the robot's physical constraints.

5.4 Connecting Robot and Auxilary Computer

To connect a Techman TM7S robot with a computer running MATLAB, the method *TCP/IP socket communication*was used, the robot's control system had to be configured to accept incoming socket connections. This was done through the *TMflow interface* by adding a "Socket Listen" node with a specified port (e.g., 5890) and message format set to "String".

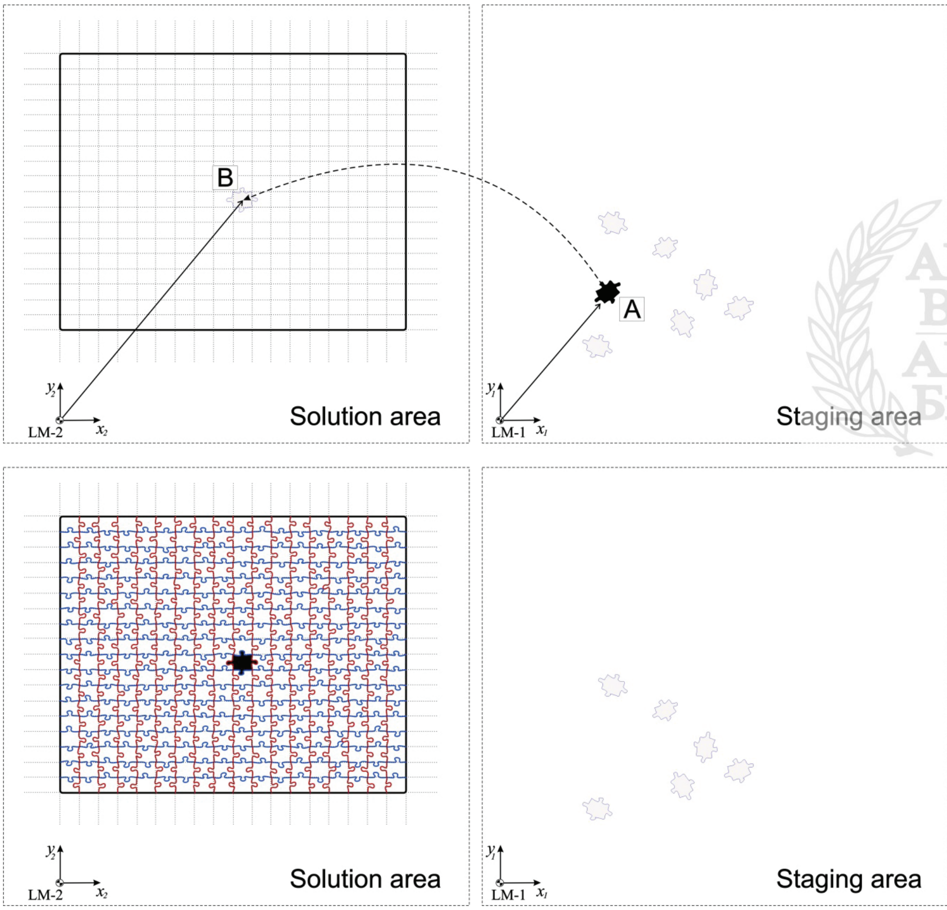

Figure 6. Visual-motor manipulation of puzzles from the Staging Area to the Solution Area.

The incoming messages were then passed to a "String to Command" node to interpret the received strings as robot commands (e.g., MoveJ, MoveL).
On the computer side, MATLAB used the *TCPclient function* to establish a connection to the robot's IP address and designated port. Commands generated in MATLAB (such as trajectory points from Peter Corke's Robotics Toolbox) were formatted as strings matching the robot's expected command syntax and sent over the TCP connection. This setup enabled MATLAB to stream joint or Cartesian commands in real time, allowing the TM7S robot to execute the desired trajectory, e.g. from point „A“ to point „B“ shown in Fig. 6.

Industrial analogs can be programmed using similar steps, where CAD data or visual templates replace the puzzle image.

6. Challanges and Considerations

Despite the growing capabilities of robotic systems, several critical challenges continue to impede the widespread and seamless deployment of intelligent robotic manipulators in complex environments. These challenges span across perception, decision-making under uncertainty, computational performance, and safety — especially in collaborative human-robot workspaces.

Perception in Cluttered Environments
One of the foremost challenges is achieving robust perception in real-world industrial settings that are often cluttered, dynamic, and partially observable. In puzzle-inspired robotic tasks, the robot must detect, recognize, and localize parts or objects in a scene filled with occlusions, overlapping components, reflective surfaces, and inconsistent lighting conditions. Traditional computer vision techniques often falter in such scenarios. Recent advances in deep learning and 3D vision, including the use of convolutional neural networks (CNNs), depth sensors, and attention mechanisms, have improved accuracy, but achieving consistent and reliable perception across varying contexts remains an open problem. Temporal coherence and sensor fusion approaches (combining visual, tactile, and even auditory data) are being actively explored to enhance robustness.

Uncertainty Handling
Industrial robots must operate under significant uncertainty due to sensor noise, variations in object placement, mechanical tolerances, and unpredictable external interactions. This uncertainty can lead to misclassifications, inaccurate localization, or failed grasps. Probabilistic models such as Bayesian networks, Monte Carlo localization, and partially observable Markov decision processes (POMDPs) offer theoretical tools to model and manage uncertainty. Moreover,

data-driven approaches using reinforcement learning and imitation learning enable robots to adapt and improve performance over time, even under noisy conditions.

Real-Time Constraints

Many industrial applications impose stringent real-time requirements, where the robot must perceive, plan, and act within milliseconds. This necessitates highly optimized algorithms for perception, planning, and control, as well as efficient hardware integration. Balancing the trade-off between computational complexity and execution speed is essential. Edge computing, GPU-accelerated processing, and lightweight neural networks are emerging solutions that aim to deliver the necessary performance while maintaining power and resource efficiency. Additionally, techniques such as motion primitives and pre-computed action libraries are employed to speed up decision-making without sacrificing flexibility.

Safety and Compliance

As robots increasingly share physical spaces with humans, ensuring operational safety becomes paramount. Collaborative robots (cobots) must be equipped with capabilities for dynamic obstacle avoidance, compliant motion control, and human-intention prediction. Tactile sensors, force-torque sensors, and proximity detectors are commonly used to monitor interaction forces and adjust behavior in real time. Additionally, control strategies such as impedance control and admittance control allow the robot to respond flexibly to external disturbances, reducing the risk of injury or equipment damage. Regulatory standards such as ISO/TS 15066 provide guidelines for safety in human-robot collaboration and continue to shape the development of compliant robotic systems.

Addressing these challenges requires not only technical innovation but also interdisciplinary collaboration across robotics, artificial intelligence, human factors, and system integration. As robotic systems evolve, ongoing research must continue to push the boundaries of perception, decision-making, and interaction in order to achieve safe, adaptive, and intelligent behavior in complex industrial domains.

7. Experimental Results and Case Study

A simulated environment using the TM7S robot was constructed to perform puzzle assembly. Using a dataset of jigsaw piece images and a neural network trained for edge detection and piece matching, the robot successfully assembled puzzles with over 90% accuracy. The same framework can be adapted to a cable-routing task, showing successful generalization to an industrial scenario.

8. Future Work and Research Directions

As robotic systems continue to evolve, several key research directions emerge that aim to push the boundaries of robotic manipulation, autonomy, and adaptability in real-world industrial environments. These future developments are essential for enabling robots to handle increasingly complex tasks and collaborate more effectively with humans.

Multimodal Perception
One of the most promising avenues for enhancing robotic perception is the integration of multiple sensory modalities. While vision remains the primary source of information in many systems, combining it with tactile and auditory data can lead to a significantly richer and more robust understanding of the environment. For example, tactile sensors embedded in grippers can detect slippage, contact force, and material properties, enabling fine manipulation of delicate objects. Auditory cues, such as sounds generated during contact or motion, can also offer valuable information in determining success or failure in grasping tasks. Research in sensor fusion techniques, attention-based perception models, and cross-modal learning is critical to developing systems that can reason about the environment in a more human-like and adaptive manner.

Reinforcement Learning in Manipulation
Traditional model-based planning approaches often struggle to generalize across dynamic and unstructured environments. Reinforcement learning (RL), particularly deep reinforcement learning (DRL), has shown significant promise in enabling robots to learn optimal policies through trial-and-error interaction with their environment. In the context of robotic assembly or puzzle-like tasks, RL can be used to discover efficient action sequences, adapt to unknown object properties, and even recover from failures. Combining RL with imitation learning, hierarchical policy structures, and transfer learning techniques can further improve sample efficiency and generalization across tasks.

Scalability to Complex Assemblies
Current robotic assembly systems are typically limited to tasks involving a small number of components and fixed configurations. Future research must focus on scaling these systems to handle complex assemblies involving hundreds of parts, irregular geometries, and dynamically changing layouts. This requires improvements in task decomposition, modular planning, and memory-based reasoning. The development of scalable software architectures that support long-horizon planning, as well as efficient storage and retrieval of learned behaviors, is key to handling such complexity.

Human-Robot Collaboration: As manufacturing environments become increasingly flexible and decentralized, the role of collaborative robots (cobots) becomes more prominent. Future systems must be capable of intuitively understanding human intent, adapting to shared workspaces, and operating safely alongside human partners. This involves advancements in real-time human pose estimation, natural language understanding, shared autonomy, and adaptive behavior modeling. Effective human-robot collaboration also necessitates trust-building mechanisms, interpretable decision-making, and interactive learning, where robots can be guided and corrected by human workers in real time.

These research directions not only aim to improve technical performance but also aspire to create robotic systems that are socially and cognitively aware. The ultimate goal is to transition from task-specific automation to intelligent, general-purpose robotic co-workers capable of operating autonomously or cooperatively across a diverse range of industrial scenarios.

9. Conclusion

The puzzle assembly task offers a compelling metaphor for advanced robotic cognition and manipulation in industrial environments. Through the integration of AI, machine vision, and real-time planning, robots can transition from mere tools to intelligent collaborators. This methodology can be extended to a wide range of adaptive industrial applications, promoting efficiency, flexibility, and autonomy in modern manufacturing systems.

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Towards a Smart Maintenance Model

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Abstract: *Smart maintenanceis a model created on the concept of Industry 4.0, and uses its advanced technologies, the Internet of Things (IoT), artificial intelligence (AI) and predictive big data analytics (BDA), in order to reduce equipment failures and extend its life, thus reducing maintenance costs, and technological resources are used optimally. By monitoring data in real time, from sensors and IoT devices, the condition of the equipment is predicted, decisions are made automatically, and the operational performance of the equipment (OEE) is improved. Equipment failure prediction is done by analyzing the behavior patterns of equipment entities, which are obtained by machine learning (ML), generated by digital twins (DT) and supported by cloud computing.*
Today, we are witnessing the full maturity of Industry 4.0, and the emergence of its advanced or future version, Industry 5.0. However, we must state that the creators of the Industry 4.0 model (German Academy of Engineering Sciences) believe that the Industry 5.0 model today, as promoted by its creators, is not a NEW model, but only a somewhat improved version of Industry 4.0 in the areas of: greater human integration into this automation model (operator 4.0/5.0), greater environmental aspects of production (green production) and the application of artificial intelligence (AI), which we are witnessing today in the Industry model as well 4.0.
Starting from the above facts, this paper deals with the current level of development of the maintenance model in the context of Industry 4.0, which is the smart maintenance model (SM). System analysis of predictive maintenance model, smart maintenance framework model was performed. Some results of our research in this area are also given at the end of the paper.

Keyword: *Industry 4.0, Smart Maintenance, Deep Machine Learning, Proactive Maintenance.*

1. Introductory Notes

The evolution of the maintenance model in the new era moved through the following models [1-3] : (i) corrective maintenance ((the machine is repaired only when a failure occurs, low maintenance costs, minimal planning (if any), major production stoppages and consequently losses, this model was created in

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the first industrial revolution (IR), and was also used in the II IR)), (ii) preventive maintenance (represents the planned maintenance model, which was established in the II IR, and was used in the III IR, maintenance operations are performed regularly (planned), regardless of the state of the machine entity, sudden failures are reduced and the life of the machine is extended, but maintenance costs may be increased, (iii) condition-based maintenance is closely related to the development and application of computers in technological systems.

This model also had its variants - total productive maintenance, world-class maintenance and the like, and (iv) with the advent of Industry 4.0 and the application of its technologies, smart maintenance, based on the real state of the machine entity and guided by AI, is being developed and increasingly applied today. This model generates data using IoT sensors in real time, predicts failures with deep learning models (DML) and provides reliable information for maintenance operations, only when they need to be done. In this way, sudden stoppages are eliminated, costs are reduced and resources are optimized.

On the other hand, this model requires the application of advanced Industry 4.0 technologies, qualified workforce and additional investments in hardware/software infrastructure of the model. That is why it is applied on equipment of high technological value (turbines, aircraft engines, special machine tools, robots and others), or on systems where it is justified to do so due to safety, high downtime costs (mining, railways, etc.). An overview of the development of the maintenance model is shown in Table 1.

Table 1. Evolution of Maintenance models (adopted according to [4-6])

Industrial revolution	**Industry1.0 (1760 – 1880)**	**Industry2.0 (1890 – 1960)**	**Industry3.0 (1970 – 2000)**	**Industry4.0 (2010 –)**
Main characteristics	Mechanization, steam power (Traditional era)	Mass production, assembly lines (Industrial growth)	Automation, Maintenance information system (Digitalization)	IoT, AI, BDA, Cloud computing (Artificial intelligence)
Type of maintenance	Corrective maintenance	Preventive maintenance	Condition-based maintenance	Smart maintenance (SM)
Key maintenance operation	Visualinspection	Instrumental inspection	Sensormonitoring	Predictiveanalysis
OEE (*Overall Equipment Effectiveness*)	<50%	50 – 75%	75 – 90%	> 90%
Maintenanceteam reinforcement (Key person)	Trainedcraftsmen	Maintenance worker	Reliability engineers	Datescientists
Application of AI	-	-	Expert and knowledge based systems	Machine learning and deep machine learning

Smart Maintenance (SM) is defined by the elements of Industry 4.0, which is based on the digital transformation of the industry through advanced automation, real-time data analysis and interconnected entities (machines, processes, parts). Using CPS, IoT sensors and AI-driven analytics, SM enables industries to: (i) predict failures before they happen, with online entity condition monitoring and machine learning, (ii) automate maintenance decisions, with real-time diagnostics and cloud-based computing systems, (iii) improve interoperability by integrating smart factory (SF) entities and digital twins (DT) for maintenance operations.

The most important advantages of SM are: (i) cost reduction (through the elimination of unnecessary (planned) maintenance operations and timely prevention of sudden failures), (ii) improved efficiency and productivity (the overall effectiveness of the equipment (OEE) is maximized), because this is achieved with real-time data analytics, (iii) improved reliability and equipment life, because continuous monitoring enables early detection of failures, preventing major failures.

Also, continuous monitoring and application of the maintenance strategy according to the condition - predictive maintenance (PrM), extends the life of equipment, thus reducing capital costs, (iv) energy efficiency and sustainability (optimizes energy use, while reducing resource consumption and waste generation, thus supporting green industrial practices), (v) improving workplace safety and compliance with standards and industry regulations. To conclude, SM has revolutionized traditional maintenance models, making them more efficient, cost-effective and reliable, and in all this automation and digital transformation based on Industry 4.0 are the key framework.

1.1 Objectives of the Papers

The aim of this paper is to provide a comprehensive analysis of SM, including its technologies, applications, challenges as well as future development. The key objectives are: (i) research on SM models and technologies (the place and role of IoT, AI, machine learning, big data, cloud computing and digital twins in predictive and proactive maintenance) that enable real-time monitoring, failure detection and automatic decision-making, (ii) analysis of industrial case studies (application of SM in industries such as manufacturing, energy, transport and healthcare, as well as evaluations of the impact of smart maintenance on reducing maintenance costs and increasing equipment efficiency and reliability), (iii) case studies, through the analysis of rounded software products for SM and PdM, open source platforms and database (knowledge) models for the same purpose (SM, PdM), (iv) EXMAS model and (v) conclusions with future trends and possibilities of application of generative AI, and blockchain technology in SM and PdM models.

2. Literature Review

The basic framework for the development and application of the smart maintenance (SM) model is Industry 4.0, so this analysis refers to the period from 2011 to the present, and included only the most cited references in this field[3].
Reference [7] is part of the European SERENA Project, which involved a collaboration between fourteen partners, including academic institutions, technology companies and industrial plants, Table 2, and the model was developed for SMEs.

Table 2. Overview of smart maintenance model development

Purpose	Ref. / year	Method	Goal	Application
SM for SMEs	[7]2021	Deep learning models	Increasing model accuracy	Predictive maintenance (PdM)
Online analysis of big data	[8]2018	CNN, RNN	Optimization of computer resources	Cloud/fog computing
Anomaly detection	[9]2017	Seven different models	Selecting the appropriate model for a maintenance problem	PdM
The infrastructure of the Industry 4.0 model	[10]2015	5C architecture for CPS	Building a smart factory	Predictive maintenance of CPS
Detailed analysis of the SM model	[11]2020	Industry 4.0 technologies for PdM	Application of the Industry 4.0 model	Smart factories
Data mining for PdM	[12]2019	Collection, analysis and processing of signals and data	Creating reliable BDs	PdM
Classification of learning models	[13]2022	Determining the appropriate anomaly detection model	Online monitoring of possible cancellation status	PdM
Improve manufacturing process	[14]2023	Data mining to detect and predict potential anomalies	Knowledge representation in SM	Heterogeneous nature of industrial data
Improve manufacturing process	[15]2021	Financial implications of production downtimes	Define PdM model	Automotive industry

This approach means that such companies (SMEs) are limited in resources, especially in expertise in data analysis. And in this area, the biggest challenges are related to the heterogeneity and scalability of data, offering a model for the development of a robust data infrastructure. A critical analysis of various algorithms, such as Bayesian networks, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Term Memory (LSTM) networks, is performed, discussing their suitability and performance in the context of smart manufacturing (SM). Hybrid methods, which combine multiple algorithms, are also applied to improve the accuracy of PdM models. The potentials of integrating advanced technologies such as: digital twins (DT), autonomous systems and 5G network, in order to further improve SM capabilities, are analyzed. The authors suggest that embracing these innovations could lead to more proactive and autonomous SM strategies, thereby sustaining the growth of manufacturing intelligence.

Reference [8] gives an overview of the application of deep learning techniques in the online analysis of big data, from the aspects of quantity, speed, variety and variability. Convolutional neural networks (CNN), recurrent neural networks (RNN) and autoencoders proved to be the most suitable. As computer support, the following are suitable: cloud computing, for applications where real-time response is not required (equipment condition monitoring, to predict failures), but large data sets and complex DL models are involved, and fog computing, which provides decentralized computing resources, closer to IoT devices, facilitating real-time data processing and reducing latency.

Online monitoring of the state of entities of machines, processes and parts, in order to develop a model of predictive maintenance, requires the development of the concept of recognizing anomalies that arise from entity monitoring [9]. For these reasons, seven different methods have been developed: (i) distance - based anomaly detection approaches, uses the distance metric, defining application scenarios, (ii) clustering - based anomaly detection approaches, examines techniques that detect anomalies by identifying data points that do not belong to any cluster, addressing the nuances of points near the cluster boundaries, (iii) model - based anomaly detection approaches, covers strategies that rely on modeling the basic processes of data generation, enabling the identification of points data that deviate from expected patterns, (iv) distance and density based approach, considers methods that take into account both the distance between data points and the density of surrounding regions to detect anomalies, (v) rank based approach, uses techniques that rank data points based on their probability of being anomalies, offering an alternative perspective to distance and density methods, (vi) ensemble methods, describes the use of multiple algorithms in tandem to improve the performance of anomaly detection, taking advantage of different methods, and (vii) algorithms for time series data, addresses anomaly detection in sequential data, emphasizing the importance of temporal context. Each of the methods found has its advantages and disadvantages, for example, the last one is suitable for monitoring the state of vibration of control bearings, based on which the moment when the bearing should be replaced can be determined.

One example of the 5C architecture for CPS, adapted to the Industry 4.0 model, which provides the integration of physical and digital systems in production [10]. The key components of the 5C architecture are: (i) connection layer (defining sensor networks and IoT devices to collect real-time data, enabling their visibility into machine operations), (ii) conversion layer (transforms raw data into forms that can be generated by cloud/edge computing, creating a base for BDA analyses), (iii) cyber layer (generates DT, creating virtual replicas for simulation and monitoring, improving predictive capabilities), (iv) cognition layer (uses AI/ML models for diagnostic and prescriptive analytics, enabling autonomous decision-making, and (v) configuration level (facilitating feedback for system optimization, ensuring adaptability to dynamic environments).This model has the following characteristics: (i) structured framework, the 5C model provides a hierarchical approach to CPS, bridging the gap between physical infrastructure and digital tools, (ii) interoperability, emphasizing standardized communication protocols, although the specifics of existing standards (e.g. OPC UA) limited, and (iii) human-machine cooperation, interface for communication with users. This model is particularly interesting for predictive maintenance, as it enables real-time BDA to reduce downtime by predicting failures. Compared to other models, for example with IIRA (Industrial Internet Consortium), it focuses on broader IoT integration, while 5C emphasizes manufacturing-specific CPS layers, and RAMI 4.0 is aligned for digital twin use, but lacks 5C's explicit cognitive layer for AI-driven decisions. The advantages of this model are: holistic integration of data processing in real time and adaptable to management, as well as a clear roadmap for the application of the Industry 4.0 model, confirmed through case studies (eg smart factories), while the limitations are related to cyber security (can be improved by applying blockchain) and user training. The work became a fundamental reference, influencing subsequent DT and AI research in manufacturing (including maintenance) and remains key to understanding CPS in Industry 4.0, offering a balanced blend of theory and practical application.

In [11], a systematic literature review is given, which synthesizes research on PdM in Industry 4.0, providing insight into technologies, challenges and future research directions. Key technologies for PdM are: IoT and sensors, for collecting data from machines in real time, AI/ML models, especially deep learning models, cloud/edge computing, for storage/processing of BD data, DT as virtual models for condition monitoring and equipment behavior simulation. In this concept, there are special challenges related to data quality (noise, missing values), heterogeneity (multi-source integration) and scalability, then cybersecurity risks and high initial costs, and finally lack of knowledge and skills in implementing AI-driven solutions. Case studies in the automotive, energy and manufacturing industries show a 20 to 30% reduction in downtime due to sudden failures. Special aspects of the application of this model (PdM) are the standardization of its elements and interoperability. Therefore, future research will be directed towards: technology (edge AI for real-time decision-making, federated learning for privacy), modeling (hybrid approaches (physics-based + data-driven) and explainable AI (XAI)) and sustainability (PdM's role in reducing waste and energy consumption). Compared to previous review works in this area, this paper highlights the close interaction between PdM and the core technologies of Industry 4.0 (eg DT). The rapid evolution of Industry 4.0 technologies requires constant updates (sustainability metrics and the impact of 5G on the operation of PdM models in real time).

Research on the integration of Industry 4.0 elements such as CPS, IoT and data mining to improve the PdM model in SM is presented in [12]. The key components of this model are: (i) sensor and real-time data collection on various parameters, providing immediate detection of anomalies, (ii) signal and data processing, where noise filtering and extraction of significant information are performed, in the time and frequency domain. Techniques such as Wavelet Packet Decomposition (WPD) and Fast Fourier Transform (FFT) are utilized to transform time-domain signals into the frequency domain, aiding in accurate fault detection, (iii) and feature extraction (processed data is analyzed to identify specific features indicative of equipment health. This step is crucial for distinguishing between normal operational variations and potential faults), (iv) maintenance decision-making (leveraging AI and data mining, the system diagnoses current equipment conditions and predicts future failures. This proactive approach enables timely interventions, reducing unexpected downtimes), (v) maintenance scheduling optimization (based on diagnostic insights, maintenance activities are strategically scheduled to minimize disruptions and optimize resource allocation), and (vi) feedback control and compensation (the system incorporates feedback loops to adjust operational parameters in real-time, compensating for detected anomalies and maintaining optimal performance). The practical application of the PdM framework through a case study involving a pressure blower. Vibration sensors collected data, which was then decomposed using WPD and transformed via FFT. Features extracted from this analysis trained an Artificial Neural Network (ANN), enabling the system to diagnose faults and predict the Remaining Useful Life (RUL) of components. This approach demonstrated higher efficiency and effectiveness compared to traditional maintenance methods.

The paper [13]provides a comprehensive overview of PdM models in the context of Industry 4.0, focusing on technological developments, model frameworks and practical challenges. A particularly important aspect of this research is the analysis of machine learning models suitable for application in the PdM model, namely: (i) supervised learning (random forest, support vector machines (SVM), gradient boosting) - for failure classification and anomaly detection in machinery vibration data, (ii) unsupervised learning - clustering (eg, k-means) for identifying unknown failure patterns, (iii) deep learning (DL), used two models - CNNs for image-based fault detection (eg, thermal imaging of equipment) and recurrent neural network (RNN) and long short-term memory

(LSTM) for time-series sensor data (eg, predicting bearing wear), and (iv) hybrid and emerging models - physics-informed ML, combines domain knowledge (eg, mechanical wear equations) with data-driven models), and reinforcement learning (RL) for adaptive maintenance scheduling in dynamic environments.

In this study [14], the authors address the challenges posed by the heterogeneous nature of industrial data in achieving effective maintenance decision-making and interoperability among diverse manufacturing systems. They propose a hybrid approach that integrates ontologies, machine learning techniques, and data mining to detect and predict potential anomalies in manufacturing processes. The focus is on designing an intelligent system with standardized knowledge representation and predictive capabilities. By bridging the semantic gap and enhancing interoperability, ontologies facilitate the integration of various manufacturing systems, optimizing real-time maintenance decision-making. The experimental results demonstrate that this approach not only ensures system reliability but also promotes a seamless, integrated, and efficient production environment.

Reference [15]provides a comprehensive examination of PdM within the context of Industry 4.0. The authors highlight the significant financial implications of production downtimes, citing the 2016 Volkswagen incident where production issues led to losses of up to 400 million Euros per week. This underscores the critical importance of effective maintenance strategies in modern manufacturing environments. The authors propose a classification framework for PdM approaches. This framework categorizes existing methodologies, facilitating a clearer understanding of the diverse strategies employed in predictive maintenance within Industry 4.0. The paper delves into recent advancements in PdM, discussing how emerging technologies and data-driven approaches are being integrated into maintenance strategies. This includes the utilization of machine learning, IoT sensors, and data analytics to predict and prevent equipment failures. The transition from traditional maintenance schedules to more sophisticated, data-driven approaches that anticipate and prevent equipment failures. As industries continue to adopt Industry 4.0 principles, such comprehensive analyzes will be instrumental in guiding the development and implementation of effective PdM strategies.

3. Key Technologies in Smart Maintenance

Smart maintenance has evolved significantly, integrating advanced technologies to enhance equipment reliability, reduce downtime, and optimize maintenance processes. Key trends include using AI and IoT, because the convergence of AI and the IoT enables PdM by collecting real-time data from sensors embedded in machinery. AI algorithms analyze this data to predict equipment failures before they occur, allowing for proactive maintenance scheduling.

3.1. IoT and Sensor Networks

IoT and sensor networks play a crucial role in SM by enabling real-time monitoring, PdM, and automation in various industries [1,2,13]. SM leverages IoT devices and sensors to collect data, analyze performance, and optimize maintenance schedules to reduce downtime and improve efficiency.

Key aspects of IoT and sensor networks are: (i) real-time monitoring - IoT sensors continuously monitor machinery, infrastructure, and assets, tracking parameters like temperature, pressure, vibration, humidity, and energy consumption. This helps in detecting early signs of equipment failure, (ii) predictive maintenance (PdM), where sensors collect historical and real-time data, after that ML analyze patterns to predict failures before they occur, and maintenance is scheduled based on actual equipment conditions rather than a fixed schedule, reducing unnecessary maintenance costs, (iii) automated alerts and remote diagnostics, where IoT-enabled maintenance systems send automatic alerts to technicians when anomalies are detected, and remote monitoring allows experts to diagnose issues without physical inspections, reducing response time, (iv) energy efficiency and cost reduction, where sensors optimize energy usage by detecting inefficiencies in heating, ventilation, and air conditioning (HVAC) systems, motors, and lighting, and preventing unexpected breakdowns reduces downtime and repair costs, (v) DT and simulation, where a DT is a virtual model of physical assets that updates in real-time using IoT data, and it allows engineers to simulate scenarios, optimize maintenance schedules, and test solutions before implementing them, (vi) edge computing (processes sensor data closer to the source, reducing latency and network bandwidth usage) and cloud integration (cloud platforms store and analyze large datasets, providing insights into asset health and maintenance strategies). Today we have applications of those concepts in various industries, such as: (i) manufacturing for monitoring production lines for equipment (like CNC machine tools, robots, CMM), wear and tear, (ii) healthcare, where IoT-enabled medical devices ensuring operational efficiency, (iii) smart cities (infrastructure maintenance, including bridges, roads, and utilities, (iv) energy sector - wind turbines and power grids with predictive analytics, and (v) automotive and fleet management, where AI powered diagnostics for vehicle maintenance, etc. Challenges and future trends are related on: (i) cybersecurity risks - protecting IoT networks from hacking and data breaches, (ii) integration complexity - combining legacy systems with new IoT solutions, (iii) scalability, managing vast sensor networks efficiently, and (iv) AI / ML advancements, more accurate predictions and self-healing systems. At the end, IoT and sensor networks revolutionize smart maintenance by enabling proactive rather than reactive maintenance strategies. They enhance operational efficiency, reduce costs, and extend the lifespan of assets, making them indispensable for industries moving towards Industry 4.0.

3.2.Artificial Intelligence (AI) and Machine Learning (ML)

AI and ML are transforming smart maintenance by enabling predictive analytics and anomaly detection, where these technologies help organizations move from reactive or scheduled maintenance to a more proactive, predictive approach, reducing downtime and operational costs. AI and ML leverage sensor data, historical maintenance logs, and real-time operational data to optimize asset performance and improve reliability [1].
What are the main advantages of this maintenance model compared to others: (i) early fault detection, identifies potential failures before they occur, (ii) reduced downtime, prevents unexpected shutdowns and saving costs, (iii) optimized maintenance scheduling, means reduces unnecessary inspections and repairs, (iv) enhanced equipment lifespan is prolongs asset usability by ensuring timely intervention, and (v) automated decision-making, AI-driven systems can suggest or even initiate repairs.
Predictive analytics uses AI / ML models to analyze historical and real-time data to forecast when equipment might fail, based on the following steps: (i) data collection, by IoT sensors gather data (vibration, temperature, pressure, energy consumption, etc.), (ii) data processing, where AI cleans and preprocesses raw data to remove noise, (iii) feature engineering, identifies key parameters influencing failures, (iv) model training, using by ML models (eg, regression, neural networks, decision trees, etc) learn from past data, and (v) failure prediction, where AI predicts when maintenance should be performed.
Different AI techniques are used as learning models, which have different purposes in the PdM model: (i) time series analysis, for the forecasts future failures based on historical trends, (ii) regression models used to estimate the remaining useful life (RUL) of assets, (iii) neural networks and deep learning for recognizes complex patterns in equipment behavior, and (iv) bayesian networks, for estimates failure probability based on multiple factors.
By applying the aforementioned models, anomaly detection identifies unexpected deviations in operational data, signaling potential failures. The whole concept is realized as follows: (i) baseline learning, where AI learns normal operating behavior from historical data, (ii) continuous monitoring, sensors provide real-time data streams, (iii) deviation identification by AI detects abnormal variations (spikes, drifts, or sudden drops), (iv) root cause analysis, the system analyzes contributing factors and suggests corrective actions. The analysis of the learning model, according to the types of anomaly identification, was done in the previous point [13].
Future trends and challenges are : (i) integration of AI and IoT (AIoT), for real-time decision-making, (ii) use of digital twins to simulate maintenance scenarios, (iii) AI-powered for autonomous repair bots, and (iv) edge AI for faster anomaly detection at the device level.

On the other hand, possible difficulties, as challenges are: (i) data quality and availability, which means, inconsistent or incomplete sensor data can affect AI predictions, (ii) cybersecurity risks, where AI-driven maintenance systems are vulnerable to hacking, and (iii) high initial investment – AI implementation requires infrastructure and expertise. AI / ML are revolutionizing SM through predictive analytics and anomaly detection, ensuring efficiency, cost savings, and reliability. As AI continues to evolve, future maintenance systems will become even more automated, intelligent, and self-healing.

3.3. Big Data Analytics (BDA)

PdM leverages big data analytics to monitor equipment, predict failures, and optimize maintenance schedules [1,13]. Traditional maintenance methods—reactive (fixing after failure) and preventive (scheduled maintenance)—are inefficient, leading to unnecessary costs or unexpected downtimes. BDA in PdM transforms maintenance strategies by using sensor data, machine learning (ML), and real-time processing to anticipate failures before they occur.

Big data in PdM comes from multiple sources: (i) industrial IoT (IIoT) sensors, for following vibration, temperature, pressure, acoustic, etc., (ii) machine logs and operational data, where error logs, usage statistics, (iii) maintenance records, with history of past interventions, parts replaced, and (iv) environmental data, including humidity, external temperature affecting machinery. Data is collected in structured (databases), semi-structured (JSON, XML), and unstructured (video, images, audio) formats.

Data storage and management, handling vast amounts of data requires advanced storage solutions: (i) cloud storage (by platforms AWS, Azure, Google Cloud), scalable, distributed storage, (ii) edge computing, where localized data processing for real-time insights, and (iii) distributed file systems (using platforms such as HDFS, Apache Cassandra), efficient storage for high-velocity data. Data cleaning and preporocesing / processing and decision making with advanced analytics are performed, as already analyzed in point 2 [12].

Advanced PdM systems use real-time analytics to provide instant failure warnings by : (i) s treaming data processing (using platforms as apache kafka, apache spark streaming), (ii) processes continuous sensor data, using edge AI (processes data locally for faster decision-making), and DT for virtual models simulate and predict equipment behavior. The problems that arise in the application of the BDA model relate to: data quality issues (incomplete or noisy sensor data affects accuracy), computational complexity (high-dimensional data requires efficient processing), integration with legacy systems (many industries still use old equipment) and cybersecurity risks (vulnerability to cyberattacks on IIoT networks). Future trends in this area in the following research directions : (i) AI-driven prescriptive maintenance, which means recommends optimal actions after failure prediction, (ii) 5G-enabled PdM refers to ultra-low latency for real-time machine monitoring, (iii) explainable AI (XAI), which means improves interpretability of complex ML models, and (iv) federated learning, which means the use of decentralized training of ML models across multiple factories or machines. BDA is revolutionizing predictive maintenance by improving failure prediction accuracy, reducing operational costs, and optimizing asset performance using AI, IoT, and cloud computing evolve, predictive maintenance will become more intelligent, autonomous, and cost-effective.

3.4. Digital Twins

Digital Twins (DTs) are virtual representations of physical assets, systems, or processes that integrate real-time data, simulations, and analytics to optimize performance and predict failures. In PrM, DTs serve as a crucial technology by enabling proactive monitoring, fault detection, and operational efficiency improvements [1,13-15]. A DT is a dynamic, real-time digital counterpart of a physical entity. It is continuously updated with data from sensors, historical records, and operational parameters, providing a comprehensive model for analysis and decision-making.

The basic elements of DT are: (i) physical entity, which includes the real-world asset or system being monitored, (ii) data sensors and IoT connectivity (devices that capturereal-time data for analysis), (iii) virtual model - a software-based simulation representing the behavior and conditions of the asset, (iv) analytics and AI algorithms, including machine learning and AI-driven models that process data for predictions, and (v) feedback mechanism, meaning a bidirectional flow of information that allows for real-time optimization. PrM aims to reduce unplanned downtime, extend asset life, and optimize operational efficiency.

Digital twins enhance PrM by leveraging data-driven insights for better decision-making, and the whole concept provides the following: (i) real-time condition monitoring, where DTs provide continuous tracking of asset health, identifying anomalies early, (ii) failure prediction and risk assessment by analyzing historical and real-time data, DTs forecast potential failures, allowing timely intervention, (iii) scenario simulation and optimization, where DTs enable the testing of different maintenance strategies in a virtual environment, minimizing disruptions, (iv) prescriptive maintenance recommendations, where AI-driven DTs suggest optimal maintenance actions based on performance trends, and (v) reduced downtime and cost savings by proactive maintenance strategies lower repair costs and enhance system reliability.

Simulation and optimization are core functionalities of DTs in PrM, and depending on the field of application, they can be used for: (i) physics-based simulations, where models that replicate real-world behaviors using engineering principles, (ii) data-driven simulations, used AI and ML-based models that predict outcomes using historical data, and (iii) hybrid approaches is a combination of physics-based and data-driven models for accurate predictions.

Despite their benefits, several challenges hinder the widespread adoption of DTs: (i) data integration complexity, ensuring seamless data collection from heterogeneous sources, (ii) high implementation costs, because initial investment in hardware, software, and expertise, can sometimes be large, (iii) cybersecurity risks, where increased vulnerability due to connectivity and data exchange should be taken into account, (iv) scalability issues, meaning that difficulty in applying DTs across diverse assets and large-scale systems, and (v) model accuracy and maintenance, means ensuring that the digital twin remains an accurate representation of the physical asset over time.

Future trends in DT for PrM can be defined as: (i) AI and edge computing integration, which means enhancing real-time decision-making capabilities, (ii) Blockchain for secure data exchange, which means addressing cybersecurity concerns through decentralized data management, (iii) 5G connectivity, refers to enabling faster and more reliable data transmission, (iv) autonomous maintenance systems, is a trend that means combining robotics and AI-driven DTs for automated repair processes, and (v) cross-industry applications, means expanding DTs beyond manufacturing to healthcare, energy, and smart cities. As industries continue to embrace digital transformation, digital twins will play an increasingly vital role in achieving efficiency, cost reduction, and reliability in asset management.

3.5. Cloud/Edge Computing

A critical aspect of PdM is efficient data storage and processing, where Cloud and Edge Computing play pivotal roles. These architectures determine how data is collected, stored, and analyzed for actionable insights [13-15]. PdM systems rely on sensor data from industrial machinery, such as: vibration analysis, temperature monitoring, acoustic emissions, oil and fluid analysis, power consumption, wear of machine elements. These data streams generate vast amounts of information that must be processed efficiently to detect anomalies, predict failures, and recommend maintenance schedules.

Cloud computing provides scalable and cost-effective storage solutions, including: (i) object storage (for example used AWS S3, Azure Blob), for stores raw sensor data, logs, and images, (ii) time-series databases (eg, InfluxDB, AWS Timestream), for handles large-scale telemetry data, and (iii) relational databases (eg, MySQL, PostgreSQL, Snowflake), for stores structured historical maintenance records. Cloud processing and analytics hardware amd software support should solve the following tasks: (i) AI/ML model training, which

includes the cloud enables large-scale training of PrM models using platforms like AWS SageMaker, Google Vertex AI, and Azure Machine Learning, (ii) BDA using platforms like Apache Spark, Hadoop, and Databricks process massive sensor datasets, (iii) building of DT, where cloud services help create real-time virtual models of equipment for continuous monitoring, and (iv) historical data analysis, which means storing years of operational data in the cloud supports trend identification and failure pattern recognition. Benefits of cloud computing in PdM refer to: scalable data storage and compute power, centralized model training and updates, integration with IoT platforms (AWS IoT, Azure IoT Hub), and global accessibility for maintenance teams. On the other hand, the challenges of cloud computing in PdM are: latency issues in real-time decision-making, high bandwidth consumption for transmitting large datasets, and data privacy and regulatory compliance concerns.
Instead of sending all data to the cloud, edge computing stores and processes data closer to the source using: local databases (SQLite, TimescaleDB), on-premise servers and industrial gateways, and embedded storage within IoT devices. Also, this model (edge computing) realizes the function of edge processing and analytics in the following way: (i) real-time anomaly detection - AI models run locally on edge devices (eg, NVIDIA Jetson, Raspberry Pi, Intel Movidius), (ii) edge AI/ML inference, which means - instead of cloud-based model execution, trained models are deployed at the edge using frameworks like TensorFlow Lite, ONNX Runtime, or AWS Greengrass, and (iii) event-driven alerts, where edge computing enables real-time response, such as stopping a machine upon detecting a failure risk.
When compared with cloud computing, this model (edge computing) has the following advantages: (i) low latency - faster decision-making and reduced downtime, (ii) reduced bandwidth costs - limits unnecessary cloud data transfers, (iii) enhanced security - local data processing minimizes cloud exposure, and (iv) offline functionality - systems can continue working even without cloud connectivity. On the other hand, the disadvantages of this model are: limited processing power compared to cloud platforms, requires frequent firmware and model updates, and higher initial infrastructure cost.
However, we must point out here that there is also a hybrid cloud-edge architecture in PrM, where many industries implement this concept for: (i) edge devices perform real-time anomaly detection and initial processing, (ii) cloud platforms handle long-term data storage, model training, and deep analytics, and (iii) IoT gateways serve as an intermediary between edge devices and cloud platforms. It is interesting to mention here an example hybrid workflow, in the PdM model, such as: (i) data collection, where sensors collect vibration and temperature data from industrial machines, (ii) edge processing, where edge AI models analyze real-time data and generate alerts if anomalies are detected, (iii) selective cloud upload, where only relevant or summarized data is sent to the

cloud for further analysis, (iv) model retraining in cloud - ML models are updated based on aggregated historical data, and (v) model deployment to edge - improved models are pushed back to edge devices for enhanced accuracy.
Concluding this analysis, we will also look at aspects of the application of these models in various industries: (i) manufacturing - edge-based vibration monitoring for CNC machines, and cloud-driven failure prediction for robotic arms, (ii) energy sector - wind turbine edge analytics for real-time fault detection, and cloud-based maintenance planning for power grids, (iii) transportation and automotive - edge AI for fleet vehicle predictive diagnostics, and cloud-enabled maintenance scheduling for airlines, and (iv) healthcare - edge-based failure prediction for MRI and CT scanners, and cloud AI for predictive hospital equipment maintenance.Concluding this analysis, we will also look at future trends in cloud/edge computing for PdM: (i) 5G integration, faster connectivity enables smoother cloud-edge coordination, (ii) federated learning, which means decentralized AI training improves edge-based model learning, (iii) quantum computing, enhances predictive accuracy with complex simulations, and (v) blockchain for security, means that it protects PdM data integrity in cloud and edge environments. PrM thrives on efficient data storage and processing, where cloud computing offers scalability and advanced analytics, while edge computing ensures real-time insights with lower latency. A hybrid cloud-edge approach is emerging as the optimal solution, balancing real-time processing and large-scale data analysis.

3.6. Robotics and Drones

The role of Robotics in PdM can be twofold: automated inspections, where robots equipped with sensors (vibration, thermal, acoustic) can patrol industrial environments (eg, factories, power plants) to monitor machinery health, and consistency and safety, where they perform repetitive or hazardous tasks (eg, inspecting high-temperature equipment) with precision, reducing human risk [7,14,15]. For example, in the refinery autonomous mobile robots (AMRs), or robotic arms with vision systems for detecting cracks in pipelines.
The role of drones can be threefold: accessibility, where drones excel in inspecting hard-to-reach infrastructure (wind turbines, bridges, transmission lines) using cameras, LiDAR, or thermal imaging, efficiency, where rapid aerial surveys replace manual inspections, cutting time and labor. For instance, drones detect blade erosion on wind turbines or corrosion in oil rigs, and data collection, by high-resolution imagery and multispectral sensors provide rich datasets for AI-driven anomaly detection. In order for these systems, robots and drones, to be adequately applied in the PdM model, they are supported by the elements of Industry 4.0, namely: sensors, for vibration analyzers, infrared thermography, ultrasonic detectors, and gas sniffers, then AI/ML models where algorithms

process sensor data to identify patterns (eg, bearing wear) and predict failures, and integration, where data from robots/drones feeds into centralized platforms (eg, CMMS) for actionable insights, requiring robust IT infrastructure. The application of this technology brings the following benefits: cost savings, because it reduces reactive maintenance costs and downtime, then increases safety, because it limits human exposure to dangerous environments, and scalability, because it is suitable for large or distributed assets (eg, solar farms, rail networks).
However, there are also challenges, which can be defined as: initial investment, which can be high upfront costs for robotics/drone systems and training, then, data accuracy, which means that sensor reliability and algorithm precision are critical to avoid false positives/negatives, and then, regulatory hurdles, which especially relates to drone operations face airspace restrictions and certification requirements, and finally, maintenance of tools, which means ensuring robots/drones remain operational adds complexity. Now it is important to list examples of the real application of these technologies, namely: energy, where drones inspect offshore wind farms; robots monitor nuclear facilities, then transportation, where drones assess bridge integrity; rail robots check tracks, and finally, manufacturing, where for example AGVs patrol factories, while collaborative robots (cobots) assist in real-time equipment monitoring. In this area, future trends are: AI advancements, which means improved predictive models using deep learning for earlier fault detection, then 5G/edge computing, which refers to enables real-time data processing and faster decision-making, and swarm robotics - coordinated drone/robot fleets for large-scale inspections. Robotics and drones are transformative for predictive maintenance, offering efficiency, safety, and scalability. While challenges like cost and integration persist, technological advancements and growing industry adoption signal a promising future. Companies should evaluate ROI, pilot projects, and invest in training to fully harness these tools.

4. Case Studies

In this part of the paper, four case studies are presented, one of which refers to the PdM model of a well-known software manufacturer, and the other three represent open source platforms to support the development of PdM models.

4.1. Siemens PdM Model

This study [16], defines DT as virtual replicas of physical systems, enabled by IoT, AI and real-time data analytics, to optimize performance and maintenance. Smart maintenance, especially predictive maintenance, uses these technologies to predict failures, minimize downtime and reduce costs. Siemens, a leader in

industrial automation and digitization, emphasizes their role in the application of the Industry 4.0 model through these innovations. Siemens uses its MindSphere IoT platform for data collection and analytics, integrated with software NX (product design) and Teamcenter (product life cycle management), to create DT from design to customer use. The model uses AI and machine learning as enhanced predictive algorithms, which analyze historical data, along with real-time data, to predict sudden equipment failures. Siemens has developed AI models that are highly accurate in detecting anomalies. Special emphasis is placed on real-time data processing via 5G networks and edge computing, for low-latency decision-making in critical applications such as energy networks.
This Siemens model has a variety of applications today, to name just a few: in manufacturing - an automobile manufacturer reduced downtime by 30% using Siemens tools for PdM, energy - wind turbines monitored through DT achieved a 20% increase in operational efficiency through PdM, and healthcare - MRI machines modeled with DT enabled proactive replacement of parts, reducing service costs by 15%. Detailed research into the application of this concept in practice shows that by applying the PdM model, unplanned downtime is reduced by up to 50% in industrial plants. Also, this concept is used to optimize energy consumption in factories, reducing the carbon footprint by 25% in implemented projects. Also, modular DT solutions have enabled SMEs to use phased solutions to have a return on investment within 12 months. Problems can arise due to data security, so Siemens has developed and implemented encrypted data transmission with blockchain technology. Upgrading of existing Siemens solutions is possible, using middleware gradual digital transformation. The lack of knowledge is solved by training through certified Siemens training courses.
Further research is being done to develop autonomous AI DTs, which will define application parameters themselves, using ML models. As far as sustainability is concerned, future research will make even more use of circular economy and green agenda paradigms. Application areas will expand to smart cities, precision agriculture and other areas. Siemens defines DT and SM as key elements for the application of the Industry 4.0 model in maintenance. Although challenges remain, their holistic ecosystem and focus on AI and 5G networks will be the leading directions in shaping future industrial applications. The study also highlights the need for continued investment in education and digital security to accelerate implementation in various fields.

4.2. Azure IoT Hub and Azure Digital Twins

Microsof Azure IoT Hub and Azure Digital Twins are the base components of Industrial IoT (IIoT) and DT ecosystem [17]. Azure IoT Hub serves to manage the platform in the cloud, as well as for two-way communication between IoT devices and the cloud. Azure Digital Twins enables the creation of dynamic

digital models of physical models using graphs (eg factories, smart cities, smart grid). Together, they provide a scalable open-source framework for real-time tracking of real objects (machines), predictive analytics, and application of SM models. Open source integration is supported by software development kit (SDK), application programming interface (API) and tools (eg Azure IoT Edge, Raspberry Pi integration).
Interoperability is built on industry standards such as the OASIS standard messaging protocol for the IoT (MQTT), Advanced Message Queuing Protocol (AMQP) and HTTPS, ensuring compatibility with various IoT devices. The flexibility of the hybrid cloud is provided through integration with on-premises systems through Azure Arc, thus providing hybrid applications. Azure IoT Hub has the following features: (i) Device Provisioning Service (DPS) provides automatic secure device registration and authentication using X.509 certificates and Trusted Platform Module (TPM), (ii) data ingestion is performed by handling telemetry from millions of devices, with support for message routing to Azure services (eg, Blob Storage, Event Hubs), (iii) security is provided by end-to-end encryption, with Role-based access control access control (RBAC) and integration with Azure Active Directory, and (iv) using the edge computing model allows Azure IoT edge to work with AI/ML models locally on devices, reducing latency and bandwidth costs.
Azure Digital Twins has the following features: (i) uses the open-source Digital Twin Definition Language (DTDL) modeling language to create hierarchical, property-rich digital DT models (e.g., machines in a factory, assembly components), (ii) Twin Graph represents a database of graphs that map relationships between entities (e.g., "sensor X follows machine Y"), (iii) works in real-time, updates the model using IoT Hub telemetry and external data sources (e.g., APIs for machines in operation), and (iv) API and SDK modules enable integrations with Python, C#, Node.js models. And the integration itself is performed in several steps: (i) device connection is done by entering data from sensors, PLCs or other entities into the IoT Hub, (ii) model creation is done by using Azure Digital Twins and the use of DTDL to build a virtual representation of the physical system, and (iii) model enrichment is done by integrating Azure services such as: time series (analytics), Azure ML (predictive models) and power BI (visualization). Applications of this concept are best seen in the smart factory model for SM, where for example IoT Hub collects vibration/temperature data from CNC machines and then Azure Digital Twins models machine health by predicting bearing failures. Also, a well-known car manufacturer reduced downtime by 25% by using Azure IoT Edge to detect local anomalies. In the smart city model, traffic management is performed by digital twins simulating traffic flow based on real-time IoT data (eg congestion sensors), and energy optimization is performed by integrating data from the grid and renewable sources and dynamic load balancing. In healthcare, monitoring of

asset equipment (CT, MR) is carried out, with the IoT hub monitoring the location/status of medical equipment and digital twins monitoring its health.
Microsoft's Azure IoT Hub and Azure Digital Twins provide a robust open source platform for building scalable solutions for DT. Although challenges such as complexity and cost still exist, their interoperability, security and integration with the Azure AI/ML ecosystem make them a good choice for enterprises working to implement Industry 4.0 models. Future innovations in AI/ML, edge computing and sustainability analytics are likely to cement their place and role in the SM model and IoT-driven digital transformation.

4.3. Smart Factory Dataset (SFD)

This platform was designed to support the development of the PdM model, to detect anomalies and predict failures in the SM model [18]. It is used to collect multimodal data, namely: time series (vibration, temperature, pressure), equipment health status monitoring (normal, degraded, faulty), production log monitoring (batch ID, cycle time, quality metrics), contextual data generation (operator work, maintenance log), and synthetic data generation (digital failure scenario).
Data sources are: IoT sensors (high-frequency data from CNC machines, robotic arms, conveyor belts, and HVAC systems), process histories (logs from SCADA/MES systems that monitor production parameters), maintenance records (timescales for repairs, part replacements, and root cause analysis), and environmental data (ambient temperature, humidity, and energy consumption). All this data can be structured (Comma-separated values (CSV)/Parquet files with labeled sensor readings), unstructured (images/video (eg thermal image of machines)), and metadata (JavaScript Object Notation (JSON) files describing equipment specifications and factory layout). The temporal granularity of the data shows us that sensor data is generated at the millisecond level for real-time analysis, the rest on an hourly, daily or weekly basis, as an aggregated production metric. Digital Twin integration is performed by generating synthetic failure scenarios using physics-based simulations (eg Ansys, MATLAB).
This is how testing scenarios are realized, according to the "what - if" principle (eg equipment degradation under changing load). And the anomalies of the machine entity are linked to the underlying causes (eg bearing wear - lubrication failure) using sensor data. AI model validation (e.g. SHapley Additive exPlanations (SHAP)/LIME compatibility), is performed when cyber security incidents occur (logs of simulated cyber attacks (e.g. false sensor readings, PLC hacking) are kept to study resilience. Application of this model is done through several elements: PrM - train ML models (LSTM, Transformer) to predict equipment failures, following reference metrics: precision/accuracy, mean time time to failure (MTTF), anomaly detection, using unsupervised methods

(autoencoders, isolation forests) to identify process deviations, process optimization, reinforcement learning (RL) agents to minimize energy use or maximize throughput, explainable AI (XAI) validation, is test if XAI methods (eg, Grad-CAM, counterfactuals) align with ground-truth root causes, and cyber security allows us to detect hostile attacks on sensor networks using anomaly detection.

Technical challenges and limitations in the application of this model are: data volume and complexity (petabyte-sized data require distributed computing (Spark, Dusk) for processing and high dimensionality complicates feature engineering), labeling accuracy (manual labeling of root causes is a source of error and wastes more resources), generalization (models trained on synthetic data may fail in real-world application (sim-to-real gap), and privacy and compliance (anonymization of proprietary factory data Future improvements of this model will move in the following directions: real-time streaming - integration with Kafka/Flink for live anomaly detection, federated learning - enable privacy-preserving model training across factories, sustainability metrics - include carbon footprint data to align with green manufacturing goals, Human-in-the-Loop - incorporate operator feedback to refine AI predictions. SFD represents a valuable contribution to the development of SM and PdM models in them, multi-modal data with ground-truth labels for failure diagnosis and XAI validation. Its integration of synthetic scenarios and cybersecurity logs makes it a versatile tool for research and industry. However, challenges like data complexity and sim-to-real gaps require ongoing innovation. Future iterations could focus on real-time streaming and sustainability to further align with Industry 5.0 goals.

5. EXMAS Model

In this part, an example of research in the field of development of an expert system model for maintenance, which was carried out at the Department of Technological Systems, Faculty of Mechanical Engineering in Belgrade [19], is cited. It is an Expert Maintenance System (EXMAS) model. It is a knowledge-based system for planning the maintenance of workstations in flexible technological systems (FMS), which include CNC machine tools, robots and CNC numerically controlled measuring machines, whose knowledge base uses IF-THEN rules, of which there were 264, Figure 1.

The knowledge base had two knowledge domains: facts and rules, and ES had three modules: (i) communication interface, (ii) shell ES (knowledge base and inference engine), (iii) processor (recognition of diagnosis and maintenance plans), and was developed in the Prolog language.

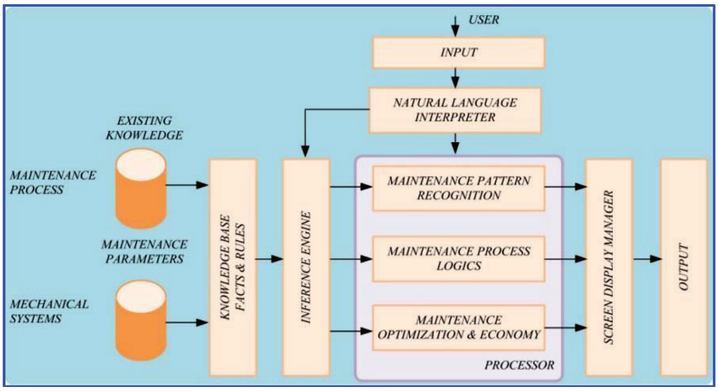

Fig. 1. EXMAS – Basic structure

The conclusion was made by searching the knowledge base backwards (backward searching), from symptoms to diagnosis. ES was developed and implemented as a laboratory prototype for FMS workstations. According to the classification from Table 1, it belonged to the models that were suitable for the concept of Industry 3.0 - KBS.

6. Conclusions and Future Research

Smart maintenance in the context of Industry 4.0, includes the integration of CPS, IoT, DT, AI/ML and cloud/edge, where these technologies are used to predict and prevent equipment failures, optimize maintenance schedules and reduce downtime. CPS is an entity where IoT devices collect real-time data, which DT then uses to model and simulate the state of the equipment. AI/ML analyze this data to predict maintenance needs and activities. But how exactly do these components integrate? IoT provides a data layer, continuously feeding information to DT, which processes this data, using simulations to predict future states or diagnose problems. ML models analyze historical data as well as real-time data to predict failures or maintenance needs. However, traditional ML models can be "black boxes", so using XAI would make these predictions understandable. For example, if AI predicts an engine failure, XAI could highlight that vibration levels have consistently exceeded a certain threshold over the past week, leading to the appropriate conclusion.
One of the most important future research directions is the application of generative AI (GAI) to synthetic data in maintenance. It has enormous potential and can revolutionize the way PrM systems will be developed and optimized[14]. Here's how, and why. Simulation of rare failures - in real industrial conditions, certain failures are very rare, which means that there is little real data to train the model. Generative AI can create synthetic data that

simulates such events and thereby improve its ability to predict failures, reducing costs and time for data collection - traditional data collection requires sensors, time-consuming testing and expensive experiments, and GAI can reduce these costs of generating realistic data based on existing samples, increasing data diversity - ML often suffers from imbalanced datasets, but this is why generative models like GANs (Generative Adversarial Networks) and diffusion models can generate a variety of scenarios, including unusual or extreme ones system operating conditions, improving the accuracy of diagnostics and prognostics - by combining real and synthetic data, maintenance models can better adapt to unexpected situations, which increases their ability to detect and predict failures, and reliable testing and development of AI models - GAI enables the development and testing of models in a simulation environment before they are implemented in real industrial conditions, thus reducing the risk of costly errors. GAI is a powerful tool for improving maintenance through synthetic data, but it should be used carefully in combination with real industry data. Its true value lies in its ability to enhance and extend existing data sets, but not to replace them entirely.

Blockchain technology can bring significant benefits in the field of maintenance, especially when it comes to ensuring traceability, transparency and data security[15]. In an industry where data reliability and accuracy are key (aerospace, rail, energy sector), blockchain can provide an immutable and transparent record of all maintenance activities. The advantages of blockchain technology in the development and application of PrM are: immutability and data security - every generated data in the blockchain is cryptographically protected and cannot be changed or deleted. This means that maintenance data is authentic and protected from manipulation, which reduces the possibility of fraud and inaccurate reports, transparency and traceability - blockchain allows full tracking of the entire maintenance history of a particular equipment. All data (repair date, who performed the work, used parts) is visible and verified, which is useful for history, user and internal checks, automated smart contracts (Smart Contracts) - these contracts can automate certain maintenance processes, such as service activation after a certain number of working hours, automatic ordering of spare parts or verification that maintenance is carried out according to prescribed standards, resistance to data loss and cyber attacks - classic databases can be hacked or modified without authorization. Blockchain distributes data across the network, making it secure and available even in the event of a server failure, and simplified compliance with standards and regulations - industries with strict standards and regulatory requirements (e.g. aviation and pharmaceuticals) can use blockchain to securely store maintenance data, thus reducing red tape and speeding up the internal and supervisory review process. Its combination with IoT, AI/ML and smart contracts can create a fully automated, secure and reliable maintenance management ecosystem. Future trends in this area refer to: a combination with digital twins for accurate monitoring of the life cycle of equipment, private blockchain networks that offer a balance between security and speed, decentralized applications (dApps) for managing audits and data verification. It is believed that blockchain will become a key technology for the verification and security of PrM data in the future.

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Enhancing Human-Robot Collaboration Through Multimodal Data and Robot Learning in Human-Centered Industry 5.0 Systems

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Abstract: *The transition from Industry 4.0 to Industry 5.0 emphasizes the development of human-cantered robotic systems designed for seamless and adaptive collaboration with human operators in complex industrial environments. Advances in multimodality within human-robot collaboration (HRC) are enabling richer and more natural interactions by leveraging diverse communication channels, including auditory inputs (speech recognition), visual perception (RGB-D and depth cameras), gestural understanding (pose estimation), haptic feedback, and even brain-computer interfaces. Moreover, the capability to understand human behaviour, particularly in terms of intent prediction and motion analysis, plays a critical role in fostering mutual human-robot assistance.*
This review provides a comprehensive analysis of state-of-the-art approaches that integrate multimodal data with advanced robot learning paradigms, such as imitation learning and reinforcement learning. Within this context, the study presents an overview of the current landscape of multimodal HRC and its applications while outlining key challenges and future research directions.

Keywords: *Human-Robot Collaboration, Industry 5.0, Multimodal Data, Robot Learning*

1. Introduction

The industrial landscape is undergoing a profound transformation, shifting from the automation-centric paradigm of Industry 4.0 to the human-cantered vision of Industry 5.0. While Industry 4.0 focused on digitalization, cyber-physical systems, and interconnected smart factories, Industry 5.0 emphasizes the synergistic collaboration between humans and intelligent machines, promoting values such as sustainability, resilience, and personalization. This evolution demands not only smarter technologies but also adaptive, intuitive, and cooperative robotic systems that can operate seamlessly alongside human workers.
At the core of this transition is Human-Robot Collaboration (HRC), a paradigm in which humans and robots share physical workspaces, coordinate actions, and jointly complete tasks in dynamic and often unstructured environments.

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Technological advancements in artificial intelligence, robotics, soft materials, and bioelectronics are key factors in enabling human-robot collaboration in industrial environments[1].
A key enabler of such capabilities lies in the integration of multimodal data - including vision, speech, gesture, and contextual information—with robot learning methods such as self-supervised learning,imitation learning, and reinforcement learning. Multimodal perception allows robots to interpret complex human communication cues, while learning algorithms enable them to improve and personalize their behaviour over time.
This review aims to provide a comprehensive overview of recent advances in the intersection of multimodal sensing and robot learning for HRC in the context of Industry 5.0. We discuss existing frameworks, representative applications, and open challenges, with a focus on creating robotic systems that are not only functional, but also trustworthy, adaptive, and human-aware.
The remainder of this study is organised as follows. Section 2 provides key characteristics of human-robot collaboration and discusses real-world applications.Challenges and open issues are presented in Section 3. Section 4presents an overview of input modalities, followed by a discussion on sensor fusion and real-time data processing. Section 5 presents the key components of effective human–robot collaboration, emphasizing how cognitive perception, safe and adaptive actions, and continuous learning enable robots to understand human intent, plan cooperative behaviours, and improve performance in dynamic environments. The discussion of future directions is presented in Section 6, outlining emerging trends, unresolved challenges, and potential advancements that could enhance the effectiveness and adaptability of human–robot collaboration systems.Finally, Section 7 concludes this study.

2. Human-Robot Collaboration in Industry 5.0

Human-robot collaboration has emerged as a transformative approach in modern manufacturing and logistics, enabling the seamless integration of human expertise with robotic precision and efficiency. By working side by side with humans, collaborative robots (cobots) address the limitations of fully automated systems and empower flexible, adaptive workflows, Figure 1.This synergy is particularly valuable in industries characterized by high variability, customization, and the need for quick reconfiguration of production lines[2].
Collaborative robots are often used in industrial processes, such as assembly, packaging, inspection, or the transportation of items from conveyor belts. The key advantages of human-robot collaboration include:

- ***High level of automation.*** Cobots complement human workers' capabilities and enable rapid automation of production steps.

- ***Reduced employee workload.*** Physically demanding, dangerous, and monotonous tasks can be taken over by cobots, thereby relieving workers.
- ***High quality.*** Repetitive processes that require high concentration are executed by cobots with maximum precision, improving production quality.
- ***Maximum flexibility.*** Collaborative robot tasks can be flexibly adapted to changing requirements.

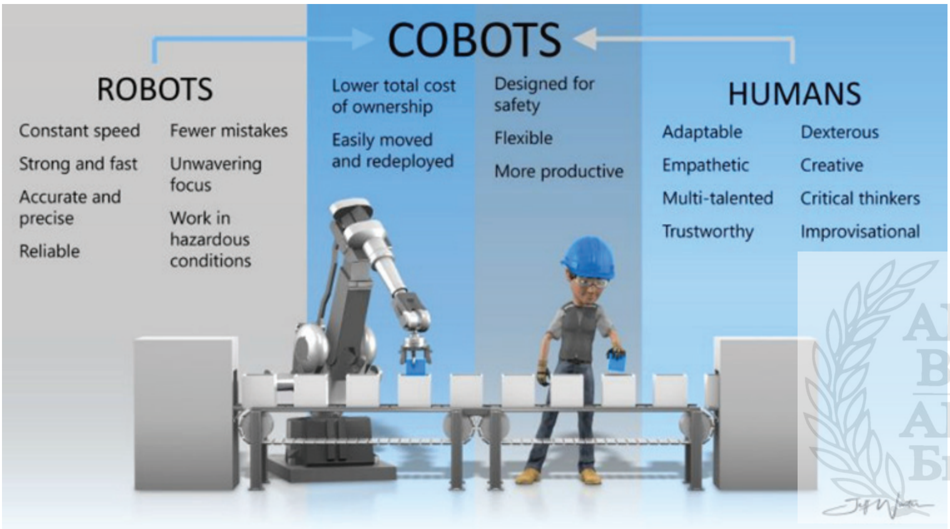

Figure 1. Traditional Robots vs. Collaborative Robots in Human–Robot Collaboration[3].

The types of human-robot cooperation are illustrated in Figure 2. They encompass varying levels of interaction, each defining different degrees of shared tasks and communication between humans and robots[4]:

- **Coexistence:** Humans and robots do not share the same workspace and operate independently on different tasks.
- **Cooperation:** In human-robot cooperation, humans and robots work in the same workspace, alternately performing different tasks within the process. There is no direct interaction.
- **Collaboration:** Humans and robots interact within a shared workspace; both work simultaneously on the same product.

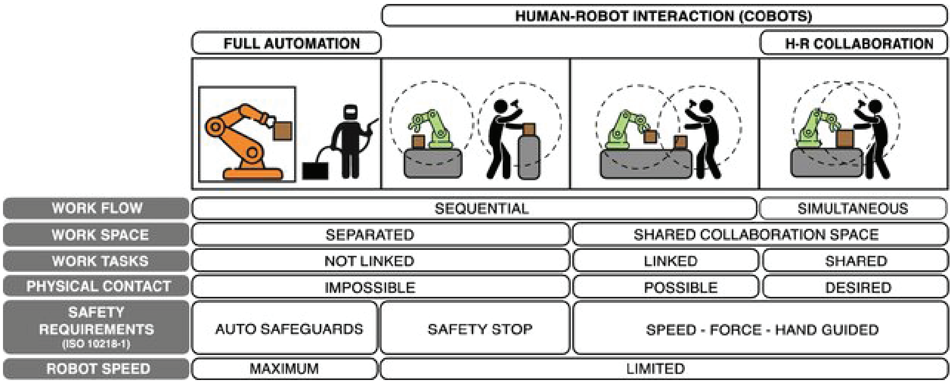

Figure 2. Typesof human-robot cooperation: coexistence, cooperation and collaboration[5,6].

In industrial assembly, HRC enhances productivity by allowing cobots to handle repetitive or ergonomically challenging tasks while humans focus on high-skill operations such as quality adjustments, problem-solving, and fine-tuning components[7]. Cobots equipped with force-torque sensors and advanced vision systems can assist with tasks like screwing, welding, and component placement, ensuring precision and consistency. For example, in automotive manufacturing, robots can preassemble complex parts or hold components in position while a human operator performs intricate manual tasks, resulting in improved efficiency and reduced cycle times.

Collaborative robots are increasingly deployed in inspection processes due to their ability to combine advanced computer vision algorithms with consistent, fatigue-free operation. In electronics manufacturing or aerospace industries, cobots can perform real-time visual inspections, detect micro-defects, or use non-destructive testing (NDT) techniques such as ultrasonic or laser scanning. When combined with human oversight, this ensures both speed and accuracy in identifying production anomalies. Through multimodal sensing, cobots can detect quality deviations, while humans make final judgments that require domain expertise or creativity[8].

In logistics, warehouse automation, and intralogistics, cobots streamline workflows by transporting goods, sorting items, and assisting with order fulfillment. Unlike traditional automated guided vehicles (AGVs), mobile cobots can operate safely alongside human workers in dynamic environments, adapting to changing layouts and workflows. Applications include palletizing, depalletizing, and collaborative picking, where robots lift heavy loads while humans handle delicate tasks such as product verification and packaging[9]. This is particularly beneficial in e-commerce and retail distribution centers, where demand for fast and flexible order processing is high.

An example of human-robot collaboration in an industrial environment is shown in Figure 3**.**

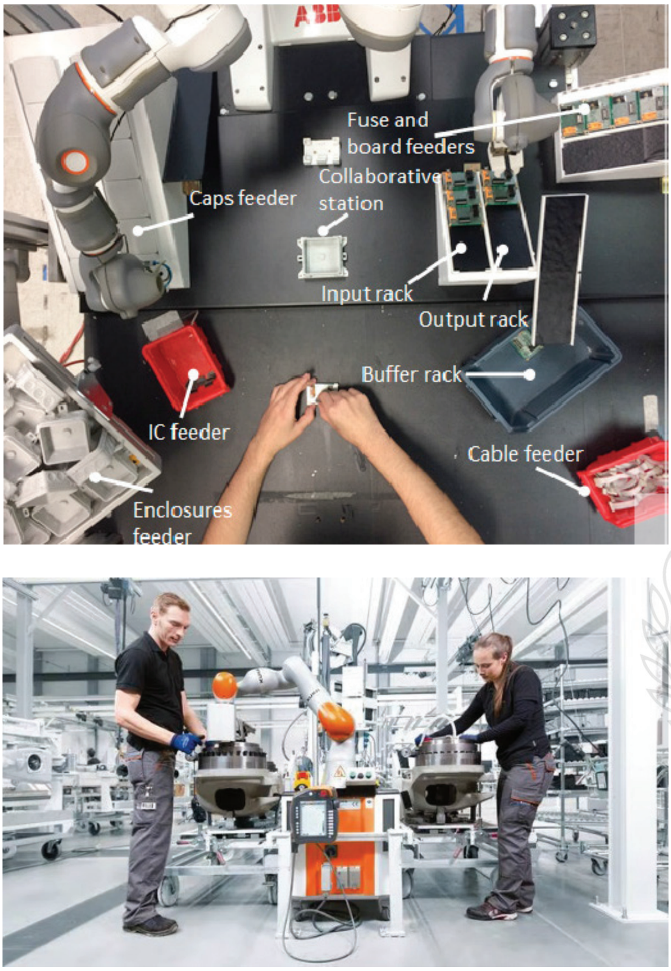

Figure 3. Examples of human-robot collaboration in industrial settings[10,11].

3. Challenges and Open Issues

Developing effective collaborative systems is a complex challenge that involves technical, cognitive, and design-oriented considerations. Key challenges include perception, communication, learning, optimization, and explainability, each of which directly impacts the safety, efficiency, and trustworthiness of HRC systems[12,13].

- ***Perception.***Accurate perception of the environment is a fundamental requirement for successful collaboration. Robots must be capable of recognizing and classifying objects, understanding spatial relationships, and tracking dynamic elements in real time. Beyond object recognition, advanced perception includes interpreting **human activities, intentions, and emotional states** using visual cues such as facial expressions, body posture, and gestures. This requires robust multimodal sensing, integrating data from cameras, LiDAR, tactile sensors, and other devices, combined with deep learning algorithms for reliable human-robot interaction in unstructured and dynamic environments.
- ***Communication.***Effective communication between humans and robots is essential for smooth collaboration. This includes both **verbal and non-verbal communication.** Verbal communication relies on **natural language processing (NLP)** for interpreting spoken commands, contextual understanding, and generating human-like responses. Non-verbal communication, such as interpreting hand gestures, pointing, or body posture, is equally critical in industrial and service contexts, where verbal instructions may not always be practical. A failure to understand subtle non-verbal cues can lead to inefficiencies or safety risks.
- ***Reactive Control-Based Approaches.***In collaborative settings, robots must dynamically adjust their behaviour in response to changing conditions. **Real-time feedback mechanisms** allow robots to adapt to unexpected human actions, task changes, or environmental disruptions. This demands low-latency sensor data processing and control algorithms capable of reactive planning, ensuring both task success and human safety.
- ***Learning.***Robots in HRC scenarios must be capable of **continuous learning** to adapt to human preferences, new tools, or novel environments. Methods such as **Learning from Demonstration (LfD)**, reinforcement learning, and human-in-the-loop training enable robots to refine their behaviours and tasks based on feedback. Continuous learning not only improves adaptability but also enhances the robot's ability to share workloads effectively with human partners.
- ***Optimization.***Task planning and motion trajectories must be optimized to ensure efficiency and safety during collaboration. This includes minimizing energy consumption, avoiding unnecessary robot movements, and maintaining safe distances from human co-workers. Optimized planning also accounts for task sequencing and resource allocation, which are vital for high-mix, low-volume manufacturing or logistics environments.
- ***Robot Design.*** The physical design of collaborative robots plays a crucial role in building trust and ensuring usability. Cobots must feature

ergonomic, safe, and intuitive designs, often incorporating lightweight materials, rounded edges, and limited power or force to reduce the risk of injury. User-centric design, combined with intuitive interfaces, ensures that operators can work with robots without extensive training or fear.

- ***Explainable Robotics.***Transparency is vital for trust in HRC systems. Robots must be capable of explaining their **decisions, actions, and reasoning** in ways that are understandable to human collaborators. Explainable robotics not only enhances user confidence but also improves debugging, safety verification, and regulatory compliance in industrial settings.

4. Muti Modal Modalities in HRC

Most methods for learning robotic policies emphasize only one modality of task description, failing to exploit the wealth of information offered by cross-modal data. Modern robotic systems are designed to process and integrate data from multiple sensory modalities, such as vision, speech, text,and voice commands as well as tactile and psysiological sensing, Figure 4 [1,14].

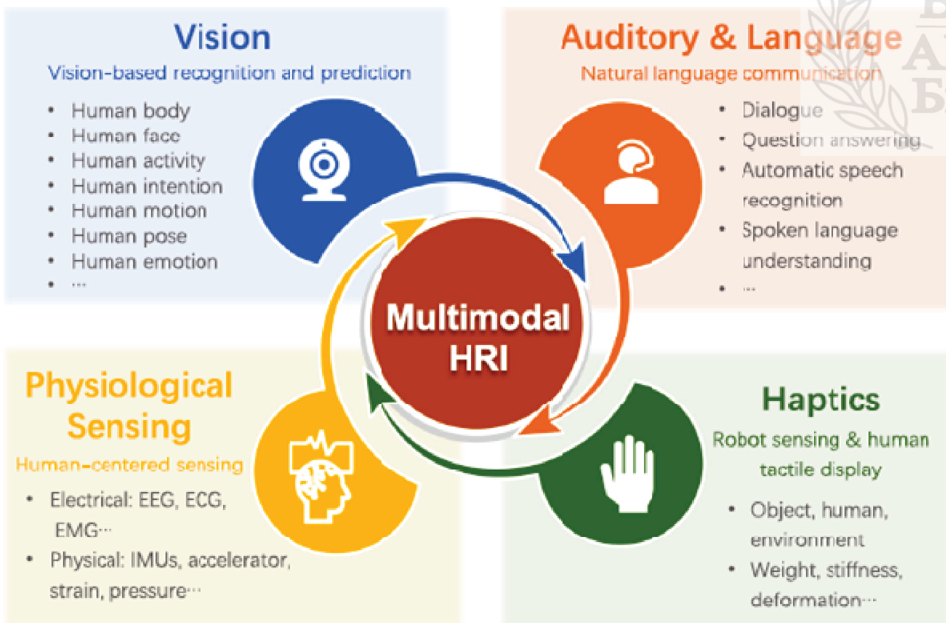

Figure 4. Four typical modalities of Human Robot Interface [1].

For example, combining visual perception with tactile sensing allows for precise manipulation of deformable objects, while coupling language and vision facilitates semantic understanding of tasks described by humans. Furthermore, the integration of physiological or biosignal data (e.g., electromyography or EEG) enables robots to anticipate human intent, optimize ergonomic factors, and respond proactively during collaboration.
Vision-based technologies in Human-Robot Collaboration (HRC) rely on advanced computer vision and deep learning techniques to detect and analyze human position, activity, pose, and emotion [1]. Convolutional Neural Networks (CNNs), Graph Convolutional Networks (GCNs), and Vision Transformers (ViTs) are widely used for tasks such as pose estimation, activity recognition, and facial expression analysis, enabling robots to understand and respond to human behaviour in dynamic environments.An example of multimodal fusion of gesture recognition and object classification using Vision Transformers (ViTs) in human–robot collaboration is presented in Figure 5 [15].

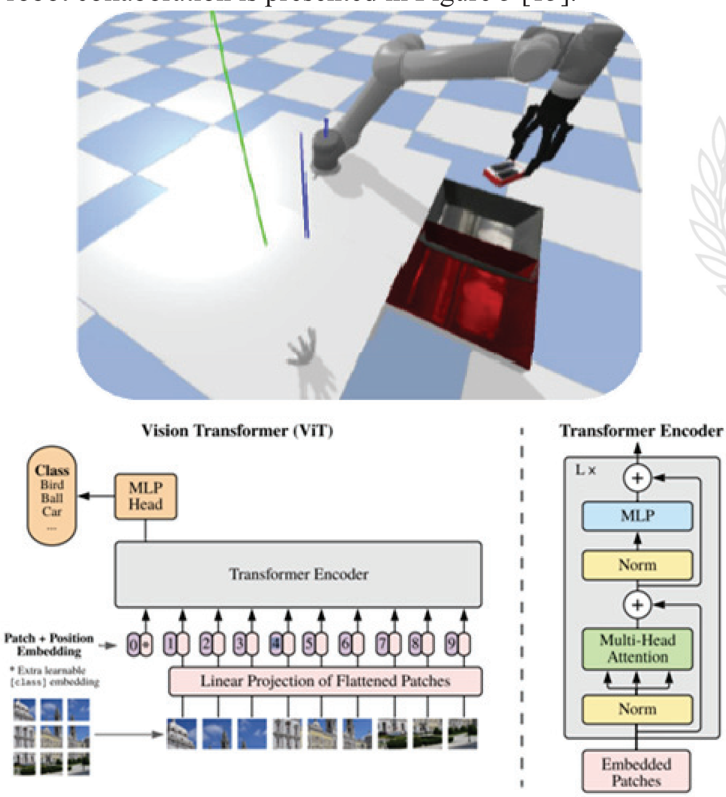

Figure 5. Multimodal Fusion of Gesture and Object Classification in Human-Robot CollaborationusingViTs[15].

Language-based interaction leverages Natural Language Processing (NLP) and machine learning models to enable natural communication between humans and robots. Automatic Speech Recognition (ASR) is powered by deep neural networks (DNNs) and Transformer-based models, while Spoken Language Understanding (SLU) often employs Recurrent Neural Networks (RNNs), BERT-like models, or sequence-to-sequence architectures. Question-answering (QA) and dialogue systems use large language models (LLMs) and reinforcement learning techniques to support context-aware and conversational HRI.

Haptics-based technologies utilize AI algorithms for tactile signal interpretation and adaptive control. Machine learning methods, such as Support Vector Machines (SVMs), Random Forests, or CNNs, are applied to process tactile sensor data for recognizing object properties (e.g., texture, stiffness) and human touch patterns. Reinforcement Learning (RL) is often integrated for dynamic adjustment of haptic feedback and robotic manipulation, ensuring safe and effective physical collaboration in real and virtual environments.

Physiological sensing incorporates AI-driven signal processing and classification techniques to monitor human states using EEG, ECG, and EMG signals [1]. Methods like convolutional and recurrent neural networks (CNNs, LSTMs) or hybrid deep learning models are employed for emotion recognition, stress detection, and cognitive state assessment.

Efficient fusion of multimodal data remains one of the primary challenges in achieving robust performance, particularly in complex tasks such as human–robot collaboration. Various strategies have been proposed to address this issue, with the most used approaches - early fusion, late fusion, and hybrid (middle) fusion[1].

- *Early Fusion:*In early fusion, all modalities (e.g., images, audio, text, or sensor data) are integrated at the input stage of the model, Figure 6a).Typically, feature vectors extracted from different sensors are concatenated into a single high-dimensional vector, which is subsequently processed by a unified neural network (e.g., a combination of CNN and LSTM layers or a transformer-based architecture). The main advantage of early fusion is that it enables the model to directly learn cross-modal correlations. However, this approach can be challenging due to differences in the nature and dimensionality of the input data, potentially leading to training inefficiencies or model overfitting.
- *Late Fusion:*In late fusion, each modality is processed independently through dedicated subsystems (e.g., separate neural networks designed for visual and audio inputs), Figure 6b). The outputs of these subsystems—typically feature embeddings or intermediate decisions—

are then combined at a higher level, either through concatenation of latent vectors or decision-level integration. The primary strengths of late fusion lie in its modularity and flexibility, making it straightforward to add or remove modalities. Nonetheless, it may fail to capture deeper inter-modal correlations that emerge in earlier stages of processing.

- *Hybrid (Middle) Fusion:*Hybrid fusion represents a compromise between early and late fusion. In this approach, individual modalities are first partially processed through their respective encoders, after which the resulting intermediate representations are fused at a middle layer of the network, Figure 6c). This strategy aims to balance the advantages of both early and late fusion, offering improved flexibility while maintaining the ability to learn efficient multimodal representations.
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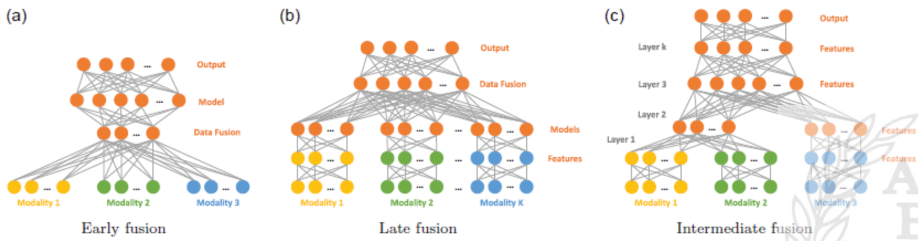


Figure 6. Forms of Multimodal Fusion: a). Early fusion, b). Late fusion; c). Intermediate fusion [1].

Multimodal fusion often relies on specialized architectures that integrate heterogeneous data streams into a unified representation.

a. *Multimodal encoders* process each modality through dedicated networks (e.g., CNNs for visual inputs, RNNs or transformers for audio and text), after which the resulting embeddings are combined via concatenation, attention mechanisms, or element-wise operations.
b. *Attention mechanisms* allow the model to dynamically prioritize modalities based on contextual relevance, improving robustness when certain inputs are noisy or missing.
c. *Gating mechanisms* adaptively regulate the contribution of each modality using learned weights, often implemented as sigmoid-based layers.
d. *Multimodal transformers* are increasingly adopted due to their ability to capture complex inter-modal dependencies through self-attention and hierarchical representation learning.

The choice of method depends on the application, with early fusion suited for strongly correlated data and attention-based approaches excelling in context-aware tasks.

Figure 7 illustrates multimodal learning that integrates voice recognition, hand movement, and human body posture. This approach leverages various deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks with specialized architectures such as long short-term memory (LSTM), and related transfer learning methods[16].

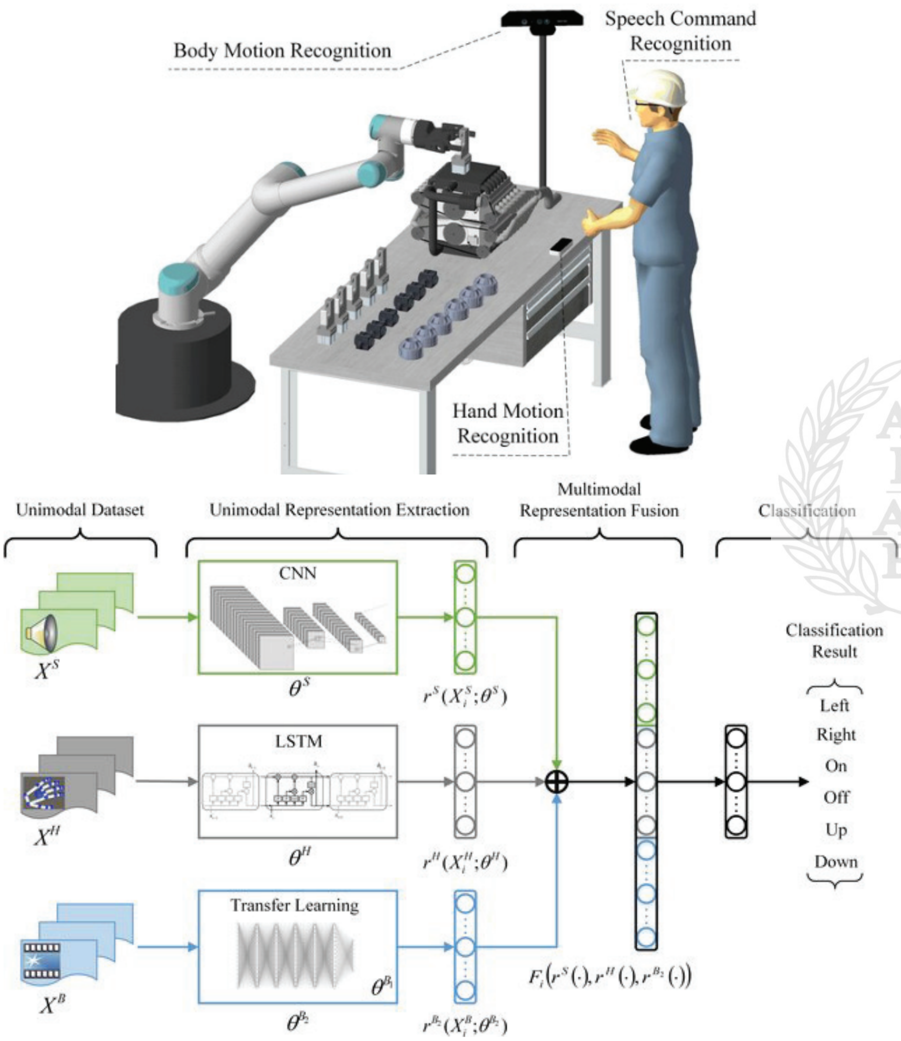


Figure 7. Example of multimodal fusion combining three types of deep learning approaches: (1) voice command recognition, (2) hand position detection, and (3) body pose estimation, enabling comprehensive interpretation of human intent and actions [16].

Figure 8 depicts a human-centered human-robot collaboration (HRC) scenario that leverages multiple modalities to achieve collaborative objectives, structured into four main phases. Initially, within a shared workspace, the human and robotic arm jointly execute a complex assembly task, utilizing both visual and tactile feedback for precise coordination. In the subsequent phase, an autonomous guided vehicle (AGV) moves toward the storage zone to locate necessary materials while engaging with the human operator through a visual-language navigation (VLN) framework that combines visual and auditory cues. The third phase involves the AGV-mounted robotic arm retrieving the identified material and handing it to the human, again relying on visual and tactile modalities. In the final phase, the human operator is equipped with EMG electrodes to enable ergonomics evaluation through integrated physiological sensing.

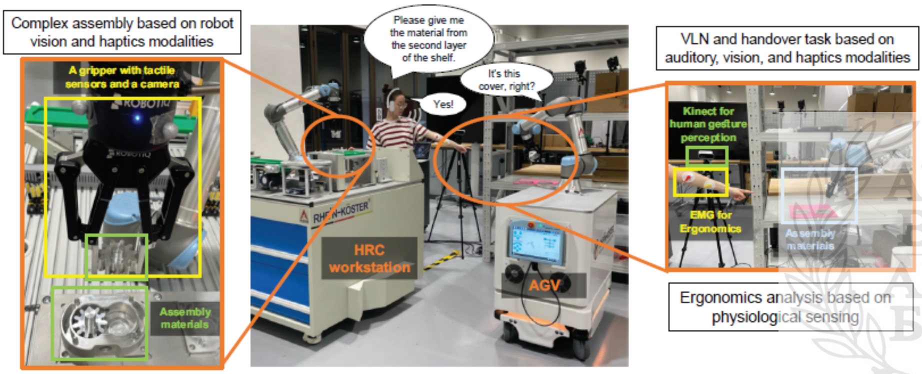


Figure 8. Typical human-centric smart manufacturing application scenario based on multimodal HRI[1].

The core challenge of multimodal approaches with AI in robotic learning lies in the **effective fusion of heterogeneous data modalities**—such as visual input, speech, haptic feedback, and natural language—into a coherent representation that enables **reliable, robust, and adaptive robot behaviour in real-world environments**. Achieving this fusion requires addressing a set of complex, interrelated challenges[17]:

- ***Semantic misalignment between modalities.*** Different modalities (e.g., video and speech) operate on distinct temporal scales, levels of semantic granularity, and structural representations. Achieving temporal and conceptual alignment remains difficult, particularly when interpreting commands such as “grab that,” where the robot must correctly link the verbal cue to the visual context (e.g., the object currently detected by the camera).

- ***Fusion of heterogeneous representations.***Each modality is typically processed by specialized neural architectures—e.g., Vision Transformers (ViT) for vision, LSTMs for speech, and BERT for language. Integrating these diverse feature spaces into a unified, task-relevant representation is inherently nonlinear and computationally demanding.
- ***Dynamic attention and modality selection.***A robot must be able to dynamically determine which modality to prioritize depending on the context. For instance, speech may dominate in low-noise settings, whereas visual information should take precedence when acoustic signals are unreliable. This necessitates **modality-adaptive attention mechanisms** capable of weighting information in real time.
- ***Lack of large, synchronized multimodal datasets.***Collecting realistic, high-quality multimodal datasets for robotics is challenging, resource-intensive, and often task- or domain-specific, which limits generalization and transfer learning capabilities.
- ***Real-time learning and adaptability.***Multimodal policies must achieve efficient, low-latency learning to operate under real-world constraints, especially in reinforcement learning (RL) scenarios where interaction with the environment is costly.
- ***Explainability and transparency.***It remains difficult to disentangle the contribution of each modality to the final decision, which complicates debugging, performance evaluation, and the establishment of trust in safety-critical domains such as industrial automation or healthcare.
- ***Robustness to modality degradation or failure.***Ensuring continuous functionality when one or more modalities fail (e.g., camera malfunction, speech input loss) requires the design of **graceful degradation mechanisms** and fallback strategies.

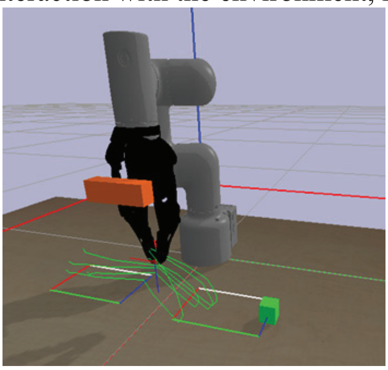
5. Cognition, Action, and Learning in HRC

Following multimodality, cognition, action, and learning are essential components of effective human–robot collaboration (HRC). *Cognition* involves a robot's ability to perceive, reason, and interpret human behaviour and environmental context. This includes understanding task goals, predicting human intentions, and adapting to dynamic conditions. Cognitive models often integrate multimodal perception with semantic reasoning, probabilistic inference, or graph-based representations to create a human-aware decision-making process [18]. For example, recognizing gestures, gaze direction, or speech commands can provide contextual cues that guide collaborative tasks.
Action refers to the generation of safe and contextually appropriate behaviours based on cognitive insights. In collaborative environments, this includes motion

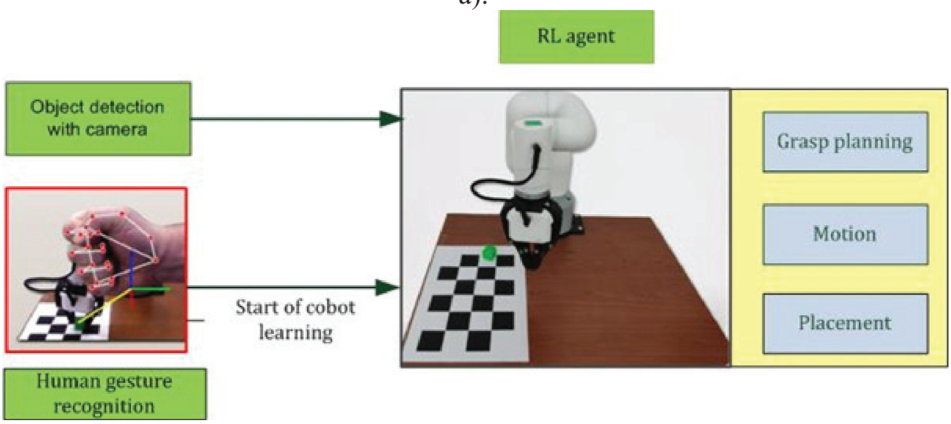
planning, trajectory adaptation, and compliant control to ensure fluid cooperation with humans. Modern approaches leverage real-time feedback loops and optimization algorithms, enabling robots to perform tasks such as handovers or co-manipulation in a natural and intuitive manner [19]. Shared autonomy strategies and dynamic re-planning ensure that robots remain responsive to human inputs and environmental changes.

Learning allows robots to improve their performance over time, adapting to novel situations and user preferences. *Learning from demonstration (LfD)*or *imitation learning*provides a direct way to acquire skills by observing human behaviour [20,21]. This paradigm facilitates fast adaptation in flexible manufacturing and has proven effective for trajectory generalization and task sequencing.

In contrast, *reinforcement learning (RL)* allows robots to learn optimal policies through trial-and-error interaction with the environment, Figure 9.



a).



b).

Figure 9. Training process of a robotic agent using DRL within the PyBullet environment to develop robust pick-and-place strategies, emphasizing the integration of policy refinement and simulation-to-real transfer techniques [22].

While RL has demonstrated success in collaborative assembly and manipulation tasks, its application in HRC requires safety-aware mechanisms to mitigate risks during exploration [22]. In human-robot collaboration systems for assembly tasks, reinforcement learning (RL) and deep reinforcement learning (DRL) methods are increasingly being utilized. A collaborative reinforcement learning approach was applied to evaluate the use of a fixed-arm robot to determine the optimal strategy for emptying the contents of a plastic bag [23]. Furthermore, *online and incremental learning* enables robots to update their models during operation, allowing them to adapt to evolving human behaviour, tools, or workflows—critical for unpredictable industrial settings [24].
To enhance human alignment, *human-in-the-loop learning* integrates feedback and corrections from human operators, allowing real-time adaptation and personalized behaviour shaping [25]. Additionally, *transfer learning and simulation-to-reality (Sim2Real) techniques* are increasingly used to pre-train models in virtual environments, minimizing costly or dangerous real-world trials and improving deployment efficiency[26].
Hybrid frameworks that combine DRL with LfD and transfer learning have shown great promise in reducing sample complexity and enhancing generalization [27]. These methods, when integrated with cognitive reasoning and adaptive action control, create robust HRC systems capable of operating effectively in unstructured, human-centric environments.

5.1. Multimodality-Based Robot Learning

The incorporation of multimodal data significantly strengthens robot learning methodologies. By combining information from various sensory channels, these systems develop a richer understanding of their environment, enabling better generalization to diverse scenarios and the successful execution of complex tasks such as object detection, gesture recognition, and natural language processing. Multimodal fusion enhances both the resilience and flexibility of learning algorithms while promoting more natural and efficient interactions between humans and robots. Consequently, multimodal approaches drive higher levels of autonomy and performance across multiple domains, including industrial automation, assistive technologies, and service robotics.
One example of robot policy learning from multimodal task specifications is presented in Figure 10. It trains a transformer-based architecture to facilitate cross-modal reasoning, combining masked modeling and cross-modal matching objectives in a two-stage training procedure[28]. After training, MUTEX can follow a task specification in any of the six learned modalities (video demonstrations, goal images, text goal descriptions, text instructions, speech goal descriptions, and speech instructions) or a combination of them. This approach systematically evaluated the benefits of MUTEX in a newly designed

dataset with 100 tasks in simulation and 50 tasks in the real world, annotated with multiple instances of task specifications in different modalities, and observed improved performance over methods trained specifically for any single modality.

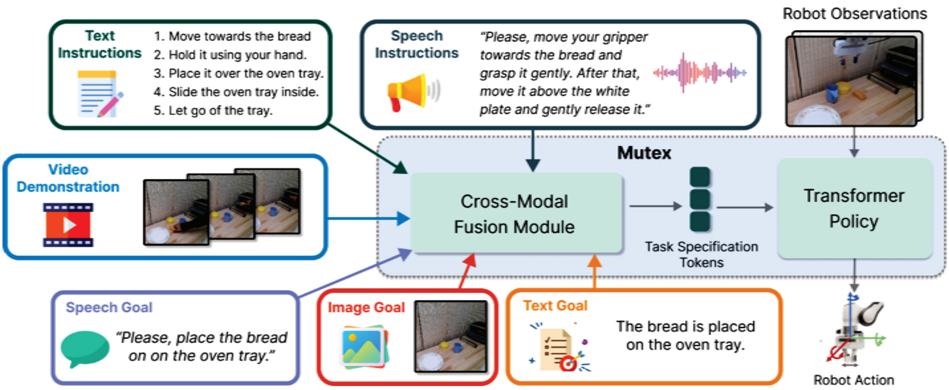


Figure 10. Learning Unified Policies from Multimodal Task Specifications[28].

Everyday tasks involving extensive physical interactions—such as peeling, cleaning, and writing—require robust multimodal perception to ensure accurate and effective execution, Figure 11. For robots, however, such contact-rich tasks pose significant challenges due to their limited capability to integrate and interpret diverse sensory modalities. Existing learning-based approaches for contact-rich manipulation have attempted to address this issue but typically rely on large datasets and task-specific reward functions, which constrain their scalability and generalization. To overcome these limitations, the paper [29]introduced a generalizable, model-free learning-from-demonstration framework that enables robots to acquire contact-rich skills without the need for explicit reward engineering. A novel multimodal sensor data representation was proposed, enhancing the efficiency and accuracy of the learning process. The framework is validated through experiments on a Sawyer robot across three representative contact-rich tasks: cleaning, writing, and peeling. The results demonstrate a 100% success rate for both peeling and writing, and an 80% success rate for cleaning. These findings indicate that the proposed approach offers a scalable foundation for extending skill acquisition to a wide range of physical manipulation tasks. Humans skillfully manipulate deformable objects by relying on multimodal perception, enabling them to accomplish everyday tasks such as opening bags, unwrapping candy, or retrieving keys from pockets. Transferring these abilities to robots is highly challenging due to the complex and unpredictable properties of deformable materials.

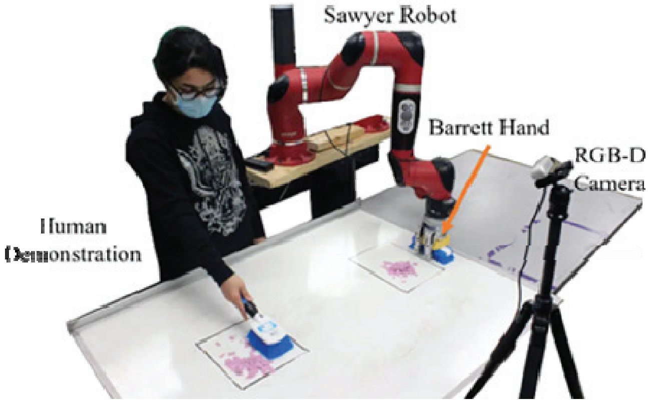


Figure 11. The experimental setup for learning-from-demonstration framework [29].

To tackle this problem, a human-inspired exploration and purposeful manipulation framework has been developed for robots, focusing on multimodal learning and adaptation[30]. As illustrated in Figure 12, the framework enables robots to autonomously explore and learn the characteristics of a class of deformable objects. Using the knowledge acquired during this exploration phase, the robot can execute purposeful manipulations to complete specific tasks.

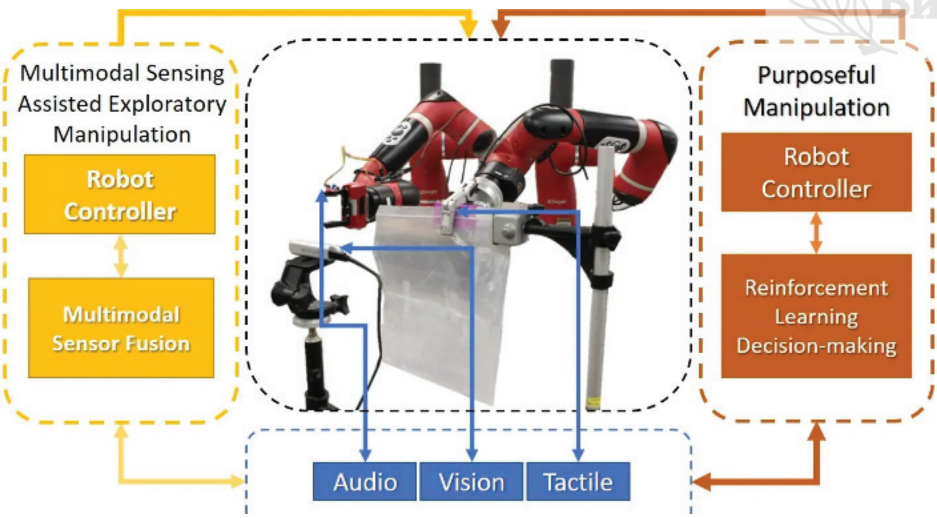


Figure 12. Multimodal Reinforcement Learning and Decision-making [30].

6. Future Directions

Future research in human-robot collaboration (HRC) aims to address the limitations of current systems by enhancing adaptability, intelligence, and trustworthiness in dynamic real-world environments. Emerging trends focus on integrating multimodal perception, large-scale foundation models, and lifelong learning mechanisms to create robots capable of personalized, context-aware, and safe collaboration with humans [14].

- *Personalized and Context-Aware HRC.*Future robotic systems must adapt to individual human users by learning their preferences, expertise levels, and working styles. This requires integration of online learning, user modeling, and context-aware adaptation, enabling robots to act as personalized collaborators rather than generic tools.
- *Continual and Lifelong Learning.*Robots in real-world settings must operate in non-stationary environments where tasks, users, and workflows change over time. Lifelong learning mechanisms will allow robots to incrementally acquire knowledge, avoid catastrophic forgetting, and build richer experience-based policies without exhaustive retraining.
- *Large Language Models and Natural Communication.*The rise of Large Language Models (LLMs) opens new possibilities for natural, high-level interaction between humans and robots. By embedding LLMs into HRC systems, robots can better interpret verbal instructions, generate contextual responses, and support collaborative dialogue, paving the way toward semantic-level understanding in industrial environments.
- *Robotic Foundation Models for Science and Generalization.*Inspired by foundation models in natural language processing, the future of robot learning will be shaped by Robotic Foundation Models (RFMs)—large, pre-trained multimodal models that can generalize across tasks, environments, and embodiments. These models will integrate vision, language, force, and state data into a unified representation, enabling zero-shot or few-shot adaptation to novel contact-rich tasks. RFMs will also accelerate scientific discovery, allowing robots to autonomously conduct experiments, simulate hypotheses, and collaborate with human researchers in domains such as material science, chemistry, and advanced manufacturing.
- *Multimodal and Cross-Modal Reasoning.*Next-generation collaborative robots will increasingly rely on joint reasoning over multiple modalities (e.g., speech, vision, force feedback) to robustly interpret ambiguous situations or resolve conflicts. Techniques such as multimodal transformers and cross-modal attention mechanisms will be critical for fusing diverse signals.
- *Explainable and Trustworthy AI.*Building trust between human workers and robotic systems requires transparency and interpretability. Future HRC

systems must provide explainable actions and justifications, particularly in high-risk or safety-critical environments. Human-understandable feedback and behaviour prediction are key components of trustworthy collaboration.

- *Edge AI and Real-Time Decision Making.*To meet the latency and reliability requirements of industrial HRC, future solutions will increasingly leverage Edge AI architectures that enable on-device processing of multimodal inputs and learned policies. This supports scalable, real-time decision making in decentralized and bandwidth-limited factory floors.
- *Open Benchmarks and Standardized Evaluation.*There is a growing need for shared datasets, simulation platforms, and evaluation protocols that reflect realistic HRC scenarios. Open-source frameworks and benchmarking environments (e.g., Isaac Sim, ROS2) will support reproducibility, comparison, and rapid innovation.

By aligning technological development with human needs and values, future HRC systems will not only improve productivity, but also foster a new generation of collaborative, inclusive, and ethically grounded industrial workspaces. The integration of multimodal intelligence and adaptive learning stands as a cornerstone of this human-cantered industrial revolution.

7. Conclusion

Human-centered Industry 5.0 systems demand seamless collaboration between humans and robots, where flexibility, safety, and adaptability are key priorities. By leveraging multimodal data - including vision, haptics, audio, and language - robots can develop a richer contextual understanding of their environment, enabling more intuitive and responsive interactions with human operators. Robot learning approaches, such as deep reinforcement learning, imitation learning, and foundation models, play a pivotal role in equipping robots with the ability to generalize across complex, unstructured tasks and adapt to individual user needs. This study emphasizes that the fusion of multimodal sensing and advanced learning methods not only improves task efficiency and precision but also contributes to building trustworthy, explainable, and ergonomic human-robot collaboration frameworks. The integration of these technologies is central to achieving the vision of Industry 5.0, where robots act as collaborative partners rather than passive tools, supporting human creativity and decision-making.

Future research will focus on lifelong learning, multimodal reasoning, and large-scale robotic foundation models to further enhance adaptability and cross-domain generalization. The synergy between multimodal AI, edge computing, and human-centered design will be the cornerstone for developing intelligent robotic systems capable of safe and meaningful collaboration in next-generation industrial environments.

The future of Industry 5.0 will be defined by collaborative intelligence, where humans and robots form symbiotic ecosystems that push beyond traditional automation toward a more resilient, innovative, and human-centered industrial landscape.

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"Text to 3D Model" Artificial Intelligence (AI) and Additive Manufacturing (AM) in the Field of Product Design, Development and Manufacturing

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Abstract: *Computer aided design (CAD) 3D modelling is one of the engineering tasks which is largely routine tasks with a large amount of repetition of the same operations to get from the initial idea for a new product to a 3D model ready for manufacturing. As with all other forms of routine tasks, artificial intelligence (AI) will certainly play a significant role in the future and it will largely automate such jobs. On the other hand, additive manufacturing (AM) can use AI generated CAD 3D models to produce finial product without the need (or with minimal need) for human labour. The combination of these two technologies will certainly shape the future of product design, development and manufacturing. Overview of the current possibilities of using artificial intelligence (AI) and additive manufacturing (AM) in the field of product development, design and manufacturing is presented in this paper. From the point of view of CAD modelling, special attention is given to the so-called "text to 3D model" systems. The challenges, possibilities and further directions of development of these technologies are shown through two real case studies (design, development and manufacturing of two stool chairs). Stool chairs design was generated with the help of "text to 3D model" AI System in a form of 3D models. The generated 3D models were then manufactured with the help of AM.In the last chapter of the paper a comparative analysis of the time spent by human labour for the development, design and manufacturing of this two stool chairs using conventional methods and using AI and AM is carried out.*

Keywords: *artificial intelligent, AI, additive manufacturing, AM, product design, CAD, text to 3D model*

1. Introduction

It has become obvious that artificial intelligence (AI) will reshape industry in the future. This process is currently taking place and mostly affects those jobs that require a large volume of the same repetitive work. Various engineering fields have such types of jobs. Although these are jobs that are currently performed by highly qualified people (calculations, engineering, design, etc.), it is still believed that such jobs will be automated by AI. Although monotonous and repetitive jobs will be automated, the knowledge and experience of engineers

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remains an irreplaceable factor in making final decisions when implementing engineering projects. AI can generate solutions and perform the “physical” part of the work, however, the engineer must have a sufficient level of knowledge and experience to assess and decide whether the generated model or performed calculation is in accordance with all necessary norms, mechanical characteristics and applicable standards. Another part of engineering jobs on which AI will also have a great impact is the creative part of engineering (design). AI can be a great tool in the new product design process where it can be used to generate initial concept design.Also, the experience and knowledge of the user (engineer) comes to the fore here as well. User has to choose a concept that meets all the conditions in terms of stability, stress state, manufacturing possibilities, etc.

In the field of mechanical engineering, there are a large number of repetitive tasks that will certainly be greatly influenced by AI. In the field of product development and design, AI is already widely used, and it will have a particular impact in the field of computer aided design (CAD) 3D modeling. In the field of product development and design process AI is often used to try to replace human based knowledge experience with AI based decision. This is showed in the paper [1] where the authors states that today many approaches suitable for smart manufacturing systems involving maintenance workers are based on Artificial Neural Networks (ANN). They presented an approach to measuring the effectiveness of the use of an IT system supporting the realisation of business processes in the maintenance department and described the empirical research results of maintenance workers (121) within Polish manufacturing companies with automotive branches. In addition, in this paper authors seeks to integrate the first two main research results and ANN, into a novel, decision-making model regarding the implementation of activities and investments aimed at increasing the level of a company’s automation.Extensive research on the use of Big Data and AI in the field of product design was conducted in the paper [2]. Authors claim that traditional product design methods fall short due to their strong subjectivity, lack of real-time data, limited survey scope and poor visual display. The most important goal of paper [2] was to show how different types of collected data can be used in product development and design process. Big data in the product lifecycle contains valuable information, such as customer preferences, product evaluation, market demands and visual display. Product images contain shape, colour and texture information that can inspire designers to quickly generate initial design schemes or even new product images. This is one of the first papers which mention how AI generated images can be used for the inspiration of new products. Paper [2] provides a comprehensive review of big data and AI-driven product design, focusing on how big data of various modalities can be processed, analysed, and exploited to aid product design using AI algorithms. It identifies the limitations of traditional product design methods and shows how textual, image, audio, and video data in product design cycles can be utilized to achieve much more intelligent product design. In paper [3] it is stated that deploying big data analytics to establish industrial intelligence is an active but still under-researched area. In this paper, an intelligent product design framework is proposed to incorporate fuzzy association rule mining (FARM) and a genetic algorithm (GA) into a recursive association-rule-based fuzzy inference system to bridge the gap between customer attributes and design parameters. Taking in consideration the product design process, most researchers agree that the collaboration between designers and AI is the most important thing, not just the full use of AI [4]. This paper is one of the most recent papers which explain the potential of AI and human collaboration in design process. Through this paper, answer to the question “How does AI currently support the design process and how could it do so in the future?” is answered. Result showed that AI agents can potentially assist designers by providing inspirations, defining design problems with constraints, offering grounded metaphors, and exploring design materials. Connection between innovation and AI is explored in detail in the paper [5]. Authors in this paper proposed a framework for understanding the design and innovation in the age of AI. They discuss the implications for design and innovation theory. Specifically, they observe that, as creative problem-solving is significantly conducted by algorithms, human design increasingly becomes an activity of “sensemaking”, that is, understanding which problems should or could be addressed. This shift in focus calls for the new theories and brings design closer to leadership, which is, inherently, an activity of “sensemaking”.

When it comes to the use of AI in the field of additive manufacturing (AM), most of the current research is related to the application of AI technologies in the field of optimizing AM production parameters. It is known that AM has a large number of parameters that can be adjusted before the part is released for manufacturing. Combinations of different parameters gives different properties to the manufactured parts. It is hard to find ideal combination of parameters to achieve desired properties of manufactured part. This is the reason why AI has found a wide application in this field [6, 7]. In addition, large number of research is based on the development of materials and designs inspired by bio-structures and so-called lattice structures. Such structures together with topology optimizations can have significant advantages compared to standard products designed in a form of solid materials with full volume materials inside [8, 9]. Such materials achieve significant advantages over conventional forms of design and manufacturing. The advantages are primarily reflected in the reduction of the mass of product while maintaining the same or similar stress state. Generative AI techniques, including generative adversarial networks (GAN), genetic algorithms, and large language models (LLMs) offer efficient solutions for optimizing material properties,accelerating the development timelines and reducing manufacturing costs[10].

3D Model creation and the use of AI Technologies in CAD 3D modelling is currently in its early stages. There are currently AI systems that can generate 3D models based on a text query (“text to 3D model”) or an image as a reference.There are several commercially available websites, but they are all based on generating simple 3D models. First paper which basically open up this field is paper by the authors from Google [11]. In this paper they presents their system DreamFusion. It is text-to-3D using 2D Diffusion system. One of the best papers that provides a general overview of AI methods and technologies for "text to 3D" generation of 3D models is the paper [12]. This paper present different AI technologies which exist today. Also, this paper presents places of usage of text-to-3D technology in various applications, including avatar generation, texture generation, scene generation and 3D editing, but it lacks mentioning possibilities of usage these technologies in engineering fields for creation of precise CAD 3D models. Paper [13] presents two systems for text to 3D model AI generator Dreamfusion and Magic3D. This paper shows very well that AI is not just chatGPT, AI is much more than that. Authors in paper [14] propose a novel method that generates high-quality and diverse 3D models from text prompts in a feed-forward manner.

In the near future, rapid growth and development of AI systems for generating 3D models based on text descriptions is expected. The current focus of such systems is not on the engineering side but more on generating 3D models that can be used in the field of video game development or virtual and augmented reality. Although the focus of such systems is not currently on engineering and generating usable 3D models for manufacturing, such systems will still have a huge impact on the process of product development and design, and in combination with AM technologies, on the process of automatic manufacturing of generated 3D models. All of the above applies especially to products where high precision is not of crucial importance (such as products from the furniture industry), i.e. to products that are more design-oriented (products where design is more important than precision and engineering).
The time that a person has to spend to get from the initial idea for a new product to a functional product is drastically reduced by the combination of AI and AM compared to conventional technologies for 3D modelling (CAD modelling using software’s like SolidWorks) and conventional manufacturing methods like injection moulding.In this paper, we have shown, through a two case studies of the design and manufacturing of a stool chair, how much impact the combination of AI and AM will have on the manufacturing and product development and design process in the near future.

2. Product Design Usign AI – a Case Study

Several commercial systems for generating 3D models from text description or picture appeared this year.Although these are systems that are currently in the early stages of their development, 3D models generated with the help of such systems can already be used for various purposes, such as video games, animations and graphic design. Also, the generated 3D models can be used for the manufacturing of final, fully functional, physical products in areas where precision engineering is not required, such as the furniture industry.In this research, design of chairs is chosen as case studies. More precisely stool chairs. Stool chair is chosen because it is a relatively small product that can be manufactured as a fully functional product using currently available AM devices. In this research web system Meshy AI (https://www.meshy.ai/) is used. Meshy AI can generate 3D models from text description or using image as a reference. In the first step several stool chairs are generated using different text description. For every text input system gives four designs. Figures 1 and 2 shows generated stool chairs for two different text inputs.

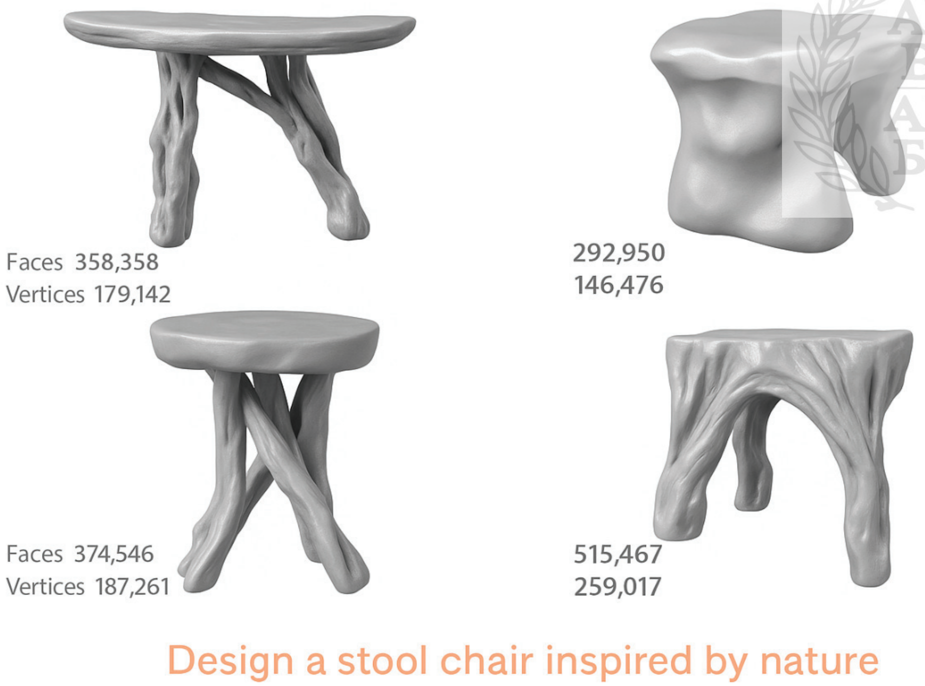


Figure 1. AI generated 3D models of stool chairs based on text description: "Design a stool chair inspired by nature".

Figure 2. AI generated 3D models of stool chairs based on text description: "Design a stool chair optimized for additive manufacturing.".

From figures 1 and 2 it can be seen that AI system do not fully "understand" the engineering concepts that are required of it. It can be seen from figure 2 that the system did not generate 3D models ideallyoptimized for additive manufacturing in every variant (design without supports, with less amount of material used, etc.).but the system did incorporate some aspects of topology optimization and some of the chairs could be manufactured almost without support materials such as, for example chair number 4 in figure 2. Also, when the system was asked to design a chair inspired by nature, it can be seen that the designs of all four chairs from figure 1 contain natural shapes.

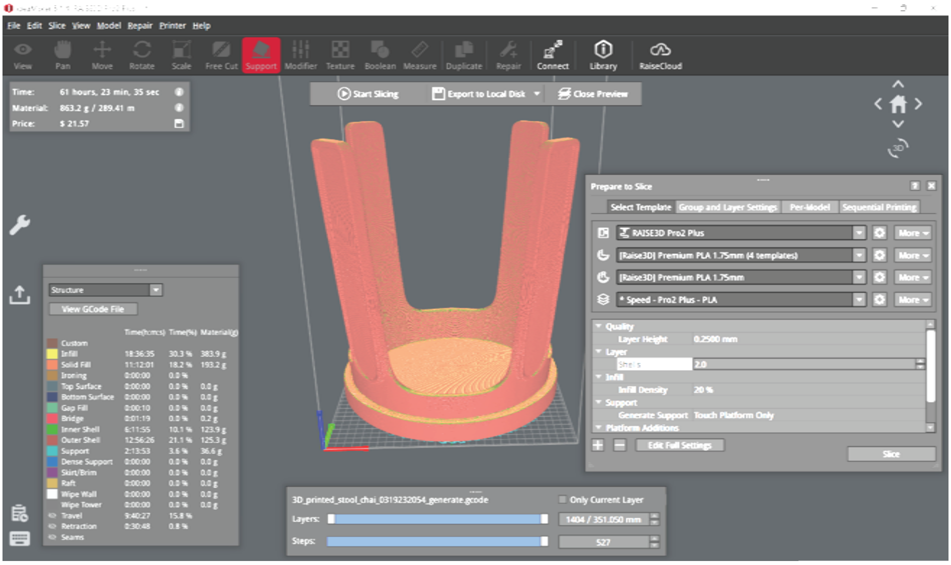
Generating all of these 3D models of chairs took significantly less time (only few minutes) than it would have taken to manually 3D model all of these variants in some of the CAD modelling software's. After several iteration of generating 3D models for different text descriptions and after analysing generated designs from the field of optimization for manufacturing using AM (printability), two chairs shown at Figure 3 are selected for further manufacturing.This chairs can be considered relatively well optimized for AM, primarily because they donot need much support materials during manufacturing. They will be manufactured in upside down position. Also, this design of stool chair is a good example that such AI systems for generating 3D models should have the ability to further edit the model through text descriptions. In this specific case, the 3D model of these two chairs could be further optimized for AM technologies by levelling the upper surface of the chairs (seat). It should be possible to further edit the 3D model through a text description such as for example: "add additional leg to the design of a chair". More engineering knowledge and experience needs to be imported in this types of systems in the future. Especially from the aspects of stability, mechanical properties, stress conditions, etc.

Figure 3. AI generated 3D models of stool chairs selected for additive manufacturing

3. Additive Manufacturing of AI Generated 3D Models

AM technologies enable the manufacturing of products completely autonomously and practically without the need for human labor. In order to manufacture something with the help of AM, the only form of human labor that needs to be spent is the preparation of a 3D model on a computer for manufacturing and periodic maintenance of the device (3D printer). It is important to emphasize that these tasks can also be partially or fully automated. As for the preparation of a 3D model for production, it is possible to create a larger number of ready-made profiles with set parameters. These profiles can later be automatically called up for every next manufacturing. Device maintenance (changing materials, removing the manufactured model from the device, etc.) can also be further automated with the help of robotic arms and automation.In the case of AM, total human working time is around 1% in the total time of the product manufacturing. Also, one worker can maintain production on significant amount of machines in the same time. In the case of regular 3D printers, it is estimated that one worker can work with up to the 30 devices in the same time. In the case of print farms, it is estimated that 500 devices can be operated by 15 workers. In the case of fully automated print farms it is estimated that one worker can operate more than 100 devices [15, 16]. Much research has been conducted in the field of integrating AM into manufacturing processes and their impact on the human workforce [17, 18].In the case of this research Fused Deposition modelling (FDM) AM technology was used for manufacturing of a two stool chairs showed at Figure 3. Rase3D Pro2Plus AM machine (3D printer) was used. This printer is selected because it has large build volume 305×305×605 mm, which is needed to manufacture AI generated stool chairs showed at Figure 3. First step was to prepare generated 3D model for AM. This is done in IdeaMaker software. The fastest profile with 0.25 mm height was selected. Infill density was 20%. Other AM parameters are left as default for Speed profile and PLA (Polylactic acid) material. PLA material is selected because it is “easy to print” 3D printing material with good mechanical properties. As it can be seen from Figure 4, both chairs will be manufactured in upside down position with a goal to avoid usage of large amount of support material. 3D printing time is approximately 60 hours for both chairs individually. The printing time is this big because this is regular Raise3D Pro2 Plus printer. It is important to notice that upgrade kit can be booth for this printer which can increase printing time up to 5 times, so the printing of this chair will be around 10 hours. Also, other AM technologies, with higher print layer, are available which can reduce the printing time up to only several hours, for example 3D printing head mounted on robot arm with print layer height of 1mm. Prepared AM generated stool chairs for AM are shown at Figure 4.

Regarding mechanical properties of these two AI generated stool chairs 3D printing parameters are selected taking in consideration author experience in the field of AM. Goal was to select parameters which will give the best relation between mechanical properties and the speed of 3D printing. Future optimization of 3D printing parameters are possible using more advance testing of mechanical properties of the chair. It will be necessary to 3D print more chairs with different parameters and make a mechanical test. Stool chairs after the manufacturing process are shown at Figure 5. It is important to notice that this is fully functional chair which can be used on regular basis as it is shown at Figure 6. Figure 6 shows a male with approximately 70kg of weight using the chair.



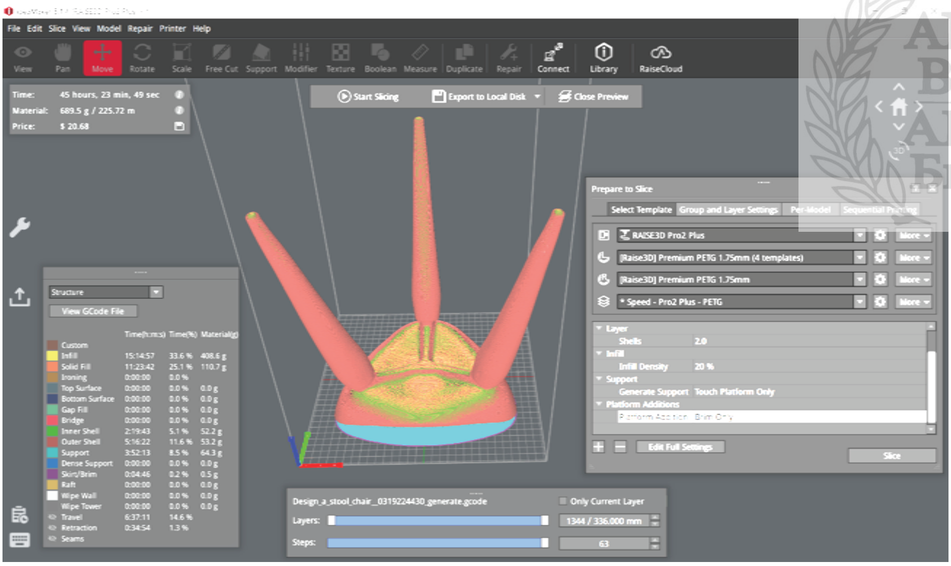


Figure 4. Preparation ofAI generated 3D models of stool chairs for additive manufacturing

Figure 5. AI generated stool chairs after additive manufacturing

Figure 6. AI generated and AM manufactured stool chair in regular use

4. Cost Analysis of Product Design, Development and Manufacturing

To bring a new product from initial idea to final product several steps needs to be carried out. Total development and manufacturing process can be divided in several individual steps. There are a lot of small steps in the process but in this analysis, we will put focus on three main steps: Design, Development and Manufacturing. Also cost analysis will be done for three case studies for one chair. Case study 1: Manufacturing of one chair, Case study 2: manufacturing of 100 chairs and Case study 3: manufacturing of 10 000 chairs. The most important advantages of usage of AI and AM in product development, design and manufacturing is a reduction of human labor working time which needs to be done to design, develop and manufacture a chair. Analysis is done using comparisonof traditional design and development methods and traditional manufacturing technology on the one side and the combination of AI and AM on another side. Injection moulding technology is selected as a representative of traditional technology because it is a polymer stool chair and in the case of traditional technology it will be manufactured using injection moulding. Cost analysis is done using hours as measuring unit instead of money units. This is done because cost of one human hour is different in different part of the world.

2.1. Cost Analysis of Design Stage

As previously mentioned, AI is currently having the greatest impact and application in the design process. The speed of design and generated solutions is significantly improved by the use of AI technologies. To generate concepts design of two stool chairs using traditional methods by drawing concepts designs by hand, one designer will need at least two days. Using AI methods, he can have several designs in few minutes. Reduction of human working time in this stage is significant. To design two chairs shown at Figure 3, total amount of human working time was around 1 hour in comparison to traditional methods where it is around 16 hours which is reduction of time by around 94%. Number of same chairs which needs to be manufactured does not play a role in this phase.

Table 1. Comparison of human working time in design stage for traditional design methods and the usage of AI

Design steps:	***Traditional methods [h]***	***AI [h]***
Concept design and evaluation phase	≈ 16	≈ 1

2.2. Cost Analysis of Development

Development stage is the next stage in the process of bringing product from design to manufacturing. Development stage includes steps like detail CAD 3D modeling, preparation of technical documentation, complete development of the tool for injection moulding and preparation of 3D model for manufacturing (slicing). Total amount of human working time in development stage for one stool chair is shown in Table 1. It can be seen that development stage is significantly reduced in the case of usage of AI tools and AM manufacturing. Mostimportant reduction is in the step of tools development. To produce something using AM technology, tools development is not needed, in comparison to the injection moulding technology. Again, number of same chairs which needs to be manufactured does not play a role in this phase. Total reduction of time is 99.6%.

Table 2. Comparison of human working time in development stage for traditional design methods and usage of AI

Development steps:	Traditional methods [h]	AI [h]
CAD 3D modelling	≈ 3	≈ 0
Preparation of technical documentation	≈ 3	≈ 0
Complete development of the tool for injection moulding including tool manufacturing	≈ 200	≈ 0
Preparation of 3D model for manufacturing (slicing)	≈ 0	≈ 1
Total:	≈ 206	≈ 1

2.3. Cost Analysis of Manufacturing

In the case ofmanufacturing, most important factor is number of chairs which needs to be produced.

2.3.1.Case study no. 1.: One chair needs to be manufactured

In the case that only one chair needs to be manufactured comparison of time needed for manufacturing is shown in Table 3.

Table 3. Comparison of manufacturing time for traditional manufacturing method and usage of AM in the case that only one chair is needed. One injection moulding machine and one 3D printer.

Development steps:	Traditional injection moulding method [h]	AM [h]
Preparation of machine and tool for manufacturing	≈ 8	≈ 1
Time of manufacturing	≈ 0	≈ 10
Total:	≈ 8	≈ 11

From Table 3 it can be seen that approximately the same time is needed to produce only one chair using both technologies. The manufacturing process is significantly lower in the case of injection moulding, but it is needed to prepare the machine, to assemble the tool and the machine, to prepare material, etc. Also, at least one worker needs to attend during the manufacturing process. In the case of AM, manufacturing process of one chair shown at Figure 3 can last around 11 hours, depending on the type of machine (3D printer) which is used and depending on the manufacturing parameters. It is important to notice that manufacturing in the case of AM is fully automatic, human working hours are only few minutes to start the manufacturing process (Table 4)

Table 4. Comparison of human working time for traditional manufacturing methods and usage of AM in the case that only one chair is needed. One injection moulding machine and one 3D printer.

Development steps:	Traditional injection moulding method [h]	AM [h]
Preparation of machine and tool for manufacturing	≈ 8	≈ 1
Human working time during manufacturing	≈ 0	≈ 0
Total:	≈ 8	≈ 1

Comparison analysis of total time needed to design, develop and manufacture one chair using traditional methods and combination of AI and AM are showed in Table 6.

Table 5. Comparison of total time needed for traditional methods and usage of AI and AM in the case that only one chair is needed. One injection moulding machine in comparison to one 3D printer.

Development steps:	Traditional methods [h]	AI and AM [h]
Design	≈ 16	≈ 1
Development	≈ 206	≈ 1
Manufacturing	≈ 8	≈ 11
Total:	≈ 230	≈ 13

Regarding the initial investment, it can be seen that usage of AI and AM in the case that only one chair is needed is obvious from Table 6.

Table 6. Cost of investments in the case that one chairs is needed to be manufactured during same amount of time using traditional injection moulding methods and AM methods.

Development steps:	Traditional injection moulding methods [Euro]	AM [Euro]
Price of machines (one injection machine and 1 3D printer)	≈ 50 000	≈ 5000
Tool development and manufacturing	≈ 50 000	0
Total:	≈ 100 000	≈ 5000

From Tables 4, 5and 6 it can be seen that in the case that only one chair needs to be designed, developed and manufactured AI and AM technologies are better in all three steps and they should be used.

2.3.2.Case study no. 2.: 100 chairs needs to be manufactured

In the case that 100 chairs are needed comparison of manufacturing time is shown in Table 7. From Table 7 it can be seen that in the case that 100 chairs are needed, time to produce these chairs using traditional methods does not change significantly from the case where only one chair is needed. But in the case that AM is used, manufacturing time is 100 time bigger (1000 hours = 41 days).

Table 7. Comparison of manufacturing time in manufacturing stage for traditional manufacturing method and usage of AM in the case of 100 chairs are needed. One injection moulding machine in comparison to one 3D printer.

Development steps:	***Traditional injection moulding method [h]***	***AM [h]***
Preparation of machine and tool for manufacturing	≈ 8	≈ 1
Time of manufacturing	≈ 1	≈ 1000
Total:	≈ 9	≈ 1000

These 41 days are manufacturing time, but human working time is only around 29 hours (Table 9). It is approximated that one worker can pull finished chair from 3D printer in 15 minutes and start a new 3D print. At first these 41 days can be seen as a significant problem, but taking in consideration that manufacturing of all 100 chairs can be operated by only one worker using 100 machines (3D printers) in the same time (fully automated 3D print farm), human working hours are basically quite similar to the traditional methods (Table 10). It is important to notice here, that increasing number of injection moulding machines will not significantly increase the speed of manufacturing using traditional methods because the time of manufacturing is already small (≈ 1 hour) and it does not play significant role in total manufacturing time in the case of traditional methods. Also every new injection moulding machine needs to have one more expensive tool for injection moulding. The question here is: What costs less, fully automated 3D print farm with 100 3D printers and one worker or one injection moulding machine with one worker and a tool. The price of one new injection moulding machine is around 50 000 Euros and the price of a 100 3D printers is around 500 000 Euros.

Table 8. Comparison of manufacturing time for traditional manufacturing method and usage of AM in the case of 100 chairs are needed. One injection moulding machine in comparison to 100 3D printers.

Development steps:	***Traditional injection moulding method [h]***	***AM [h]***
Preparation of machines and tool for manufacturing	≈ 8	≈ 4
Time of manufacturing	≈ 1	≈ 10
Total:	≈ 9	≈ 14

Table 9. Comparison of human working time for traditional manufacturing method and usage of AM in the case that 100 chairs are needed. One injection moulding machine in comparison to one 3D printer.

Development steps:	***Traditional injection moulding method [h]***	***AM [h]***
Preparation of machine and tool for manufacturing	≈ 8	≈ 4
Human working time during manufacturing	≈ 2	≈ 25
Total:	≈ 11	≈ 29

Table 10. Comparison of human working time for traditional manufacturing method and usage of AM in the case that 100 chairs are needed and fully automated print farm with 100 3D printers are used.

Development steps:	***Traditional injection moulding method [h]***	***AM [h]***
Preparation of machine and tool for manufacturing	≈ 8	≈ 4
Human working time during manufacturing	≈ 2	≈ 10
Total:	≈ 11	≈ 14

Buying 100 3D printers can seem as a significant investment but it needs to be taken in consideration that tool development and manufacturing for injection moulding is also a significant investment especially together with buying injection moulding machine and preparing whole manufacturing process and manufacturing factory. In this case detail cost analysis of the investment needs to be done before the appropriate manufacturing technology can be selected. Cost of investment is shown in Table 11.

Table 11. Cost of investments in the case that 100 chairs are needed to be manufacturing during same amount of time using traditional injection moulding methods and AM methods.

Development steps:	***Traditional injection moulding methods [Euro]***	***AM [Euro]***
Price of machines (one injection machine and 100 3D printers)	≈ 50 000	≈ 500 000
Tool development and manufacturing	≈ 50 000	0
Total:	≈ 100 000	≈ 500 000

From Table 11 it can be seen that initial investment in AM manufacturing methods in this case is 5 time bigger in comparison to the traditional injection moulding methods. This can be seen as significant difference and traditional methods are seeming to be better in this case, but some additional important factors need to be taken in consideration. In the case of traditional injection moulding methods every new chair design will need a new tool which cost additionally 50 000 Euros. This is not a case if AM is used. Using AM technologies and fully automated 3D print farm with 100 3D printer's different designs of 100 chairs can be manufactured after every new 15 hours. Total time of Design, Development and Manufacturing are again smaller but with bigger initial investment (Table 12). It can be concluded that AI and AM technologies are again recommended in this case.

Table 12. Comparison of total time needed for traditional methods and usage of AI and AM in the case that 100 chairs is needed. One injection moulding machine and 100 3D printer's.

Development steps:	***Traditional methods [h]***	***AI and AM [h]***
Design	≈ 16	≈ 1
Development	≈ 206	≈ 1
Manufacturing	≈ 9	≈ 14
Total:	≈ 231	≈ 16

2.3.2.Case study no. 2.: 10 000 chairs needs to be manufactured

Third case study is manufacturing of 10 000 chairs. Comparison analysis in the case that one injection moulding machine and one 3D printer is used is shown in Table 13.

Table 13. Comparison of manufacturing time for traditional manufacturing method and usage of AM in the case of 10 000 chairs is needed. One injection moulding machinein comparison to one 3D printer.

Development steps:	***Traditional injection moulding method [h]***	***AM [h]***
Preparation of machine and tool for manufacturing	≈ 8	≈ 1
Time of manufacturing	≈ 100	≈ 100 000
Total:	≈ 108	≈ 100 001

From Table 13 it can be seen that manufacturing of 10 000 chairs using only one 3D printer will take 100 001 hours, which is around 4 166 days. It is obvious that it is much better to use one injection moulding machine in comparison to one 3D printer. Using injection moulding machine 10 000 chairs can be manufactured in 108 hours (4,5 days). Using 100 3D printers manufacturing time can be reduced to 1004 hours (41 days). This is still to slow in comparison to the traditional injection moulding methods. (Table 14).

Table 14. Comparison of manufacturing time for traditional manufacturing method and usage of AM in the case of 10 000 chairs is needed. One injection moulding machine in comparison to 100 3D printer’s.

Development steps:	*Traditional injection moulding method [h]*	*AM [h]*
Preparation of machine and tool for manufacturing	≈ 8	≈ 4
Time of manufacturing	≈ 100	≈ 1000
Total:	≈ 108	≈ 1004

If design and development time is included, difference between traditional and AI and AM methods is around 3 times slower in the case of AI and AM. (Table 15).This means that around 300 3D printers are needed to have approximately the same design, development and manufacturing speed as one injection moulding machine (Table 15). This mean that initial investment will be much bigger. This investment can have relative quick return time if different designs of the chairs must be manufactured constantly (Table 16).

Table 15. Comparison of total time needed for traditional methods and usage of AI and AM in the case that 10000 chairs is needed. One injection moulding machine in comparison to 100 3D printer’s.

Development steps:	*Traditional methods [h]*	*AI and AM [h]*
Design	≈ 16	≈ 1
Development	≈ 206	≈ 1
Manufacturing	≈ 108	≈ 1004
Total:	≈ 330	≈ 1006

Table 16. Cost of investments in the case that 10 000 chairs are needed to be manufacturing during same amount of time using traditional injection moulding methods and AM methods.

Development steps:	*Traditional injection moulding methods [Euro]*	*AM [Euro]*
Price of machines (one injection machine and 300 3D printers)	≈ 50 000	≈ 1 500 000
Tool development and manufacturing	≈ 50 000	0
Total:	≈ 100 000	≈ 1 500 000

From above presented three case studies it can be seen that AI and AM can significantly reduce the time and investment for design, development and manufacturing of a new product. Especially in the cases when small amount of products needs to be manufactured. In the future, this will certainly lead to the further development of individual small manufacturers and individual manufacturing units. It is estimated that manufacturing will be distributed from large industrial centres to small individual manufacturers who will use fully automated AI based processes for the development, design and manufacturing of new products. Further and more detailed analyses are needed in order to find the exact limit at which one or another type of manufacturing should be chosen regarding number of products which needs to be manufactured.

3. Conclusion

Artificial intelligence and additive manufacturing are certainly two most important technologies that will fundamentally change the process of product development, design and manufacturing in the future. Creative and digital part of the product development and design process will be effected the most. AI can very easily and quickly generate a large number of potential new solutions for the design of a new product. Also, AI will soon be able to generate 3D models of designed products. Especially in cases where products are design and user oriented, like chairs. Designed products will be able to be manufactured with the help of AM without the need for human labor or with minimal need for human involvement. The mentioned technologies are in their initial development cycle, so their full application requires additional time. In terms of engineering applications, it is expected that a system for generating 3D models will be developed that allows for additional editing of the model after its initial generation via a text query. This primarily refers to editing the model in terms of incorporating the experience and knowledge of the engineer into the design of a new product. The engineer can determine, using personal experience and knowledge, whether the product is well designed in terms of stress analysis, stability or design for manufacturing. It must be possible to further edit the designed product with additional queries in order to achieve some of the above mentioned constrains.

It can be concluded that the use of AI technology will become an integral part of the product development and design process. AM technologies will also become an integral part of the manufacturing processes in the future, but not yet in cases of mass production, although AM devices are rapidly advancing and the speed of manufacturing is rapidly increasing. Additional research and analysis of the possibilitiesis it possible to use print farms to replace traditional manufacturing processes are needed. On the other hand, AM devices will enable a higher level of individual production and further decentralization of production from large industrial centers to small decentralized manufacturers.

Both technologies will lead to a reduced need for ordinary labor (ordinary machine operators), while on the other hand, the need for small number but a highly skilled workforce will increase. Workforce which is familiar with AI and AM systems and at the same time has engineering knowledge.

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From Automation to Human-Centric Innovation: Embracing Industry 5.0 in Chemical Manufacturing

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Abstract: *The transition from Industry 4.0 to Industry 5.0 (I5.0) signals a transformative shift in industrial development, moving beyond automation and digitalization to prioritize sustainability, resilience, and human-centric innovation. This paper explores the emergence and application of I5.0 principles in the chemical manufacturing sector, a domain that has traditionally lagged in adopting digital transformation. By integrating technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), machine learning (ML), digital twins, and big data analytics, I5.0 offers a strategic framework for addressing pressing global challenges including climate change, supply chain disruptions, and ethical considerations.The paper presents a strategic model that emphasizes human - machine collaboration, aiming to optimize production while safeguarding ethical values, data integrity, and safety. Particular focus is placed on the responsible use of generative AI in chemical engineering, exploring both its transformative potential and the challenges it poses. Key technological advancements, such as predictive maintenance, real-time monitoring, robotics, and augmented reality are analyzed for their role in enhancing productivity, safety, and operational flexibility.Additionally, the digitalization of research and development is discussed as a driver for innovation, accelerating discovery through smart, self-optimizing platforms and continuous-flow chemistry. Advanced materials, additive manufacturing, and circular economy principles further support the sector's transition toward sustainable and adaptive systems.By embracing Industry 5.0, the chemical manufacturing industry can shift toward more inclusive, efficient, and ethically responsible practices. This evolution not only boosts industrial performance but also aligns production with broader societal and environmental goals. The paper concludes by positioning I5.0 as a necessary step for ensuring long-term industrial competitiveness and resilience in an increasingly complex global landscape.*

Keywords: *Industry 5.0, Chemical manufacturing, Artificial intelligence, Sustainability, Human-machine interaction, Augmented reality (AR), Continuous-flow chemistry.*

1. Introduction

The most literature on Industry 5.0 has been published since 2016, with 2020 marking a turning point in research focus, driven by the societal and environmental concerns amplified by the COVID-19 pandemic. India, China,

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and the United States are the leading contributors to Industry 5.0 research, with these countries needing a shift toward more sustainable economic models. Concepts like sustainable development, human-centricity, smart manufacturing, and 6G are well-established, while emerging topics include eco-innovation and communication. Industry 5.0 research highlights links to Industry 4.0 technologies like AI and blockchain but underrepresents labor-related concerns such as wages and job satisfaction [1].

The rise of smart factories has been fueled by advancements in the Internet and data storage technologies. In the early 2000s, industries adopted advanced sensors and automation, enabling the collection of large, precise datasets. Cloud computing and big data further enhanced the ability to process and analyze this information. Initially, smart factories focused on process-related data, but Industry 5.0 (I 5.0) now emphasizes human-machine interaction (HMI). This shift aims to improve collaboration between humans and technology in manufacturing. I5.0 integrates sustainability, resilience, and human-centricity into industrial value creation, gaining attention from policymakers and academia, though it is not widely adopted in the industry (Figure 1).

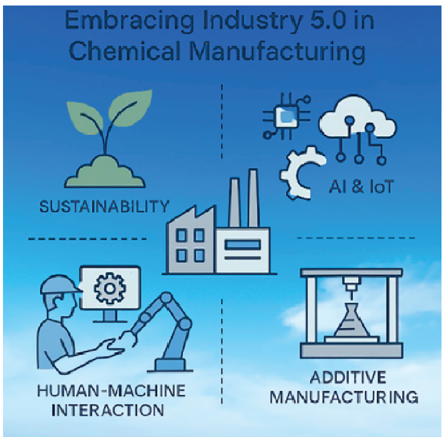

Figure 1. Schematic representation of the Industry 5.0 in chemical manufacturing

Many companies, especially SMEs, still focus on Industry 4.0 technologies but may find I5.0 more relevant in the coming years due to global challenges like climate change and geopolitical shifts [2]. Industry 4.0, introduced in 2011, integrates physical and digital systems to enhance automation and intelligence. Optimizing HMI is essential, as machines assist workers in decision-making while improving their well-being.

A key pillar of Industry 5.0 is human-centricity, aligning with the European Commission's priorities for an economy that benefits people. This vision also supports Europe's digital transformation and environmental goals outlined in the EU Green Deal [3-4]. Industry 5.0 combines human creativity with advanced automation to improve efficiency, productivity, and sustainability. It shifts manufacturing towards a more inclusive approach that integrates human intelligence and sustainable practices. This paradigm emphasizes balancing technological advancements with environmental responsibility and resource efficiency. Further research is needed to fully understand how AI, IoT, and robotics can contribute to sustainable industrial development [5].
Key features of I5.0 are shown in Figure 2.

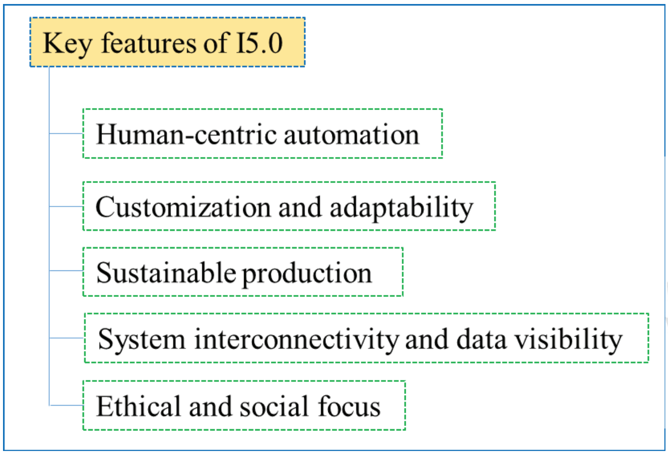

Figure 2. Key features of I5.0

Key features of I5.0 include[6]:
1. Human-centric automation focuses on enhancing human capabilities through collaboration with advanced technologies like artificial intelligence (AI) and robotics, rather than replacing human labor. The European Commission's 2021 Industry 5.0 (I5.0) framework aims to correct Industry 4.0's neglect of the human element by emphasizing human-centric innovation in smart factories [7]. However, the authors highlight ongoing gaps between the framework's vision and its practical implementation, particularly in how change processes are executed. They also point out a lack of depth in addressing work organization (WO), which is treated without sufficient differentiation or nuance.
2. Customization and adaptability highlight the move toward highly flexible manufacturing systems that can efficiently produce personalized products in smaller quantities, enabling quick responses to shifting market needs.

3. Sustainable production aims to minimize environmental impact by incorporating green practices, reducing waste, and maximizing resource efficiency throughout the production cycle.
4. System interconnectivity and data visibility leverage the Internet of Things (IoT) and AI to establish integrated networks that offer real-time analytics, boosting operational insight and informed decision-making.
5. Ethical and social focus ensures that technological advancements uphold values such as employee safety, fair working conditions, and broader social well-being.

Human-centricity

Food 4.0 focused on automation to optimize production but led to job displacement. In contrast, Food 5.0 prioritizes human empowerment by fostering collaboration between humans and technology. Instead of replacing workers, it enhances their capabilities through innovations like cobots in baking and AR for maintenance. The goal is a symbiotic relationship between humans and machines [8].

Sustainability

Food 5.0 aims to create a sustainable, efficient food ecosystem by adopting circular economy principles and minimizing waste. Unavoidable waste is repurposed for food, animal feed, or biofuel. Innovations like whey protein extraction and insect protein production enhance sustainability. Governments support these efforts through regulations and incentives.
Industry 5.0 further promotes sustainability by integrating IoT and advanced bioenergy systems, such as algae-based biofuels, reducing fossil fuel reliance and emissions. Optimized bio-refineries cut energy use by up to 40%, while smart resource management reduces waste by 20-30%. These advancements drive energy efficiency and sustainability in industrial processes[8].

Resilience - the ability to recover from adversity - is vital for managing disruptions in global food supply chains, which face threats from conflicts, climate change, and pandemics. Recent crises highlight their fragility, leading to food and labor shortages. However, technologies like IoT and big data enable real-time responses, strengthening supply chain resilience. Investing in these advancements ensures food security and safety amid an unpredictable world[8].
A recent study found that AI-driven irrigation systems can save up to 27.6% of water and 57% of energy by optimizing schedules, preventing overwatering, and maintaining ideal soil moisture levels[9].
The Adaptive Smart Factory (ASF) concept transforms traditional food production into automated, flexible, and digitalized systems. A process-product

innovation model helps SMEs adopt Industry 5.0 by integrating agile strategies and Society 5.0 principles.
Applying process reengineering to pasta production has led to a 20% increase in output, 40% less raw material waste, 80% lower machine maintenance costs, 90% reduced production failure risks, and a 60% improvement in quality[10].

Employees in Industry 5.0 fall into two categories: ***professionals*** using advanced HMI to enhance expertise and ***non-professionals*** requiring user-friendly interfaces. Effective HMI design should reduce workload, boost well-being, and encourage creativity. Sustainability and resilience are key pillars of Industry 5.0, driven by global challenges like pandemics and climate change. Emerging technologies such as Artificial Intelligence (AI), machine learning (ML), Virtual Reality (VR), and digital twins strengthen predictive maintenance and operational efficiency. The future of manufacturing depends on seamlessly integrating these technologies with human workers[11].

Augmented reality (AR) is a technology that overlays digital content - such as audio, visuals, and text - onto the real-world environment to enrich user experiences by enabling interactive engagement with physical surroundings. As tools and hardware supporting AR have advanced and become more widely available, its importance as a key driver of Industry 4.0 and industrial digitalization has grown significantly, making it increasingly accessible and easier to use.According to Moreira et al. (2024) [12] the practical implementation of AR within the chemical industries remains surprisingly limited. Despite the broader appeal of virtual reality (VR) and mixed reality (MR), augmented reality (AR) remains **essential**in high-risk industrial settings due to its real-time data integration and ability to support situational awareness without isolating users from their environment. The unique demands of the chemical industry make it **essential**to evaluate AR not merely as an optional enhancement, but as a core tool that can improve safety, efficiency, and operational continuity. As industries face increasingly complex challenges, adopting AR as an **essential** component of their digital transformation strategy can help bridge the gap between its demonstrated potential and current limited practical application [12].
A 2020 report found that 80% of surveyed companies have started their digitalization journey, with large enterprises leading the way, including companies like Nokia, Siemens, and Intel. Digitalization is increasingly recognized as a competitive advantage in the industrial sector, and companies that fail to adopt it risk falling behind. Governments, including those in Germany, France, and the UK, have supported digitalization with plans and funding to help industries stay competitive. However, the chemical process industry has been slow to adopt digital technologies, with a 2023 McKinsey report revealing underutilization, and only 35% of chemical companies in the digitalization rollout phase[13].

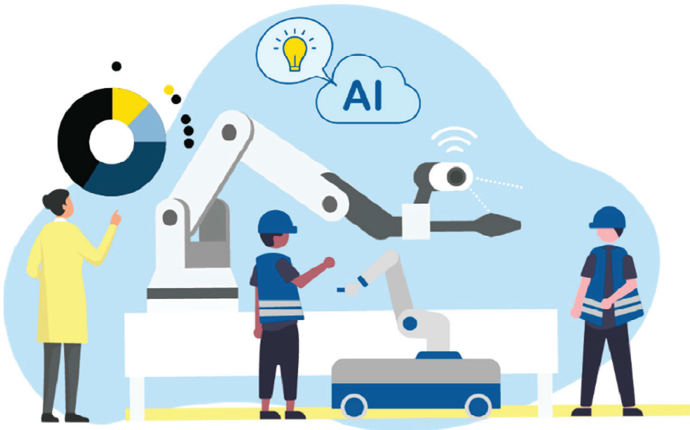

Figure 3. Human-machine teams make the most of both the expertise of each team member and the advanced abilities of smart machines[14].

The concept of Industry 5.0 envisions future factories that are sustainable, resilient, and human-centered, relying on advanced capabilities from both next-generation manufacturing systems and human operators.

2. Chemical Manufacturing

Chemical manufacturing is constantly advancing as new technologies enhance efficiency, productivity, and sustainability. Breakthrough materials and innovative processes are transforming production methods, creating fresh opportunities while tackling key challenges in the industry.A major breakthrough in chemical manufacturing is the streamlining of production processes and the reduction of resource usage [15].
Conventional batch methods are gradually giving way to continuous production, in which reactions occur within a steady flow system. This method enables greater precision, shorter reaction durations, and improved product output. In addition, continuous production minimizes waste and lowers energy use, making manufacturing more sustainable and economical[16].
Sustainable manufacturing has evolved from minimizing environmental impacts to promoting economic, environmental, and social sustainability. Industry 4.0 has supported sustainability at the firm level through innovations like the Industrial Internet of Things (IIoT) and additive manufacturing, which reduce waste and energy consumption. However, concerns remain about the broader socio-environmental impacts of Industry 4.0, particularly regarding job displacement and energy conservation. In response, the Industry 5.0 agenda aims

to address these issues by promoting human-centric, sustainable manufacturing practices. Research into Industry 5.0's potential to foster sustainable manufacturing is still in its early stages, with a focus on understanding its functions and how they can be leveraged effectively[17].

2.1 Generative Artificial Intelligence in Chemical Engineering

Generative artificial intelligence (AI) is capable of creating new content after being trained on data, including text, images, and other media types, with applications in various fields. In chemical engineering, there has been a shift towards focusing on efficiency and sustainability, driven by the need to reduce energy use and environmental impact [18]. Generative AI has started to streamline processes in the sector, such as improving warning systems, answering technical questions, and generating computer code. However, to maximize its benefits, a proactive approach is needed to integrate ethical considerations and safety standards, ensuring that generative AI can be safely and effectively used in chemical engineering.

Engineering ethics are essential for professionals, recognizing their impact on society both positively and negatively. The Royal Academy of Engineering emphasizes principles like honesty, respect for life, public good, and integrity. In chemical engineering, neglecting these ethics can lead to severe, discipline-specific disasters. Chemical engineers are particularly equipped to address safety and environmental concerns, key aspects of their field. As generative AI becomes more integrated into the industry, chemical engineers are well-positioned to manage both the technical and ethical challenges it presents[18].

Societal issues in chemical engineering, especially concerning the potential dangers of chemicals, must be considered, as generative AI models like LLMs could be misused to create harmful substances. While some safeguards exist in AI models, they are reactive rather than proactive, highlighting the need for inherently safer AI development. Chemical engineers, responsible for safety from design to implementation, must ensure AI tools meet strict safety standards. Issues such as automating engineering diagrams raise concerns about the potential for disastrous outcomes without thorough assessment. Responsible AI use in chemical engineering should focus on its impact on individuals and society, with safe data collection and transparent AI model development[18].

A major challenge in using generative AI for flow sheet automation is the lack of publicly available or machine-readable databases, limiting the quality of AI models. Current attempts at automating flow sheets often fail to integrate physical knowledge, resulting in functionally meaningless outputs. Without a responsible approach, AI-generated flow sheets may contain errors or redundancies, leading to safety hazards if poorly understood designs are rushed into development. To address this, new standards should be established to ensure all flow charts are machine-readable. Despite these challenges, generative AI has shown promise in areas like electrode design, demonstrating potential in materials and structures development[18].

The integration of physics-based and data-driven models offers opportunities for advancing electrochemical technologies like fuel cells and batteries, which are crucial for green systems and decarbonization. As generative AI becomes more prevalent in chemical engineering, its responsible use will require a multi-faceted approach, combining technology, people, and regulations. Adhering to responsible AI principles—such as ensuring AI is lawful, ethical, and robust - will foster trust and acceptance, similar to maintaining public trust in chemical processes. For AI to be trustworthy, it must be explainable and verifiable, integrating expert knowledge with machine learning to improve decision-making speed and accuracy. Ultimately, the development of explainable AI (XAI) will be crucial in ensuring transparency, accountability, and trust in the models used in chemical engineering[18].

A people-centered approach to responsible Generative AI in chemical engineering focuses on designing systems that best serve the users, considering their needs from the start to ensure synergy between human expertise and AI tools. By applying lessons from the industry's safety culture, AI systems must be designed to work with chemical engineers in a safe and effective manner, preventing unintended consequences. Tools like AI-assisted HAZOPs show potential to improve work speed and quality, but they must be thoroughly reviewed to avoid disasters and maintain trust in AI's role in the sector. Strong leadership and clear communication are crucial to integrating responsible AI use, as is fostering a culture that upholds accountability, safety, and transparency. As AI becomes more integrated into chemical engineering, maintaining high standards of honesty, accuracy, and rigor will be essential to avoid shortcuts and mistakes, with leadership setting the tone for responsible AI practices[18].

2.2 Digital Transformation in Research and Development in Chemical Manufacturing

Industry 4.0 focuses on automation and advanced technologies, while Industry 5.0 strengthens collaboration between humans and machines. In the chemical sector, the use of digital tools such as artificial intelligence, robotics, and predictive maintenance is improving efficiency and lowering costs. Research and development is one of the most important areas for digital transformation (Figure 4). Digital twin technology, which creates virtual models of real processes, enables safe and efficient testing. This reduces risks, saves time and money, and increases the profitability of research and development projects.

2.2.1 Document Management Systems

Numerous chemical companies rely on digital tools like document management systems, which provide structured documentation of process and data flows. These systems make it possible to digitally organize and handle the vast amounts of documents and data produced during the research stage.

2.2.2 Networking

Creating a new product usually requires collaboration across multiple departments and employees, often spread across different locations in large organizations. Through digital transformation, virtual networks allow seamless data sharing and communication among colleagues, significantly improving the efficiency of research and development projects.

2.2.3 Big Data

Across all sectors, the volume of data to be processed is rapidly growing, often referred to as big data. To interpret this information, chemical companies require effective digital solutions. Such tools create a strong basis for the focused development of innovative products.

2.2.4 Artificial Intelligence

Artificial intelligence was already widely used across different industries before the rise of ChatGPT, which has since made the technology more accessible to everyone. In chemical companies, AI holds significant potential for research and development by enabling automated analysis and interpretation of experiments. Through machine learning and AI algorithms, production processes can be optimized, outcomes predicted, and R&D accelerated. By examining large data sets, AI models detect patterns and refine reaction conditions, leading to better product quality, shorter cycle times, and lower waste generation.
Kanarik and Osowiecki[19]investigate the use of Bayesian optimization algorithms to evaluate how artificial intelligence can reduce the cost of developing complex semiconductor chip processes. They designed a controlled virtual process simulation to systematically compare the performance of human engineers and computer algorithms in semiconductor fabrication. The results show that human engineers perform best during the early stages of development, while algorithms are more cost-efficient as the process approaches precise target specifications. The study also demonstrates that combining expert human designers with AI in a strategy that prioritizes humans first and computers last can cut the cost-to-target by fifty percent compared to using only human designers.

2.2.5 Machine Learning
Artificial intelligence also encompasses machine learning tools, which not only manage existing processes but can also learn new ones. Leveraging these capabilities, they support research and development by generating ideas for new formulations. Machine learning algorithms aid in designing formulations, predicting material properties, and optimizing reaction pathways. These technologies promote faster innovation, more efficient decision-making, and improved product development.

2.2.6 Internet of Things (IoT)
The Internet of Things (IoT) bridges the physical and digital worlds. A common example is a smart refrigerator that can detect when supplies run low and automatically reorder items. In the chemical industry, IoT facilitates the digital monitoring of changes in physical systems during research and development. Sensors, connected devices, and data analytics platforms provide detailed information on production conditions, energy usage, and equipment performance. Using this data, companies can optimize processes, anticipate maintenance needs, and identify opportunities to improve efficiency. Additionally, digitalization strengthens supply chain management by allowing real-time monitoring of raw materials, inventory, and product shipments.

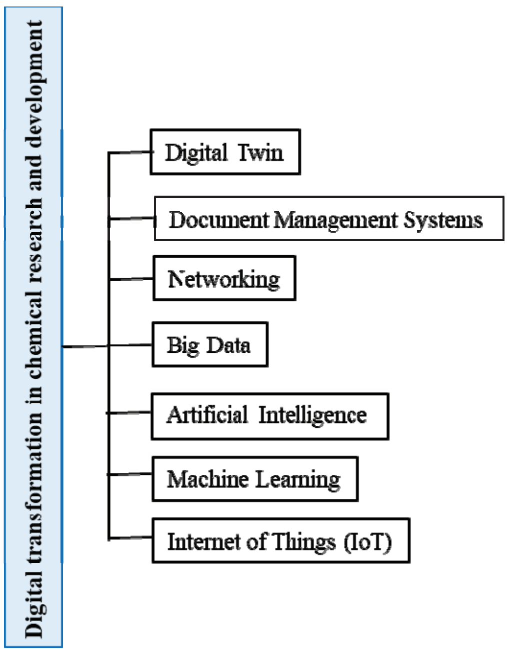

Figure 4. Digital transformation in chemical research and development

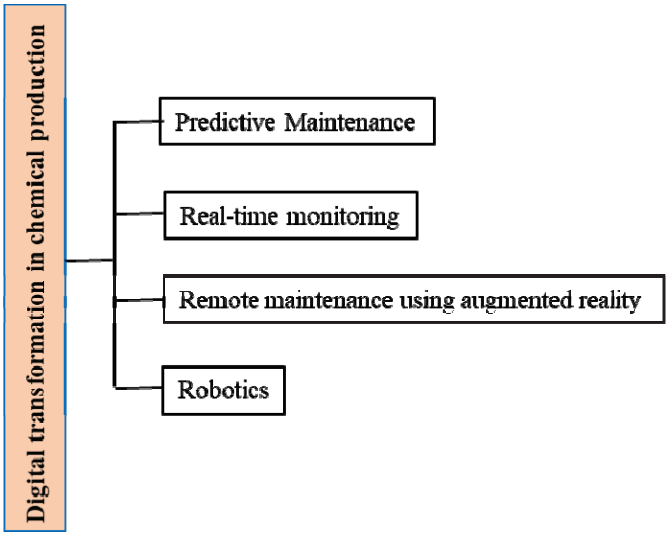

Figure 5. Digital transformation in chemical production

Digitalization holds significant potential in research and development, but the chemical industry is increasingly using digital tools for the next step - production (Figure 5). This involves automation, which streamlines operations and boosts efficiency.

2.2.7 Predictive Maintenance

Machine failures are among the most significant threats to production. Predictive maintenance tools can identify and resolve potential issues before they lead to breakdowns. By detecting early deviations and alerting the company in advance, these tools allow timely interventions and help prevent interruptions in production.

2.2.8 Real-Time Monitoring

Accurate combination of raw materials is essential for producing safe chemical products. Digitalization plays a key role by enabling real-time monitoring of raw materials, mixtures, and finished products. This allows manufacturers to quickly detect and respond to any deviations during production.

2.2.9 Remote Maintenance with Augmented Reality

Whether a problem is identified in advance or a real breakdown occurs in the chemical industry, machine reconditioning and operation are crucial. With augmented reality, maintenance becomes easier, problem-solving quicker, and all tasks can be performed regardless of location. In many cases, technical experts don't even need to be on-site. In short, augmented reality can simplify and optimize maintenance and repairs.

2.2.10 Robotics

Every manufacturing step brings challenges, some of which are repetitive. Robots are valuable in performing repetitive tasks due to their specialized capabilities. Automation and robotics are reshaping chemical production by enhancing precision, accuracy, and safety. They are employed in activities such as sample handling, ingredient measurement, and packaging. By automating these processes, companies reduce human errors, boost productivity, and protect workers from exposure to hazardous materials. Additionally, robotic systems can operate in challenging environments and consistently carry out repetitive tasks with high efficiency.

2.3 Chemical Industry: Digital Security and Data Protection

Digitalization streamlines everyday operations for companies in the chemical industry, but it also raises concerns about cybersecurity and data protection. The risk of unauthorized access to sensitive information is a common worry, particularly with cloud-based solutions. These concerns can be mitigated by selecting secure and reliable systems. Equally crucial is the safe management of chemical substances, which digital tools can support effectively. Overall, chemical companies must carefully address and critically evaluate security issues throughout their digital transformation [20].

2.3.1 Digital Transformation is Accelerating

The collected and properly connected data from industrial plants and digital twins play a decisive role in leveraging the advantages and potential of Industry 5.0 in the chemical sector, with its specific challenges. The integration of IoT and artificial intelligence allows companies to respond more quickly and flexibly to changes in the market and evolving customer needs. At the same time, emphasis is placed on protecting investments and managing total cost of ownership through customized and sustainable solutions. This includes smarter plant startups, faster engineering, and efficient commissioning, as well as maintaining high productivity, operational uptime, safe and adaptable production, and sustainability and security throughout the plant’s lifecycle. Additionally, asset availability is maximized through the use of big data analytics and artificial intelligence [21]. Technological progress is transforming chemical manufacturing by improving efficiency, sustainability, and product quality. Enhanced process methods, automation, digital technologies, advanced materials, additive manufacturing, and AI-based techniques are changing the way the industry operates, helping producers meet increasing demand while minimizing environmental impact. By adopting these innovations, the chemical sector can create new opportunities, drive innovation, and support a more sustainable future.

2.3.2 Advanced Materials and Sustainable Solutions

Progress in chemical manufacturing includes the creation of advanced materials with improved performance and greater sustainability. Researchers are developing new formulations, ranging from bio-based materials to lightweight composites, that minimize environmental impact while maintaining functionality. These materials find applications in industries such as automotive, aerospace, and renewable energy. At the same time, sustainable production practices, including green chemistry and circular economy approaches, are becoming increasingly important, encouraging resource efficiency and reducing waste.

2.3.3 Additive Manufacturing (3D Printing)

Additive manufacturing, commonly referred to as 3D printing, is transforming the production of customized chemical products and components. This technology enables the fabrication of intricate structures, complex geometries, and functional prototypes while minimizing material waste. It also supports on-demand production, reducing the need for extensive inventory. In chemical manufacturing, 3D printing is applied to catalysts, drug delivery systems, and bespoke chemical reactors, allowing for more efficient and tailored solutions. Traditionally, chemical synthesis has depended on labor-intensive batch processes, but the push for novel reactions and sustainable methods is changing this landscape. Smart, self-optimizing platforms and advanced analytical tools now enhance synthesis efficiency. Machine-assisted approaches improve resource management, enabling chemists to concentrate on discovery and experimental planning. The integration of continuous-flow chemistry with batch methods expands control and process capabilities. Emerging technologies such as AI, augmented reality, and automation are reshaping laboratory management and experiment monitoring. Nonetheless, chemical synthesis remains complex, requiring human expertise in combination with advanced tools. Ongoing innovations in flow chemistry, reaction monitoring, and automation continue to advance the capabilities of chemical manufacturing [22].

2.4 Digital Transformation in the Chemical Industry

Digitalization is transforming all sectors of the chemical industry ranging from petrochemicals to agrochemicals by enhancing productivity, optimizing supply chains, and expanding market reach. A notable example is the 2021 collaboration between Siemens and Dow, which led to the creation of a process automation test bed aimed at accelerating the adoption of digital twins in chemical manufacturing. Key growth drivers include the demand for efficient, continuous production, increased adoption of digital technologies, and the need for better batch scheduling. Government investments in R&D and the rise of technologies like IoT, AI, VR, and 3D printing are further boosting innovation and digital transformation in the sector. Despite these advances, barriers such as high implementation costs, limited technical knowledge, and regulatory constraints pose challenges. The market for digital solutions in the chemical industry was valued at USD 15.81 billion in 2023 and is projected to grow to USD 75.69 billion by 2031, with a strong CAGR of 21.7%. Key findings highlight IoT adoption, environmental concerns, and North America's market dominance, while cost-related hurdles remain a primary challenge to broader digital integration (Figure 6) [23].

Increasing awareness of sustainability is prompting the chemical industry to reassess its operations and pursue environmentally friendly alternatives that reduce ecological impact and promote resource conservation. By leveraging advanced data management, reliable AI models, and versatile algorithms, digital transformation is reshaping the chemical sector offering powerful opportunities to integrate sustainable and innovative practices into routine processes[24].

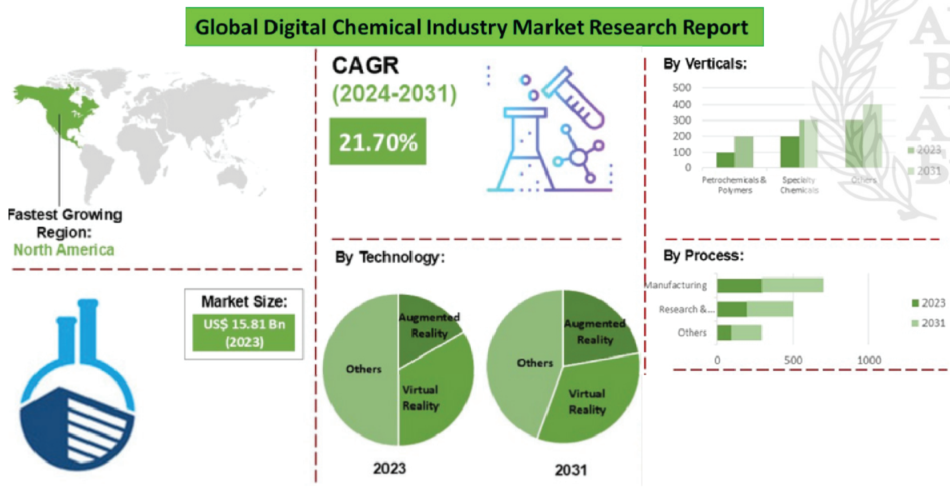

Figure 6. Global Digital Chemical Industry Market

Augmented reality (AR) enhances user interaction by superimposing digital content onto the physical environment, creating a more immersive and engaging experience.It has become a key enabler in Industry 4.0 due to advancements in hardware and software. Unlike virtual reality, AR integrates synthetic elements while maintaining the dominance of the natural environment. Its applications span multiple fields, including medicine, entertainment, and education. Industries such as manufacturing, construction, and energy are leveraging AR to

enhance processes and efficiency. AR is reshaping workflows and driving innovation across various sectors. As technology advances, AR's impact on industrial transformation is expected to grow significantly.
Augmented reality (AR) plays a crucial role in high-risk industrial environments by providing real-time information overlays and maintaining situational awareness. While virtual reality (VR) and mixed reality (MR) are useful for immersive training in hazardous scenarios, AR integrates seamlessly into existing workflows. The choice between AR, VR, and MR should depend on specific operational and safety needs rather than assuming one is superior. In chemical industries, MR may be better suited for immersive training, while AR excels in real-time guidance. A hybrid approach could optimize safety and efficiency by leveraging each technology's strengths. This study reviews the current state of AR in industrial settings, highlighting its potential and implementation challenges. It aims to bridge the gap between AR's capabilities and its practical application in industry [12].
Technological innovation involves introducing new or enhanced ideas, processes, or technologies that drive improvements in efficiency, performance, and competitiveness, especially in manufacturing. While Industry 4.0 has leveraged these innovations to digitally transform production through automation and interconnected systems, Industry 5.0 builds on this foundation by prioritizing sustainability, aiming to create more resilient and eco-friendly industrial ecosystems. The evolving relationship between technology and sustainability highlights the importance of integrating both for long-term corporate success, marking a shift from their once-perceived incompatibility toward a new paradigm of sustainable innovation.
Vacchi eta l. 2024 [25] validated the Process Technological Sustainability Assessment (P-TSA) framework - aligned with the ISO 14040 life cycle approach through its application in a ceramic tile manufacturing company, revealing its effectiveness in measuring technological sustainability via key impact categories: input/output availability (IOA), operational performance (OP), and technical quality (TQ). By developing and weighting specific indicators, the framework generated a Process Technological Sustainability Index (P-TSI), which reflected changes in sustainability performance between 2017 and 2022. Key findings showed that production interruptions (e.g., maintenance, pandemics) negatively affected IOA, while increased production volumes and strong inventory management had a stabilizing effect; however, technological upgrades like digitalization sometimes reduced technical quality scores. The study also emphasized the importance of life cycle thinking, ethical sourcing, and cross-sector collaboration in embedding sustainable practices into industrial innovation, offering both theoretical insights and practical guidance for sustainable manufacturing.

2.5 The Role of Ethics in Industry 5.0

As human–machine collaboration increases in Industry 5.0, ethical concerns about technology's impact on humans are growing. Ethics plays a crucial role in balancing self-interest and societal good while fostering a symbiotic relationship between humans and the cyber-physical world. While research on ethical issues in technology is expanding, it often focuses on individual values or specific technologies, such as ICT and robotics, rather than a holistic approach. Despite some efforts to explore ethical implications in industrial settings, most research remains limited and disproportionately emphasizes technical aspects over ethical considerations [26].

Society 5.0 prioritizes human well-being by using technology ethically to enhance lives across various sectors, including healthcare, education, and sustainability. It views technology as a tool for empowerment, inclusivity, and addressing societal challenges rather than an end in itself. Industry 5.0 builds on this vision by integrating technology with sustainable and people-centric operational systems, though its impact on supply chains remains uncertain. While Industry 4.0 aimed for sustainability, gaps in addressing key issues led to the emergence of Industry 5.0. Additionally, the rise of ChatGPT signifies a shift from algorithmic to linguistic intelligence, emphasizing real-time human-machine interactions [27].

Vidhani and Mariappan[28]highlights the importance of effective communication in guiding ChatGPT-3.5 to provide accurate and reliable responses, especially in chemistry. It finds that clearly defining terms and context in prompts improves response accuracy, as seen in chemistry topics like the isoelectronic series, while excessive elaboration can cause confusion. Using direct, field-specific questions such as in electron affinity or ionization equations proved to enhance the reliability of the responses, while iterative prompt refinement through trial and error helped achieve better results. The study also emphasizes the critical role of human oversight and suggests integrating ChatGPT-3.5 into education to foster critical thinking, allowing students to analyze and verify AI-generated outputs.

3. Conclusion

The evolution from Industry 4.0 to Industry 5.0 marks a critical inflection point for the chemical manufacturing sector. While digitalization and automation have laid the groundwork for operational efficiency, the future demands a more holistic approach - one that integrates technological advancement with sustainability, resilience, and human-centric values. Industry 5.0 enables this transition by fostering intelligent, adaptable, and ethical manufacturing systems.The integration of AI, IoT, digital twins, machine learning, and augmented reality is already reshaping the chemical industry, enhancing predictive maintenance, real-time monitoring, and remote operations. These technologies not only boost productivity but also reduce risks, improve worker safety, and enable faster, more informed decision-making. Meanwhile, emerging practices such as additive manufacturing, continuous-flow chemistry, and the development of advanced materials contribute to greater flexibility, efficiency, and environmental responsibility.Equally important is the responsible and ethical use of these technologies-particularly generative AI-within chemical engineering processes. Addressing concerns related to digital security, data integrity, and human oversight is essential for building trust and ensuring sustainable innovation.This paper underscores that Industry 5.0 is not merely an upgrade of existing systems but a fundamental rethinking of industrial operations. It positions human creativity and well-being at the center of technological development, aligning production with broader societal needs. For the chemical manufacturing industry, adopting I5.0 principles is not only a pathway to enhanced performance and competitiveness but also a necessary step toward achieving long-term environmental and social goals.As global challenges continue to intensify, the ability to innovate ethically, operate flexibly, and design for resilience will determine the future success of industrial sectors. Industry 5.0 provides the framework to meet these demands, enabling a smarter, more inclusive, and sustainable industrial era. The future research in areas like human-machine collaboration, sustainable production, cybersecurity, ethical implications, and the development of new business models within the context of Industry 5.0 is recommended.

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Industry 4.0 vs. Industry 5.0: Evolution of System Structures from Digitalization and Cybernation to Cognitization

Elvis Hozdić[*1]

Abstract: *The Fourth Industrial Revolution (Industry 4.0) has transformed manufacturing by introducing the concept of Smart Manufacturing Systems (SMS), enabling digitalization and automation of processes. This transition has led to a significant reduction in human intervention and an overall increase in production efficiency. Cyber-Physical Production Systems (CPPS) have played a crucial role in enhancing connectivity, adaptability, and intelligent management of manufacturing processes.*

Industry 5.0 introduces a new paradigm that goes beyond mere automation and digitalization—it integrates human-machine collaboration, cognitive technologies, and artificial intelligence (AI) to create adaptive, sustainable, and intelligent manufacturing systems. A key enabler of this new generation of production systems is the Cognitive Cyber-Physical Production System (C-CPPS), which facilitates autonomous decision-making, enhanced flexibility, and deeper integration between humans and machines.

This paper analyzes the fundamental differences between Industry 4.0 and Industry 5.0, focusing on the impact of digitalization, cybernation, and cognitization on the evolution of manufacturing systems. It further examines the technological challenges and opportunities associated with implementing AI and cognitive systems in production processes, with an emphasis on improving human-machine interaction and advancing sustainable industrial development.

Keywords: *Industry 4.0, Industry 5.0, digitalization, cybernation, cognitization, smart manufacturing systems, cyber-physical production systems, artificial intelligence, human-machine interaction.*

1. Introduction

The evolution of industrial revolutions has been a critical driver of technological and economic progress, facilitating breakthroughs in production efficiency and capacity across distinct historical periods. The origins trace back to the First Industrial Revolution (Industry 1.0), marked by the introduction of the steam engine, which catalyzed the mechanization of manufacturing processes. The Second Industrial Revolution (Industry 2.0), driven by the widespread adoption of electrification, enabled large-scale mass production and significantly

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enhanced productivity. The Third Industrial Revolution (Industry 3.0) introduced automation, which brought about substantial improvements in process control, operational flexibility, and integration of electronic systems within manufacturing [1], [2], see Fig. 1.

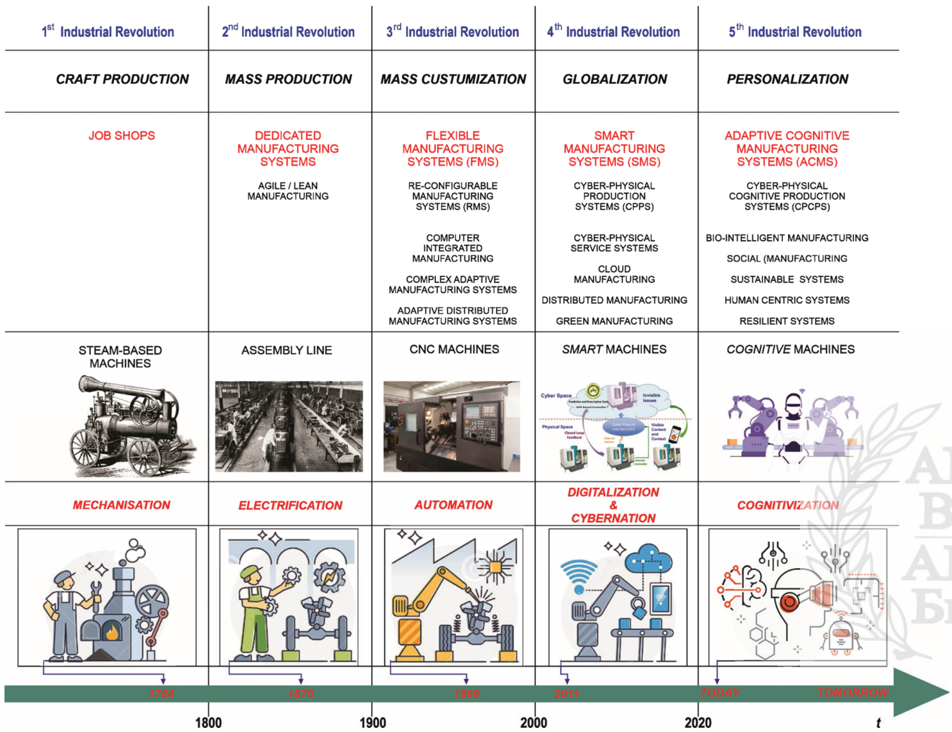

Figure 1. Timeline of Industrial Revolutions[2], [3]

Building upon these foundations, Industry 4.0 represents a transformative leap, characterized by the integration of *Smart Manufacturing Systems* (SMS) empowered by advanced digital technologies. Central to this paradigm are Artificial Intelligence (AI) [4], the Internet of Things (IoT) [5], and Cyber-Physical Production Systems (CPPS) [6], [7], which collectively enable autonomous decision-making, real-time process monitoring, and dynamic system optimization within the manufacturing environment. These developments have laid the groundwork for a new era of intelligent, interconnected, and adaptive industrial ecosystems [8], [9], [10], [11].

Industry 4.0 [8], [12], [10], [13]has introduced full automation, digitalization, and cyber-physical integration into the industrial ecosystem, resulting in enhanced productivity, increased operational efficiency, and significant reductions in manufacturing errors. However, the pursuit of complete automation also raises critical questions regarding the role of humans within the production process. The potential marginalization of human creativity, intuition, and adaptability presents a growing concern in highly automated environments.

In response to these challenges, the emerging paradigm of Industry 5.0 [14], [11]is gaining traction. Unlike its predecessor, Industry 5.0 emphasizes not only technological sophistication but also the human-centric integration of advanced systems[15], [16]. It promotes close collaboration between humans and intelligent machines, leveraging the strengths of both to foster resilient, adaptive, and sustainable manufacturing ecosystems[17], [3]. This paradigm shift marks a transition from purely efficiency-driven automation toward value-driven production that balances technological innovation with social and environmental responsibility[1]. Industry 5.0 builds upon the foundations of Industry 4.0 by advancing the integration of cognitive systems and fostering synergistic collaboration between humans and technology. At the core of this emerging paradigm is the implementation of Cognitive Cyber-Physical Production Systems (C-CPPS)[2], [3], which facilitate adaptive, context-aware, and intelligent manufacturing processes. These systems are characterized by their ability to perceive, learn, and make autonomous decisions in real time, enabling unprecedented levels of flexibility and responsiveness in production.

The transition toward Industry 5.0[9] is underpinned by key enablers such as advanced Artificial Intelligence (AI), Machine Learning (ML), and embedded decision-making architectures, which collectively support the development of smart, self-optimizing systems. The overarching objective of Industry 5.0 is to establish sustainable and innovation-driven production environments that enhance workplace quality, increase operational efficiency, and strengthen the human-machine interface. This paradigm envisions a future in which technological advancement is harmonized with human-centric values and ecological responsibility.

The evolution of industrial systems—from mechanization, electrification, and automation to digitalization, cyber-physical integration, and now cognitization—marks a significant milestone in the advancement of manufacturing (Fig. 1)[3]. While Industry 4.0 has enabled production optimization through autonomous processes and intelligent systems, Industry 5.0 places renewed emphasis on the human factor and its synergistic interaction with emerging technologies.

In this new paradigm, the development of cognitive systems plays a central role. These systems support advanced decision-making, context-aware adaptability, and real-time responsiveness, all while aligning technological advancement with the goals of sustainable industrial growth. The transition toward a human-centric, intelligent manufacturing ecosystem thus not only enhances productivity and resilience but also redefines the future of work within the industrial domain.

This contribution offers an in-depth examination of the distinctions between Industry 4.0 and Industry 5.0, with a particular focus on the transformative

impact of digitalization, cyber-physical integration, and cognitization on modern manufacturing processes. The analysis explores both the technological challenges and the practical opportunities associated with the implementation of artificial intelligence and cognitive systems, which enhance human-machine interaction and enable intelligent decision-making.
Moreover, the study highlights the importance of sustainable development, alongside the ethical and security implications of integrating emerging technologies into industrial environments. By addressing these critical dimensions, the article contributes to a more comprehensive understanding of the future trajectory of industrial production and the evolving role of humans within next-generation intelligent manufacturing systems.

2. Methodological Framework

To achieve the research objectives, a multi-stage methodological approach was employed. In the initial phase, a systematic review of scientific literature pertaining to Industry 4.0 and Industry 5.0 was conducted. The review focused primarily on core concepts such as digitalization, cyber-physical integration, and cognitive technologies. To ensure comprehensive coverage and academic rigor, relevant literature was sourced from reputable scientific databases, including Web of Science, Scopus, and Google Scholar.
Based on the insights obtained during the initial phase, a comparative analysis was conducted to examine the key characteristics of the Industry 4.0 and Industry 5.0 paradigms. Special attention was given to the differences and similarities in technological approaches, deployed system architectures, and their respective impacts on operational efficiency, sustainability, and the role of humans within production processes.
Furthermore, a qualitative assessment was conducted to evaluate the technological challenges and opportunities associated with the implementation of cognitive technologies in manufacturing systems. The study also explored in greater detail the potential barriers that companies encounter during the transition from Industry 4.0 to Industry 5.0, with an emphasis on organizational readiness, technological integration, and human-machine collaboration.
In the final stage of this research, the author presents a synthesis of the collected data and analyses, culminating in concrete recommendations for the effective implementation of Industry 5.0 concepts within manufacturing environments. Based on these findings, the study also identifies directions for future research, particularly in the development of intelligent manufacturing systems. This methodological framework provides a comprehensive overview of the examined concepts and ensures both the systematic structure and scientific validity of the study's final conclusions.

2. Industry 4.0

2.1. Globalization

Globalization has played a pivotal role in shaping and accelerating the adoption of the Industry 4.0 paradigm. It has enabled manufacturing enterprises to operate within an international context, where they face not only local but also intensified global competition. This dynamic has necessitated the development and deployment of advanced technologies and processes that support a high degree of automation, digitalization, and the efficient management of globally distributed production networks. As a result, globalization has become a key driver in the transformation toward smart, interconnected, and responsive manufacturing systems[18], [3].

With the advancement of information and communication technologies (ICT), as well as the digitalization and cyber-physical integration of manufacturing processes, globalization has become a foundational element of Industry 4.0[19], [20], [21], [7]. It enables the seamless interconnection of production units across the globe into a unified, integrated system. This interconnectivity facilitates faster information exchange, reduced production costs, enhanced product quality, and greater flexibility in manufacturing systems. Companies that leverage Industry 4.0 technologies are able to manage their operations more efficiently and respond rapidly to market fluctuations and consumer demands at a global scale.

On the other hand, globalization also introduces significant challenges, including logistical complexity, heightened cybersecurity risks, and the critical need for technological standardization and interoperability at the international level. Consequently, the successful implementation of Industry 4.0 concepts requires continuous investment in technological innovation, ongoing workforce education and training, as well as the effective management and protection of information systems. These elements are essential to ensuring resilience, competitiveness, and secure operations in a globally connected industrial landscape.

The contribution of globalization to Industry 4.0 is most evident in the enhanced capabilities for networked collaboration among enterprises, the improvement of global competitiveness, and the increased adaptability of organizations to fluctuations in international markets. In this context, globalization can be regarded as one of the fundamental pillars and key enablers driving the development and widespread implementation of Industry 4.0.

2.2. Digitalization and Cybernation in Manufacturing

Digitalization and cybernation are fundamental components of Industry 4.0, significantly transforming traditional manufacturing processes[3]. Digitalization refers to the conversion of analog operations into digital formats and their execution through digital mechanisms, enabling the efficient collection, storage, and analysis of large volumes of data. This transformation serves as the basis for data-driven decision-making, process optimization, and the development of intelligent, interconnected production environments[7].

The operations carried out within digitalized processes are referred to as digitalized functions, as illustrated in Fig. 2a. These functions are executed in a fully automated manner. The corresponding digital mechanisms are embedded in software systems—either based on traditional algorithmic solutions or enhanced through artificial intelligence—which enable the execution of digitalized functions.

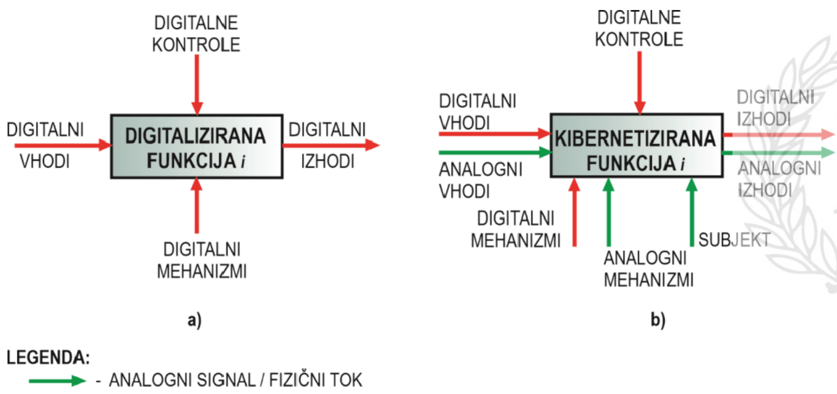

Figure 2. Digitalized and cybernated functions

Digital controls represent the digital embodiment of control mechanisms (e.g., constraints, rules, protocols), governing the execution of these functions. Examples of digitalization within the manufacturing domain include material ordering, production planning, procurement within supply chains, accounting, and financial transactions, all of which benefit from increased efficiency, traceability, and responsiveness enabled by digital transformation.

The application of digital technologies provides manufacturers with enhanced visibility and control over their operational processes. This enables real-time production monitoring, the execution of predictive analytics, and the ability to make faster and more informed decisions. As a result, such capabilities lead to a reduction in errors and production downtime, thereby contributing to higher product quality and improved efficiency across manufacturing lines.

Cybernation complements digitalization by introducing advanced automation and connectivity into manufacturing systems. It encompasses the intelligent, computer-based management, control, regulation, and supervision of physical elements within the production environment—including processes, machinery, equipment, and human operators—through the use of digital computing components such as programmable logic controllers (PLCs), digital processors, control software, and databases[7], [3].

The operations executed within cybernated processes are referred to as cybernated functions, as illustrated in Fig. 2b. These functions operate within a hybrid environment, bridging the analog and digital domains, where both inputs and outputs can be of analog or digital nature.

The execution of cybernated functions is enabled by a combination of digital mechanisms—such as algorithms, software agents, expert systems, genetic algorithms, and databases—and physical analog mechanisms, including process-executing devices, actuators, and sensors. Similar to digitalized functions, digital controls in this context serve as formalized rule sets or instructions that regulate the behavior and coordination of these hybrid systems[7], [3].

Cybernation enables seamless communication among various components of the manufacturing system—including machines, devices, and software platforms—facilitating automatic process control and adaptive responses to dynamic market conditions. This level of integration supports the creation of highly flexible manufacturing systems capable of rapid adaptation to changing demands and external disruptions.

Despite its numerous advantages, the implementation of digitalization and cybernation also presents significant challenges. These include the complexity of integration, high initial investment costs, the demand for new employee competencies, and security risks inherent to digital environments. Therefore, for companies to fully capitalize on the potential of Industry 4.0, it is essential to strategically invest in technological development, workforce training, and robust cybersecurity measures.

2.3. Enabling Technologies of Industry 4.0

Information and Communication Technology (ICT) serves as the cornerstone of the modern digital economy and has had a profound impact on the transformation of business processes within manufacturing enterprises.

Over the past three decades, the introduction of the ICT has driven one of the most significant transformations in the functioning of manufacturing systems. As noted by Weill and Broadbent [22], ICT encompasses all tools and equipment used to capture, process, analyze, and store data, with the objective of supporting and optimizing both business and production processes.

In the manufacturing domain, ICT is integrated into a variety of information systems, including Executive Support Systems (ESS), Management Information Systems (MIS), Decision Support Systems (DSS), Knowledge Management Systems (KMS), Transaction Processing Systems (TPS), Office Automation Systems (OAS), Expert Systems (EIS), and Workflow Support Systems (WSS). The functionality of these systems is not strictly delineated, but rather frequently overlaps in practice, enabling more comprehensive and dynamic support for production and managerial activities.

Advanced solutions such as Enterprise Resource Planning (ERP), Product Lifecycle Management (PLM), Customer Relationship Management (CRM), Manufacturing Execution Systems (MES), Supervisory Control and Data Acquisition (SCADA), and CAD/CAPP/CAM systems enable comprehensive digital management of manufacturing processes. However, their integration often encounters challenges due to a lack of standardization and interoperability, which remains one of the major obstacles in modern digital manufacturing environments.

Among the core functions of information systems are the acquisition, processing, organization, storage, and transmission of data. Reliable management of these processes enhances operational efficiency, reduces costs, improves understanding of customer needs, and shortens order fulfillment times.

In addition to the previously discussed information and communication technologies—such as ERP, MES, SCADA, IoT, IoS, cloud computing, and multi-agent systems—Fig. 3 highlights several other key enabling technologies, which are further elaborated in the following sections.

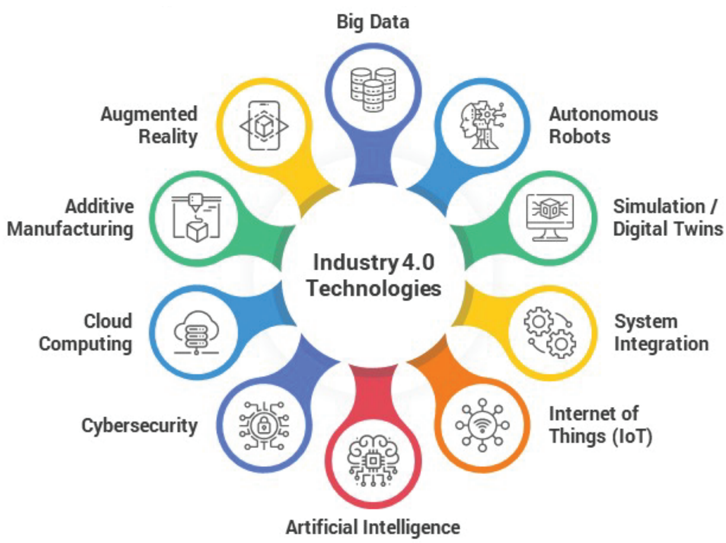

Figure 3. Enabling Technologies of Industry 4.0

With the increasing digitalization and interconnectivity of manufacturing systems, there is a growing need to protect information and production infrastructures from cyberattacks. Cybersecurity encompasses a set of policies, technologies, and processes aimed at safeguarding data, software, devices, and networks. Without a robust cybersecurity framework, the operation of a smart factory is exposed to significant risks, potentially compromising system integrity, reliability, and operational continuity.

Artificial Intelligence (AI) enables advanced data processing, decision-making, and experience-based learning. It is employed to optimize processes, predict maintenance needs, manage supply chains, and support mass customization in production. The integration of AI with the Internet of Things (IoT), Big Data, and digital twins facilitates the development of self-adaptive manufacturing systems capable of real-time responsiveness and optimization.

Digital twins are virtual representations of physical systems that enable continuous monitoring, simulation, and real-time optimization of industrial processes. Through simulation capabilities, companies can predict system behavior, test alternative scenarios, and fine-tune production parameters without physical interventions. Digital twins are essential for predictive maintenance and the implementation of changes with minimal disruption to operations.

The integration of diverse manufacturing and information systems—such as ERP, MES, SCADA, CRM, and others—enables seamless data flow, enhanced process transparency, and improved coordination across functional domains. A systematic linkage between the operational level and the strategic and informational environment ensures effective decision-making and coherent coordination throughout the entire organization.

Autonomous robots equipped with sensors, AI, and connectivity capabilities are capable of performing complex tasks without continuous human supervision. They are essential for operations that require high precision, speed, and adaptability. When integrated with AI, these robots can operate in heterogeneous work environments, dynamically adapting to changes in production conditions and collaborating with other systems and human operators in real time.

Big data generated by sensors, machines, and users necessitate the use of advanced analytical approaches. Big Data technologies enable the identification of patterns, production optimization, error reduction, and data-driven decision-making. Big Data serves as the foundation for predictive maintenance, market analysis, and real-time responsiveness to demand fluctuations, making it a critical enabler of intelligent and adaptive manufacturing environments.

Real-time optimization enables the immediate adjustment of production parameters in response to changing environmental and operational conditions. It is applied in control systems, logistics, task coordination, and energy efficiency management. The key value of this technology lies in its ability to minimize time losses and enhance the flexibility of manufacturing systems, thereby supporting responsiveness and resilience in dynamic production environments.

Cloud computing enables the storage, access, and analysis of data via the internet, offering a flexible and scalable infrastructure for modern manufacturing environments. Its key advantages include reduced infrastructure costs, scalability, and remote access to production data in real time. Cloud services support the implementation of Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS) models, thereby facilitating the flexible execution and integration of various functions within manufacturing systems.

The internet forms the foundation of modern digital communication technologies and enables the creation of smart environments, such as the Internet of Things (IoT) and the Internet of Services (IoS). The IoT connects physical objects through sensor networks, wireless communication, and IP protocols, enabling the automatic detection, collection, and exchange of data across systems and devices. The IoS builds upon this concept by offering platforms and services based on SaaS, PaaS, and IaaS models, which support business operations through web-accessible applications and cloud-based infrastructure.

Social networks also play an important role in supporting manufacturing processes by enabling new forms of interaction within the production system from the perspective of organizational communication, collaboration, and responsiveness. These interactions involve not only human actors, but also machines and devices, fostering a more integrated and communicative manufacturing environment. The inclusion of smart devices within web-based social networks further expands the capabilities for monitoring, control, and coordination across various elements of the production ecosystem.

Communication technologies such as Modbus, ProfiBus, PROFINET, Ethernet/IP, and wireless networks (e.g., WiFi, ZigBee, Bluetooth) enable real-time information exchange between distributed units within the manufacturing system. These standards support reliable and high-speed communication, serving as a foundational element for effective automation and digital control in modern industrial environments.

Machine learning enables systems to automatically learn from data, identify patterns, and predict future events. It is widely applied in process optimization, predictive maintenance, and anomaly detection in product quality. In conjunction with Big Data, machine learning serves as a key enabler for the development of self-learning systems in modern manufacturing environments.

Augmented Reality (AR) bridges the physical and digital environments, enabling operators to access real-time visualizations of device information, work instructions, alerts, and diagnostics. AR is frequently applied in employee training and maintenance procedures, improving operational efficiency and safety.

Additive manufacturing (AM) facilitates the production of complex geometries directly from digital models without the need for conventional tooling. Key advantages include rapid prototyping, reduced material consumption, and the ability to personalize products. Within the Industry 4.0 framework, additive manufacturing represents a critical step toward decentralized and flexible production systems.

2.4.Cyber-Physical Production Systems

To understand the concept of Cyber-Physical Production Systems (CPPS), it is essential to first define the notion of cybernetics. The term originates from the Greek word *kubernēin*, meaning *to govern* or *to steer*. As a scientific discipline, cybernetics gained prominence through the work of Norbert Wiener, who in 1948 published the seminal book *Cybernetics: Or Control and Communication in the Animal and the Machine*. In this work, Wiener laid the foundation for understanding control and communication mechanisms in both biological and technical systems[23],.

The understanding of cyberspace expanded significantly during the 1980s, particularly through the work of William Gibson[24], who popularized the term in his literary writings. Subsequently, various authors—among them Michael Benedikt [25] and Michael Heim[26]—offered additional interpretations of the nature of this space, describing it as an artificial informational realm shaped by the interaction between data, technology, and humans. Within this environment, multiple actors—including machines, algorithms, and people—interact, exchange information, and make decisions, forming the basis of intelligent, distributed systems.

Building upon this foundation, Cyber-Physical Systems (CPS) [6]have emerged as a new generation of complex, integrated systems, where physical and digital components are tightly interconnected. According to definition [27], CPS combine computational and communication capabilities to monitor and control events occurring in the physical environment. These systems are composed of sensors, actuators, control units, and communication interfaces, operating as networked agents. This infrastructure enables the real-time collection and processing of data, allowing for rapid adaptation of system responses to dynamic conditions.

Cyber-Physical Production Systems (CPPS) represent the implementation of CPS within manufacturing environments. According to Monostori et al.[28], CPPS are defined as systems comprising autonomous and cooperative units connected via various communication channels across all levels of the production system—from individual machines and processes to entire manufacturing and logistics networks. Their capability to be modeled and

managed in real time enables the effective execution of a wide range of tasks, including process control, dynamic adaptation, and the optimization of resources and flows. A generic model of a CPPS is presented in Fig. 4.
According to Monostori et al. [28], three fundamental characteristics define CPPS:

- Intelligence – the ability of individual elements to perceive and interpret their environment;
- Connectivity – the capacity for collaboration among devices and humans via the internet;
- Responsiveness – the capability to rapidly adapt to both internal and external changes.

The development of CPPS is also influenced by broader sociological dimensions, as highlighted by Morosini et al. [29], particularly in the context of collaborative networks and the evolving role of humans in technologically advanced manufacturing environments. These perspectives are essential for understanding the future of production systems, which will be not only technically sophisticated but also socially complex and inclusive [21]. The evolutionary shift from rigidly structured production lines to self-organizing and adaptive networks is also confirmed by recent scientific literature [30], which initiates discussions on new paradigmatic approaches in industrial manufacturing.
The integration of CPPS is a fundamental building block of Smart Manufacturing, which lies at the core of the digital transformation of modern factories. Smart Manufacturing is based on digital connectivity, where production systems are interconnected with databases, information systems, and user platforms, enabling end-to-end transparency and system-wide optimization.
Within this framework, CPPS facilitate autonomous coordination of production tasks, adaptive manufacturing aligned with market demand, energy efficiency, and rapid responsiveness to disruptions. By leveraging digital twins, machine learning, and advanced analytics, CPPS in smart factories are capable of predicting failures, optimizing maintenance, and even contributing to product development.
Beyond their technical advantages, CPPS also enable more efficient resource management, waste reduction, and improved traceability of materials and processes. The smart factories of the future will thus not only be technologically advanced but also highly responsive and adaptable. As noted by Morosini et al.[29], sociological dimensions are becoming increasingly critical for the successful deployment of these systems, as the transition toward smart manufacturing necessitates changes in organizational culture and mindset.

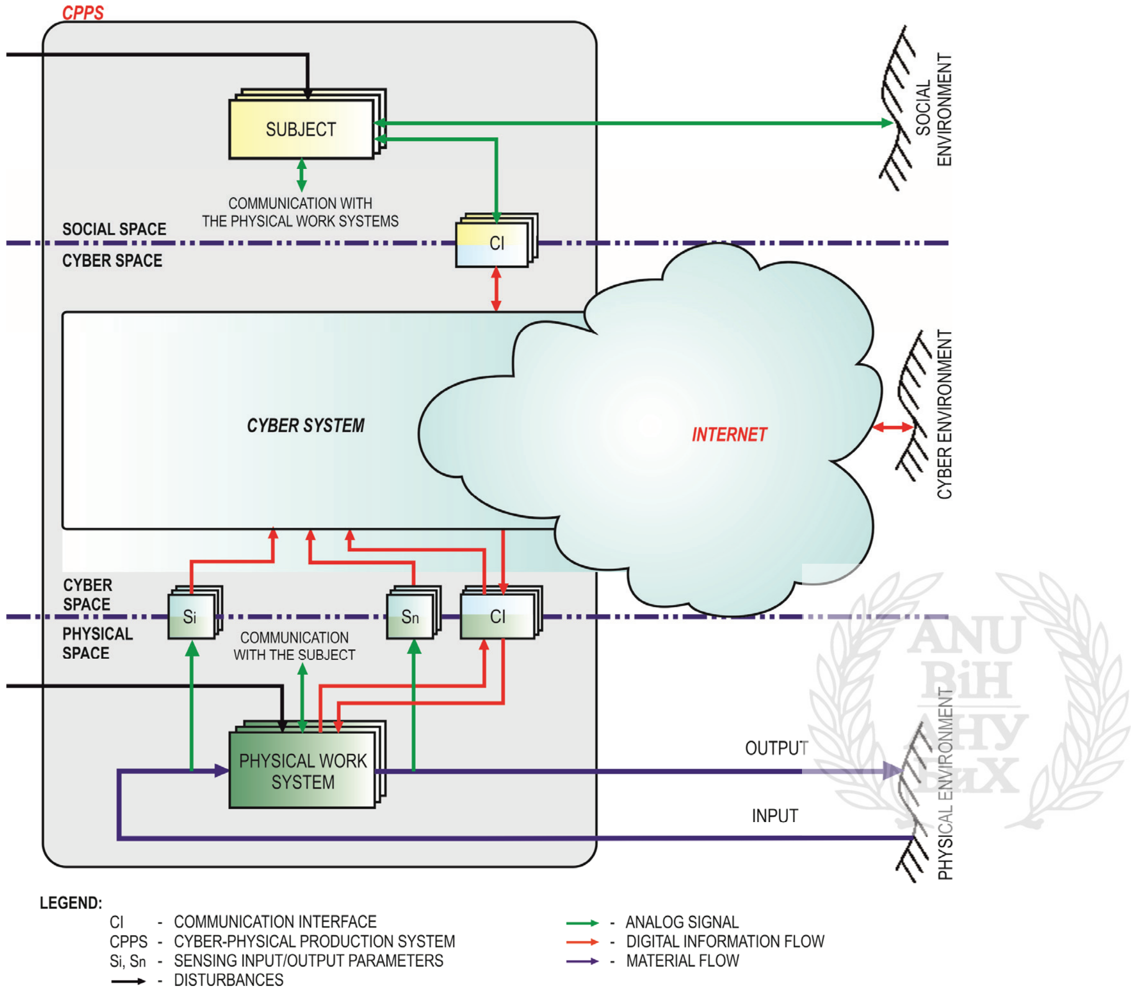

Figure 4. The Cyber-Physical Production System Model

In conclusion, CPPS are not merely a technical component of future manufacturing systems—they represent the core of the transformation toward intelligent, adaptive, and efficient production. As enabling technologies continue to evolve, the role of CPPS in smart manufacturing will become even more prominent. Nevertheless, key challenges will persist, including connectivity, security, interoperability, and the integration of humans as active partners in the production process.

2.5. Advantages and Limitations of Industry 4.0

Industry 4.0 offers numerous advantages (Table 1), including increased productivity, optimization of manufacturing processes, greater production flexibility, and enhanced product quality enabled by the use of smart technologies, AI, and automation. A key benefit also lies in cost reduction, achieved through more efficient resource management, lower energy consumption, and improved product traceability. Furthermore, digitalization and the implementation of the IoT allow for real-time monitoring of production indicators, thereby enhancing responsiveness to fluctuations in demand and market conditions.

Table 1: Advantages and Challenges of Industry 4.0

Advantages	**Limitations / Challenges**
Increased productivity and efficiency	High initial investment costs
Flexibility of production processes	Complex integration of technologies into existing systems
Improved product quality and traceability	Shortage of digital competencies and skilled workforce
Real-time data monitoring	Increased risk of cyberattacks
Possibility of customized production	Incompatibility of solutions, lack of standardization
Optimization of energy and resource consumption	Negative impact on certain job categories
Enhanced global competitiveness	Need for continuous adaptation to regulatory and security requirements

Despite its numerous advantages, the implementation of Industry 4.0 also presents certain limitations and challenges. Among the most significant are the high initial investment costs, often associated with the upgrade of existing infrastructure, the acquisition of new equipment, and the training of personnel. The complexity of integrating emerging technologies into legacy systems requires comprehensive planning and often demands a reorganization of operational workflows. Additionally, challenges related to cybersecurity and data protection arise, as increased digital connectivity also entails greater exposure to potential risks.

An additional challenge is the shortage of adequately skilled personnel. The transition to digital manufacturing requires new competencies in areas such as data analytics, programming, smart system maintenance, and a solid understanding of artificial intelligence concepts. Consequently, companies must invest not only in technology but also in the continuous education and development of human capital.

In the domain of standardization and interoperability, the diversity of solutions—which are often not mutually compatible—poses a significant barrier. This highlights the growing necessity for the adoption of uniform protocols, reference architectures, and open standards to facilitate seamless integration across systems and vendors.

Another important consideration is the impact on employment. While Industry 4.0 creates new technology-oriented jobs, it simultaneously reduces the demand for routine and low-skilled labor. This shift requires a strategic approach to issues of social equity, labor market restructuring, and the integration of digital literacy into all levels of education.

Industry 4.0 offers tremendous potential for advancing manufacturing enterprises; however, its successful realization is not guaranteed. Effective implementation requires a holistic and strategic approach that encompasses technological advancement, organizational transformation, employee training, and risk management. Only by addressing these dimensions can companies fully capitalize on the benefits of Industry 4.0 and ensure long-term sustainable growth.

3. Industry 5.0

3.1. Personalization

Industry 5.0 builds upon the digitalized and automated environment of Industry 4.0 by reintegrating the human as an active collaborator in the production process. In this context, personalization emerges as a core concept, enabling the transition from mass production to production tailored to the individual, often referred to as mass individualization.

Unlike mass customization, which offers a limited set of configurable options, personalization in the Industry 5.0 paradigm entails the active co-creation of the product by the end user. The customer becomes an integral part of the production chain, often participating as early as the design phase—enabled by technologies such as digital twins, augmented reality (AR), and open-architecture product systems (OAP). Examples of such practices include configurable furniture, custom automotive interiors, and personalized medical devices, all of which are tailored precisely to the user's individual needs.

This approach requires a high degree of interdisciplinary integration among information systems (e.g., CPPS), artificial intelligence, reconfigurable manufacturing systems (RMS), and human creativity. Co-creation platforms play a vital role by enabling users to visualize, select, and modify product functionalities, while smart factory processes dynamically adapt in the background to accommodate these changes.

The value of personalization within the Industry 5.0 framework lies not only in its economic impact—such as increased added value and stronger customer loyalty—but also in its sustainability dimension. By reducing unnecessary production, minimizing inventory, and better aligning supply with actual user needs, personalization significantly contributes to environmental efficiency.

Nevertheless, personalized production also introduces several challenges, including the complexity of planning, high demands on data and manufacturing infrastructure, and the need for systems capable of rapidly switching between varying specifications. However, it is precisely these complexities that reflect the core philosophy of Industry 5.0—a shift toward human-centricity, collaboration, and sustainability.

3.2. Cognitization in Manufacturing

Since the early 20th century, the development of manufacturing processes has been driven by the introduction of innovative approaches and technologies. The first major breakthrough occurred in 1913 with the implementation of the moving assembly line designed by Henry Ford, which fundamentally transformed not only the automobile manufacturing process but also the entire social structure. In the contemporary era, we are once again witnessing a manufacturing revolution, this time driven by the emergence of cognitive technologies as a central element.

Cognitive manufacturing is based on technologies that emulate human cognitive abilities such as learning, reasoning, understanding, and interaction. These systems enable the efficient analysis and interpretation of large volumes of data, surpassing the capabilities of traditional analytical approaches. The main advantages of cognitive technologies lie in their ability to continuously learn and improve, which directly contributes to increased productivity and enhanced product quality.

In manufacturing environments, cognitive technologies enhance human-machine interaction and enable real-time process monitoring. An illustrative example is IBM's Watson Internet of Things (IoT) solution, which employs high-resolution cameras to detect defects on assembly lines. Such systems significantly reduce the time required for visual inspection and decrease the number of production errors. Early results demonstrate an approximate 80% reduction in inspection time and a 7–10% decrease in defects, underscoring the practical value of cognitive solutions in industrial quality control.

In the future, cognitive systems are expected to possess the capability not only to identify and predict problems, but also to autonomously implement corrective actions. Although this level of automation has not yet been fully realized, cognitive technologies are already transforming manufacturing processes and opening new opportunities for advancing production towards greater efficiency, quality, and flexibility.

Cognitive machines represent specific technological solutions built upon foundational technologies such as machine learning, natural language processing, and image recognition, as well as infrastructures like cloud computing, the IoT, and Big Data analytics. These technologies support the development of innovative systems that go beyond traditional passive technologies, demonstrating capabilities characteristic of higher-order cognitive processes, including learning, understanding, decision-making, problem-solving, planning, and pattern recognition. Recent studies indicate that the deployment of such technologies can lead to productivity gains of up to 40%.

Cognitive systems, or machines, operate through two fundamental phases: training and application. In the training phase, systems acquire essential skills and capabilities by analyzing large datasets. A well-known example is AlphaGo, a Go-playing program trained on millions of game moves. In the application phase, cognitive systems continuously refine their performance by adapting to users and specific contextual environments. Examples include the Nest smart thermostat and Amazon Echo smart speaker, both of which learn user preferences and habits over time to improve their functionality.

An important concept introduced by cognitive machines is *fleet learning*, whereby data collected from an entire fleet of devices is used to improve the software performance of all units simultaneously. A prominent example is Tesla, which continuously enhances the capabilities of its autopilot systems by leveraging data gathered from its entire vehicle fleet.

Cognitive machines also facilitate enhanced customer understanding and interaction through natural language processing and affective computing technologies, which enable systems to detect and interpret users' emotional states. Notable examples include the Apple Siri and Amazon Alexa digital assistants, which are becoming increasingly sophisticated in understanding conversational context and user emotions.

Cognitive machine technologies also hold significant potential for the development of predictive enterprises, where real-time data analysis enables the anticipation of needs, preventive actions, and increased operational efficiency. Applications such as predictive maintenance, predictive logistics, and similar strategies represent key advantages that cognitive machines bring to industrial environments.

Looking ahead, we can expect an even greater integration of humans and cognitive machines in the workplace, where these systems will augment human capabilities and automate routine tasks, while humans will focus on activities that require creative thinking and intuitive decision-making.

3.3. Enabling Technologies of Industry 5.0

As previously mentioned, Industry 5.0 represents the next evolutionary stage of manufacturing systems, shifting away from the paradigm of full automation toward human-centric, resilient, and sustainable production, see Fig. 1. The realization of these objectives relies on a set of keys enabling technologies that support human-machine integration, intelligent decision-making, and advanced digital infrastructure. The following sections present the most important technologies that enable the implementation and functioning of Industry 5.0.

Big Data analytics technologies enable the processing of complex and heterogeneous datasets in real time. This supports faster and more informed decision-making, the optimization of pricing strategies, and more accurate demand forecasting. Big Data plays a crucial role in product and service personalization, as it allows for a deeper understanding of individual user needs, see Fig. 5.

Edge computing reduces latency, enhances cybersecurity, and lowers storage costs. In the context of Industry 5.0, it facilitates direct interaction with devices in manufacturing environments and increases the reliability of systems.

Artificial Intelligence (AI) enables intelligent automation, quality control, rapid anomaly detection, and decision-making optimization. AI is the foundation of cognitive machines and supports the creation of production systems that learn, adapt, and suggest actions without the need for constant human intervention.

Cobots (collaborative robots) facilitate safe collaboration between humans and machines. They contribute to increased productivity, accuracy, and robustness of manufacturing tasks, particularly in repetitive and physically demanding operations. Their role in Industry 5.0 is especially significant, as they enable complementary collaboration, rather than simply replacing human workers.

Next-generation connectivity (6G) enables ultra-low latency, high reliability, and efficient resource management. In smart factories, these technologies will ensure high data throughput and support complex real-time applications, such as distribution algorithms, digital twins, and rapid response systems.

Digital twins are virtual replicas of physical systems and devices, allowing for monitoring, simulation, and process optimization. They are used to reduce costs, predict failures, customize products, and optimize maintenance. Digital twins serve as a fundamental tool for adaptive, data-driven manufacturing in the future.

Blockchain technology enables secure decentralized data management, the creation of digital identities, and transaction transparency. In the context of Industry 5.0, it provides traceability, protects intellectual property, and fosters decentralized collaboration within value chains.

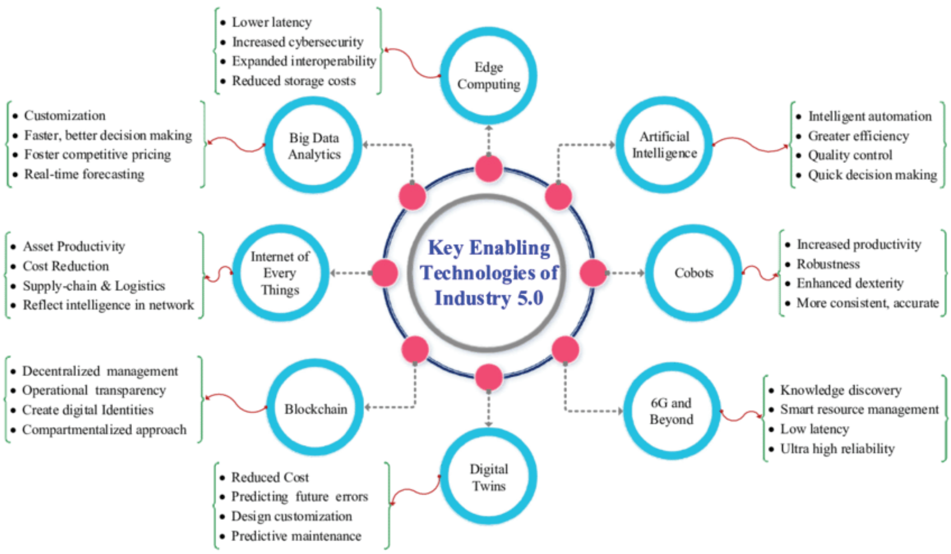

Figure 5. KeysEnabling Technologies of Industry 5.0

Internet of Everything (IoET) extends the concept of the Internet of Things (IoT) to include all types of intelligent devices and systems. It increases productivity, reduces costs, and enables intelligent logistics and supply chain management. Within Industry 5.0, IoET integrates with AI and digital twins to create dynamic, self-regulating environments.

3.4. Cognitive Cyber-Physical Production Systems

Cognitive Cyber-Physical Production Systems (C-CPPS)[3], [2] represent a key building block of the new manufacturing paradigm known as Adaptive Cognitive Manufacturing Systems (ACMS)[31], [32], which is closely linked to the concept of the fifth industrial revolution – Industry 5.0. This represents the next evolutionary stage of traditional Cyber-Physical Production Systems (CPPS)[28], [7], enhanced by the integration of cognitive technologies and artificial intelligence that enable a higher level of adaptability, learning, and collaboration between humans and machines.
At their core, C-CPPS combine intelligent algorithms, artificial intelligence, and sensing technologies to execute digitalized and cyber-physical functions. As described by Hozdić and Makovec [3], digitalized functions refer to the automation of information processes, while cyber-physical functions integrate both analog and digital mechanisms in the physical world with control in the cyber space. C-CPPS enhance these functionalities by adding capabilities such as sensing, prediction, self-adaptation, and intelligent decision-making.

The design of the C-CPPS is based on a multi-layered architecture of a multi-agent model, which enables distributed control of manufacturing systems, see Fig 6. The three-tiered structure includes the operational level, the coordination level, and the decision-making level. Each of these levels incorporates intelligent agents that communicate with both the physical and social environments. This means that physical elements (e.g., machines, actuators) send data to the digital space via sensors and communication interfaces, where they are processed by cognitive agents.

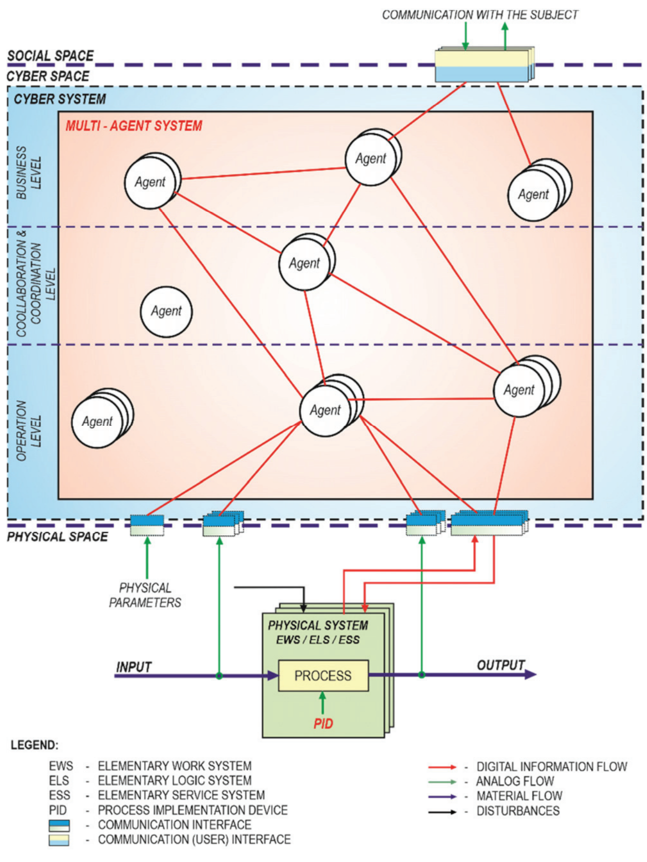

Figure 6. The Cognitive Cyber-Physical Production System Model[3]

These agents, based on advanced AI solutions, are capable of performing complex tasks such as predicting failures, optimizing workflows, detecting anomalies, and real-time decision-making. They can also learn from past events (referred to as fleet learning), which allows them to continuously improve the system's overall efficiency. An important aspect of this design is the inclusion of the human operator—through user interfaces, the operator can influence the system in real time, while also receiving enriched information to support decision-making.

C-CPPS form the foundation for the smart factories of the future, enabling complete synergy between the digital, physical, and social environments. Compared to previous systems, these systems are more flexible, intelligent, and responsive. Their integration facilitates a high degree of production customization, supports sustainability goals, and strengthens the role of the human as a co-creator in the manufacturing process.

As the authors conclude, C-CPPS are not just a continuation of existing technological trends but a breakthrough point in the development of manufacturing systems, enabling the transition to Industry 5.0—an era where technology does not replace humans but instead supports, augments, and empowers them to have greater creative freedom in value co-creation.

The significance of cognitive manufacturing systems also lies in their ability to co-decide with humans, where the human does not lose control but becomes an integral part of the intelligent ecosystem. In this way, the gap between full automation and human involvement is bridged, which is the central goal of Industry 5.0—to restore the balance between technological efficiency and human creativity.

Due to their advanced architecture and high level of intelligent behavior, C-CPPS are well-suited for environments that require high levels of personalization, agility, and resilience. Their development and integration represent a significant step towards realizing the vision of future manufacturing, where systems are not only digital and automated but also intelligent, adaptive, and deeply connected with the user experience.

3.5. Advantages and Limitations of Industry 4.0

Industry 5.0 introduces a new paradigm that goes beyond the technological focus of Industry 4.0, placing the human back at the center of production systems. Its goal is not only increased automation and efficiency, but primarily the creation of human-centric, sustainable, and resilient systems. The advantages of this paradigm are diverse and manifest at the technical, social, and environmental levels (Table 2).

One of the key benefits of Industry 5.0 is production personalization, which enables the creation of customized products tailored to individual user needs. In contrast to mass customization from the previous industrial paradigm, Industry 5.0 encourages active user participation in the product design phase. This increases the added value of products, strengthens customer loyalty, and reduces waste, leading to a more sustainable production process. Digital twins, co-creation platforms, and reconfigurable manufacturing systems are essential tools that enable this flexibility and responsiveness.

Furthermore, Industry 5.0 facilitates the deep integration of cognitive technologies, such as artificial intelligence, natural language processing, fleet learning, and Big Data analytics. These systems do not merely analyze but also learn, adapt, and make autonomous decisions.

Table 2: Advantages and Challenges of Industry 5.0

Advantages	Limitations / Challenges
Personalized production with user collaboration	High complexity of design and management
Strengthening the role of humans in production processes	High skill requirements for the workforce
Increased quality and reliability due to cognitive systems	Need for secure, decentralized data infrastructure
Greater sustainability and waste reduction	High costs for implementing advanced technologies and architecture
Intelligent automation and real-time learning	Ethical concerns regarding decision-making algorithms
Enhanced competitiveness with high added value	Unclear standardization and lack of global interoperable solutions

On a social level, Industry 5.0 contributes to the empowerment of workers, as technologies do not replace humans but rather complement them. The focus is on collaboration with cobots, intuitive user interfaces, and affective computing, which detects the emotional states of users. This improves work ergonomics, job satisfaction, and the role of the human as both creator and decision-maker.

Despite its many advantages, the implementation of Industry 5.0 is not without challenges. One of the key challenges is the high complexity of system integration, as personalized and cognitive manufacturing requires a highly modular and interoperable infrastructure. Furthermore, there is a need for an advanced data architecture capable of rapid and secure data processing, which increases the importance of edge computing and blockchain for decentralized information management.

Industry 5.0 represents a shift from technological efficiency to technology-supported human creativity. By fostering collaboration between humans and machines, intelligent decision-making, and a sustainable approach, it opens up new development horizons for manufacturing. However, its success depends not only on technology but also on systemic understanding, collaboration, and the adaptability of organizations. Only through these elements can its potential be realized in creating a more inclusive, responsible, and efficient manufacturing future.

A significant barrier remains the shortage of adequately trained personnel. The new generation of manufacturing systems requires experts in areas such as artificial intelligence, data science, ergonomics, and user experience design. Employee training and organizational culture transformation have become crucial elements for success. Additionally, ethical concerns related to automated decision-making and the transparency of algorithms present another critical challenge.

4.Comparison of Key Characteristics of Industry 4.0 and Industry 5.0

Industry 4.0 represents the transition to the digitalization of manufacturing processes, utilizing advanced technologies such as CPS, IoT, cloud computing, and AI. The primary focus is the establishment of smart factories, where autonomous systems with the ability to communicate with one another enable efficient automation, increased productivity, and the optimization of overall business processes.

At the onset of Industry 4.0, the role of humans was uncertain, as automation began to take over many tasks previously handled by humans. This raised concerns regarding the future of jobs and the quality of decision-making in the workforce.

In contrast, Industry 5.0 places humans, social responsibility, and sustainable development at the forefront. This paradigm emphasizes the importance of reintegrating humans into manufacturing processes and fostering greater system resilience. Several global challenges, such as climate change, pandemic crises, and geopolitical tensions, have highlighted the need for greater human involvement in organizational decision-making. Industry 5.0 promotes a collaborative approach, where robots and artificial intelligence systems work in partnership with humans, not as competitors, but as assistants and co-creators.

The key differences between the Industry 4.0 and Industry 5.0 paradigms are summarized in Table 3.

Despite the clear differences between the automation-driven approach of Industry 4.0 and the human-centric approach of Industry 5.0, both concepts often complement each other in practice. Researchers therefore propose an integrated hybrid model that combines the strengths of both paradigms. This model relies on the use of digital cognitive clones, which replicate human decision-making processes and enable effective interaction between humans and automated systems. By doing so, it combines the efficiency of automation, characteristic of Industry 4.0, with the social responsibility and sustainability emphasized by Industry 5.0. Such an integrated approach can create a new generation of adaptive, smart, and resilient manufacturing systems, capable of effectively responding to rapid changes in the global environment.

Table 3: Comparison between the Industry 4.0 and Industry 5.0

Feature	Industry 4.0	Industry 5.0
Main Focus	Automation, efficiency, digitalization	Human-centricity, collaboration, sustainability
Role of Humans	Replaced by technology	Partner collaborating with technology
Type of Production	Mass customization	Mass individualization
Key Technologies	IoT, Big Data, AI, CPPS, ERP, MES, SCADA	Cognitive machines, cobots, digital twins, blockchain, IoET
Decision-Making Approach	Automated, algorithmic	Co-decision by humans and machines
Goals	Increased productivity, flexibility	Sustainability, resilience, human value
Challenges	Security, interoperability, costs	Ethical dilemmas, complexity, skilled workforce

Industry 5.0 does not discard the technological achievements of the previous paradigm, but rather builds upon them, with a focus on responsible development, human inclusion, and care for future generations. This represents a new phase in the industrial revolution, where technology does not replace humans, but instead supports and enhances human creativity.

5. Technological Challenges and Opportunities

5.1. Implementing AI in Manufacturing

Artificial Intelligence (AI) in the manufacturing sector represents one of the key technological advancements of the past decade. Its implementation enables manufacturing companies to achieve greater efficiency, accuracy, and flexibility in production processes. Key applications of AI include optimization of production lines, predictive maintenance, supply chain management, and the improvement of final product quality.

Despite its numerous advantages, there are also significant technical and organizational challenges that companies face when implementing AI. Among the biggest obstacles are high initial investment costs, the need for substantial changes to existing manufacturing infrastructure, and the lack of specialized expertise for the development, implementation, and maintenance of AI solutions. Additionally, the implementation of advanced algorithms requires careful integration with the human factor in production processes, where it is crucial to maintain a clear role for humans in decision-making processes. Research shows that despite these challenges, AI can significantly increase the competitiveness of companies, making its strategic importance in modern manufacturing invaluable.

5.2. The Impact of Industry 5.0 on Sustainable Development

Industry 5.0 emphasizes the shift from fully automated and digitalized systems to a more balanced approach, where technologies are integrated with human values and sustainable development goals. This paradigm is not solely focused on technological advancement, but also on social and environmental responsibility. At the heart of this approach is the reintegration of humans into the production process, aimed at achieving greater resilience, sustainable development, and ecological responsibility.
Technological innovations within Industry 5.0, such as digital twins, collaborative robots, and smart circular products, enable more efficient resource use and reduce environmental impact. Recent research also highlights that the human-centric approach leads to improved resilience of companies to global crises and greater social acceptance of new technologies. As a result, Industry 5.0 is not just a technological shift, but also an important social step toward a sustainable future.

5.3. Security and Ethical Aspects of Human-Machine Interaction

With the increasing integration of cognitive technologies and artificial intelligence (AI) into manufacturing processes, the interaction between humans and machines is becoming increasingly complex and sensitive. Industry 5.0, which aims to establish human-centric production environments, also raises numerous security and ethical questions related to co-decision-making, control, and trust between users and machine systems.
Cybersecurity remains one of the key areas of risk. The growing connectivity of systems through the Internet of Things (IoT, IoET) and the use of digital twins expose systems to a higher risk of malicious intrusions, data manipulation, and cyber sabotage. Ensuring the integrity, confidentiality, and availability of data has become strategically crucial, as security incidents not only affect the technological infrastructure but also user trust in new solutions.
On the ethical level, key concerns include the transparency of AI decision-making and accountability for mistakes. The use of self-learning algorithms (e.g., in quality control or production planning) raises the dilemma: who is responsible for the decision—the machine, the developer, or the operator? In parallel, there is a growing need for Explainable AI (XAI), which provides

understandable justifications for decisions, a crucial aspect for maintaining human oversight and trust.
Furthermore, the affective dimension of interaction is important, particularly in collaboration with cobots and systems that detect user emotions. The ethics of such interactions include issues related to manipulation, privacy, and the appropriate boundaries between humans and machines. Improper implementation can lead to an over-reliance on technology and a diminished critical judgment from users.
Industry 5.0 thus requires a holistic approach to designing human-machine interactions, which includes:

- security protocols and protective mechanisms against misuse,
- transparent algorithms and decision-explanation mechanisms,
- respect for privacy and human dignity, and
- a clear distinction of roles between technology and users.

Adhering to these ethical and security principles contributes not only to greater societal acceptance of technologies but also to their long-term successful integration into the production environments of the future.

5.4. Technical and Organizational Barriers to the Transition to Industry 5.0

The transition to Industry 5.0 does not only represent a technical change, but also requires fundamental organizational adjustments and strategic change management. On the technical level, the biggest challenges include the integration of new technologies into existing systems, ensuring high levels of interoperability between different technologies, and securing robust cybersecurity.
In addition to these technical barriers, organizational obstacles also play a significant role, with notable challenges such as employee resistance to change, the need for extensive staff training, and the adaptation of organizational culture and work processes. Overcoming these challenges requires strategic planning, collaboration between departments, and effective communication between management and employees.
To successfully navigate these barriers, researchers recommend a gradual implementation of new technologies, proactive change management, and intensive stakeholder collaboration, all of which will facilitate the transition to Industry 5.0 and enable companies to achieve sustainable long-term growth and adaptability.

6. Future Trends

6.1. Applications of AI in Manufacturing Processes

The future of manufacturing will be largely shaped by the widespread use of artificial intelligence (AI), which is increasingly emerging as a key tool for optimizing industrial processes. One of the most promising applications of AI in the future is predictive analytics, where, based on large volumes of data, disruptions in production, machine wear, or product defects can be predicted before they occur. Additionally, the development of reinforcement learning approaches will enable systems to learn from everyday operations, thereby automatically improving their efficiency and decision-making.

In the future, artificial intelligence will significantly contribute to greater flexibility in production systems, enabling rapid adaptation to individualized customer demands and supporting the implementation of mass customization. Research predicts that AI will become a central element of self-adaptive and autonomous factories, where it will collaborate with robots, sensors, and digital twins to constantly monitor, learn, and optimize production in real-time.

6.2. Development of Smart Factories of the Future

The concept of smart factories will evolve into a more comprehensive and integrated form in the future, as technology will enable fully digitalized, connected, and self-organizing production systems. The smart factories of the future will not only be autonomous, but also predictive, responsive, and sustainable. Key characteristics will include digital twins, which will allow for the virtual simulation of the entire production process, IoT infrastructure that will ensure continuous data monitoring, and the use of AI for decentralized decision-making.

These factories will operate as cyber-physical systems, capable of real-time adaptation to changes in the environment or demand. Furthermore, future smart factories will increasingly focus on energy efficiency, waste minimization, and renewable energy sources, aligning with global sustainable development goals. In such an environment, digital infrastructure will be crucial for creating value and ensuring rapid responsiveness to market changes.

6.3. The Role of Humans in Future Manufacturing Systems

Although technology is advancing at an incredible pace, the role of humans in future manufacturing systems will not be diminished, but rather transformed[3], see Fig 7. Within the framework of Industry 5.0, the importance of a human-centric approach is already emphasized, and this will become even more crucial in the future. Instead of technology completely replacing humans, the human factor will become a key complement to artificial intelligence, particularly in the context of creativity, decision-making in complex situations, and ethical and strategic judgments.

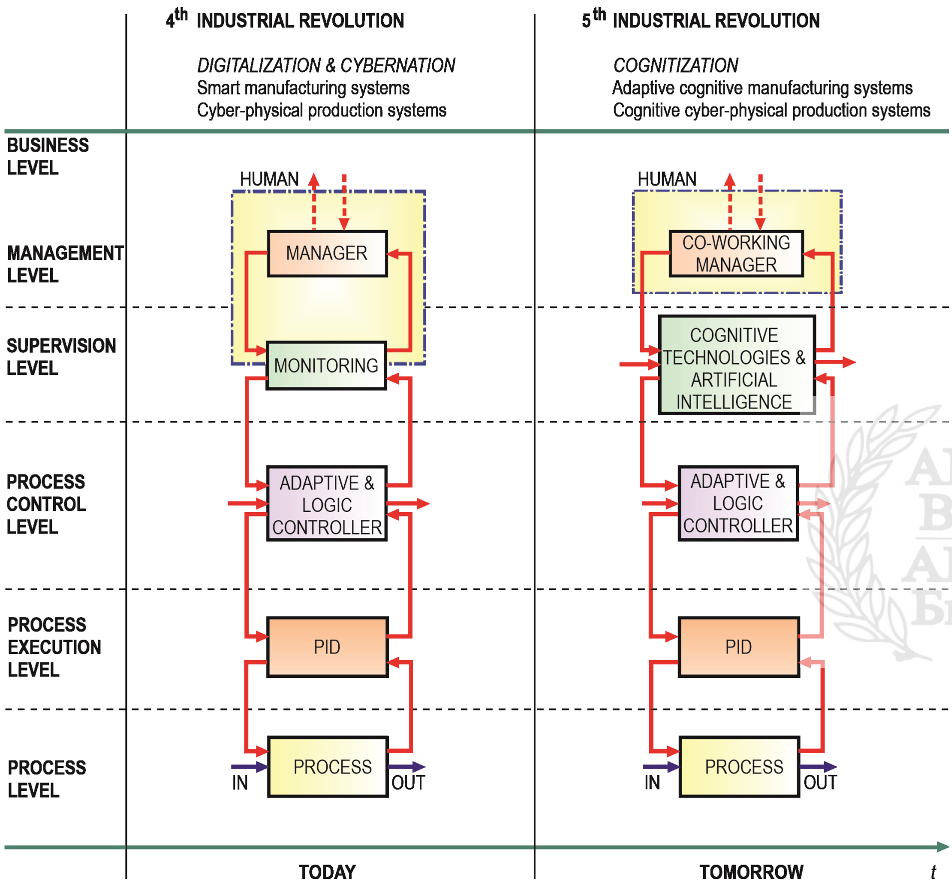

Figure 7. Transition of the human's role from Industry 4.0 to Industry 5.0.

Future manufacturing systems will include human-in-the-loop models, where humans will be actively involved in monitoring, improvements, and decision-making within automated environments. Furthermore, the focus will be on ergonomics, psychological well-being of employees, and job quality, meaning that manufacturing technologies will be adapted to humans, rather than the other way around. The role of education and continuous training will be especially important, as employees will need to develop new digital and analytical competencies in order to effectively collaborate with smart systems.

7. Conclusion

Industrial development in the 21st century has been marked by two paradigmatic shifts: first, with the digital and automated revolution, known as Industry 4.0, followed by the rise of Industry 5.0, which once again places humans at the forefront as a key component of manufacturing systems. The analysis of both approaches reveals that technological progress is increasingly focused on creating intelligent, sustainable, and human-centric manufacturing environments. Industry 4.0 is based on automation, digitalization, and the use of advanced information systems, such as IoT, AI, digital twins, and CPPS, enabling the optimization of manufacturing processes, increased efficiency, and connectivity. However, it faces challenges such as high investment costs, complex integration, and the lack of standardization.

Industry 5.0 builds on these foundations by placing humans at the center of the manufacturing system. Key elements include product personalization, the use of artificial intelligence to support decision-making, collaboration with cobots, and an overarching sustainability focus. This shift is not only about technological development but also about a societal and organizational change, requiring a high level of interdisciplinary collaboration, ethical judgment, and the creation of an inclusive work environment.

Technological challenges such as security, interoperability, and organizational culture change are significant factors in the transition to Industry 5.0. However, these challenges also present opportunities—such as the creation of smart factories of the future, where production processes can be monitored and adapted in real-time, and the development of new human-machine interactions, where technology complements human capabilities rather than replacing them.

Looking to the future, artificial intelligence, smart algorithms, digital twins, and advanced robotics will become the standard in manufacturing. At the same time, the importance of human creativity, adaptability, and ethical decision-making will continue to grow. The success of future industrial systems will therefore rely on a balance between technological capability and human values.

Industry 5.0 not only represents a new stage of development but also an opportunity for a holistic transformation of manufacturing towards a sustainable, inclusive, and responsible future.

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Evaluating the Environmental Impact of AI and Information Technologies

Samir Lemeš[*1]

Abstract: *Artificial intelligence (AI) and digital technologies are already used to address environmental challenges through applications such as climate modelling. AI-driven systems contribute to climate predictions and optimisation of energy grids. Satellite imaging and IoT sensors provide real-time environmental monitoring. These promising applications simultaneously increase the environmental burden of AI and IT infrastructure. Data centres for high-performance computing require vast amounts of energy due to enormous carbon emissions. The growing amount of hardware in data centres and IT infrastructure drastically increases the need to extract critical minerals, which are rarely environmentally friendly. This analysis aims to examine the dual nature of digital technologies and their relationship with environmental protection and investigate whether it is possible to reconcile these technologies' environmental benefits and drawbacks. Are "GreenAI" and "SustainableIT" possible, and do benefits for Industry 4.0 and societal development justify the environmental burden these technologies produce?*

Keywords: *AI, Environmental Protection, Green AI, Sustainable IT*

1. Introduction

During a time of rapid technological growth, Information Technology (IT) and Artificial Intelligence (AI) are increasingly shaping our understanding, monitoring, and protection of the natural environment. They generate new opportunities for improved resource management, accelerated threat identification, and informed decision-making. However, the deployment of these technologies poses challenges and risks, requiring an assessment of their beneficial and potentially adverse impacts.

An important application of IT and AI in environmental protection is data collecting and analysis. Sensor networks, Internet of Things (IoT) devices, and intelligent measuring stations provide real-time assessment of weather/climate, air, water, and soil quality, whereas satellites and drones offer critical insights about trends in land use, urban expansion, and biodiversity status. Data that was previously challenging to obtain or costly to examine is now processed in real time across extensive geographic regions.Artificial intelligence improves and

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can speedup the analysis of this data. Machine learning algorithms identify patterns and trends, which are essential for forecasting pollution, climate extremes like floods and droughts, and for delivering early warnings of possible environmental disasters. Moreover, AI facilitates the creation of predictive models that reveal the long-term impacts of human actions on the environment.

IT and AI can be used to enhance the management of natural resources. Smart energy and waste management systems can improve recycling operations and the allocation of energy from renewable sources. Geographic Information Systems (GIS), in conjunction with LiDAR (Light Detection and Ranging) data collection data analysis, can be used to formulate a strategy for the conservation of natural resources and urban green spaces. These technologies provide decision-makers with instruments facilitating more efficient environmental protection policies.

Interactive applications that simulate climate change and visualise environmental data can be used in education and awareness raising. Digital assistants and chatbots help citizens in adopting more sustainable practices.

Despite these advantages, these technologies possess a "dark side" that requires attention. The manufacturing and utilisation of digital gadgets demand substantial energy and resources, while the extensive aggregation and storage of data necessitate an exponentially growing number of data centres with considerable energy usage. The potential for unethical application of AI in environmental monitoring or decision-making exists, particularly when social dimensions of sustainability are disregarded.

These risks have recently become the focus of discussion among various researchers. Gundeti et al. examined the problems and unique opportunities presented by the rising use of artificial intelligence in environmental sustainability [1]. Chauhan et al. examined the environmental implications of AI, asserting that they require thorough consideration to guarantee a sustainable future [2]. Endersen focused on identifying the trends in energy usage and capital expenditure resulting from the design, development, and implementation of AI systems [3]. Akter in [4] examined solely the convergence of AI and sustainability, emphasising the utilisation of technical breakthroughs to reduce environmental consequences and foster a more sustainable future. Durai et al. examined the principles, challenges, and sustainability of AI, addressing its ethical and practical consequences. These issues encompass data privacy, AI inclusivity, and employment loss due to automation [5]. Aniko and Peyman examined the utilisation of artificial intelligence in the environmental sector [6]. Despite the advantages of AI, it is asserted that it remains in its early phase of growth, accompanied by environmental concerns. The power consumption and training duration of an AI model significantly influence its carbon emissions, hence intensifying the issues associated with climate change. Yehia and Alok examined the increasing awareness and concern over the environmental

consequences of AI and researched the development of tools and methodologies to promote Green AI [7].
Table 1 summarizes benefits and risks of digital tools use in environmental protection.

Table 1. The paradox: Digital technology both a solution and a problem

!! Digital Technology as a Solution !!	?? Digital Technology as a Problem ??
Real-time environmental monitoring: Sensors, drones, and satellites collect data on air and water quality, deforestation, emissions, etc.	**Energy consumption of data centres and networks:** Large-scale computing, including AI training and cloud storage, consumes huge amounts of electricity — often from fossil fuels.
AI for prediction and optimisation: Algorithms predict pollution, optimise energy use, reduce waste, and support smarter agriculture.	**E-waste generation:** Short device lifespans and fast tech turnover produce tonnes of electronic waste, much of it toxic and hard to recycle.
Sustainable urban planning: Geographic Information Systems (GIS) and smart city technologies enable greener infrastructure and transport.	**Resource extraction:** The production of digital devices depends on rare earth minerals, whose mining is environmentally destructive and often socially harmful.
Public awareness and behaviour change: Apps and digital campaigns educate people about sustainable practices	**Rebound effect:** Efficiency gains from technology (e.g., energy-saving apps) can be offset by increased usage or demand (e.g., more devices or services), which can cancel out the environmental benefits.

2. Positive Contributions of AI and it to Environmental Protection

Our civilisation confronts increasingly devastating effects from climate change and natural disasters; thus, the necessity for precise forecasting and prompt response has never been more critical. Artificial Intelligence (AI) came up as a powerful tool that enhances conventional scientific methodologies, providing novel approaches to comprehend complex environmental systems and augment our capacity to anticipate and address environmental hazards. In the domains of climate modelling and hazard forecasting, AI is already making substantial contributions.
Climate modelling is essential for comprehending long-term trends and forecasting future climatic conditions across many scenarios. These models are constructed using extensive mathematical calculations that replicate the Earth's atmosphere, oceans, terrestrial surface, and cryospheric processes. Nevertheless, conventional climate models often run into difficulties in accurately representing specific small-scale physical phenomena, such as cloud dynamics or ocean-atmosphere interactions, due to computational constraints. AI-driven models can

significantly decrease the computational resources needed to simulate climatic conditions, enabling researchers to conduct more simulations over a wider array of scenarios in a shorter timeframe.

AI improves climate modelling via data aggregation. Climate models require precise and updated observational data to generate accurate forecasts. The growing amount of environmental data from satellites, weather stations, and IoT devices presents a significant problem in real-time integration. AI enhances this process by learning to integrate various datasets into models more efficiently, therefore elevating the quality of the simulations. Moreover, AI methodologies are employed for downscaling—enhancing global climate model outputs to render them more applicable for local and regional decision-making, which is essential for infrastructure planning, agriculture, and urban development in response to climate hazards.

In addition to long-term climate forecasting, AI is essential for short-term disaster prediction. Natural disasters, like floods, wildfires, storms, and landslides, require prompt and precise forecasts to mitigate damage and preserve lives. AI systems utilising historical data and real-time environmental factors can accurately forecast the probability, location, and intensity of such catastrophes. For example, AI may evaluate precipitation patterns, terrain features, and soil moisture levels to predict landslides and to identify early indicators of wildfires through the analysis of satellite imagery. AI systems can evaluate data from satellites, drones, and social media to outline impacted regions, recognise individuals at risk, and allocate resources more effectively. In certain instances, AI algorithms observe mobile phone usage to identify evacuation trends or pinpoint groups of individuals who need assistance. Furthermore, AI is increasingly employed to manage infrastructure, including dams, highways, and bridges, facilitating the identification of weaknesses that may amplify the effects of natural disasters.

Early warning systems significantly benefit from artificial intelligence. When integrated with sensor networks and geospatial data, AI facilitates the creation of automated alert systems capable of issuing advance warnings for floods, storms, or tsunamis. These solutions not only improve community readiness but also provide faster and more coordinated emergency responses.

Artificial Intelligence (AI) significantly improves remote sensing and satellite monitoring by facilitating faster and more precise processing of extensive and complex environmental datasets. In the realm of deforestation, AI-driven image recognition algorithms can autonomously recognise variations in forest cover, categorise land use, and detect illegal harvesting activities in near real-time, thereby diminishing the necessity for manual analysis of satellite imagery. AI models assess satellite-derived data on sea surface temperatures, chlorophyll concentrations, and ocean colour to identify events such as harmful algal blooms, coral bleaching, and alterations in marine ecosystems, thereby contributing to ocean health.

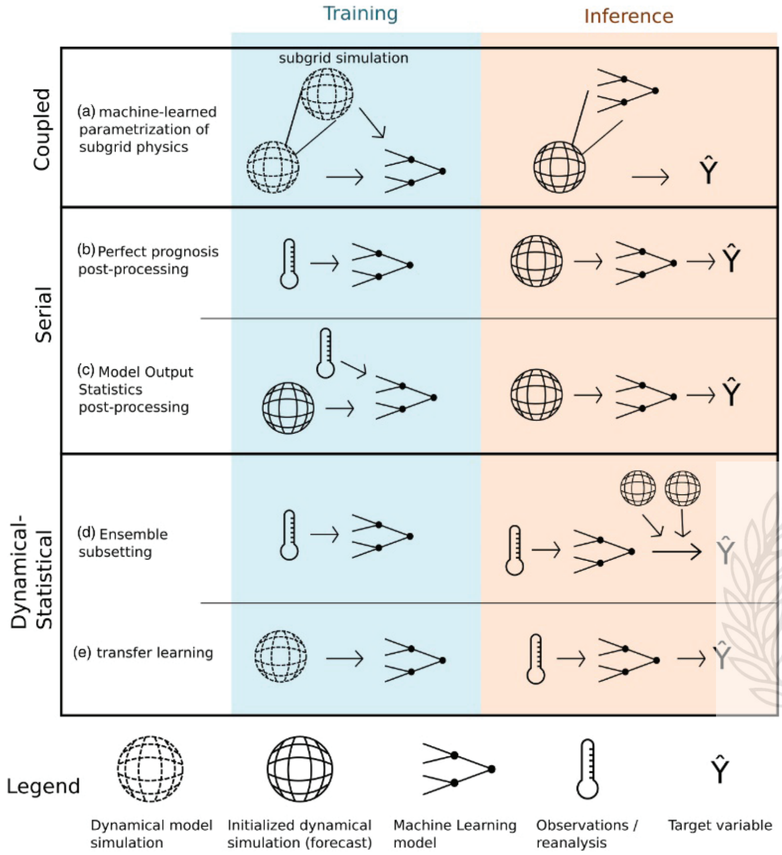

Figure 2. Combining dynamical models with deep learning to create hybrid predictions [8]

In the realm of biodiversity, AI facilitates the monitoring of alterations in habitat quality and species distribution through the analysis of multi-spectral and hyperspectral satellite data, thereby providing early alerts regarding habitat degradation or ecosystem imbalance. Integrating remote sensing with machine learning enables researchers to identify patterns, provide predictions, and enhance conservation initiatives more effectively and on a global scale.

IT and AI are rapidly transforming the development of smart grids and enhancing the efficiency of energy systems in sustainable urban environments. Smart grids employ sophisticated sensors, communication networks, and data analytics to oversee and regulate the real-time flow of electricity, facilitating enhanced efficiency and reliability in energy distribution. Artificial intelligence improves these systems by examining consumption trends, forecasting demand variations, and optimising the incorporation of renewable energy sources such as solar and wind. For instance, AI can dynamically optimise grid operations to balance supply and demand, minimise energy losses, and minimise blackouts. AI-driven technologies in buildings and urban infrastructure optimise heating, cooling, and lighting according to occupancy and weather forecasts, therefore substantially reducing energy use. IT and AI are important facilitators of low-carbon urban development and the transition to sustainable, resilient cities by enhancing the adaptability and intelligence of energy systems.

Blockchain technology provides an effective mechanism for providing transparency and trust in the tracking and trade of carbon credits. Blockchain facilitates the secure storing and public verification of all transactions related to carbon credits—encompassing issuance, transfer, and retirement—through the establishment of an immutable and decentralised ledger. This mitigates the risk of fraud, double counting, and misreporting that have traditionally compromised the integrity of carbon markets. Smart contracts can facilitate compliance and enforcement, guaranteeing that carbon credits are used uniquely and in accordance with established regulations. Moreover, blockchain facilitates real-time tracking and verification of carbon reductions, thereby simplifying the monitoring of progress towards climate objectives for governments, corporations, and consumers. Blockchain fortifies the integrity of carbon offset efforts by augmenting accountability and transparency, hence enabling more effective climate action.

3. The Environmental Costs of it and AI

Data centres and high-performance computing (HPC) facilities form the backbone of the digital world, powering everything from cloud services to scientific simulations. However, they are also significant contributors to global carbon emissions due to their immense energy demands. These facilities require continuous power not only for computing operations but also for cooling systems to prevent overheating. According to estimates, data centres account for roughly 1–2% of global electricity consumption, with HPC applications contributing disproportionately due to their intensive workloads. The carbon footprint increases further when this energy comes from fossil fuel-based sources. As digital infrastructure expands to support AI, blockchain, and big data analytics, the environmental impact of computing is becoming an increasingly urgent concern.

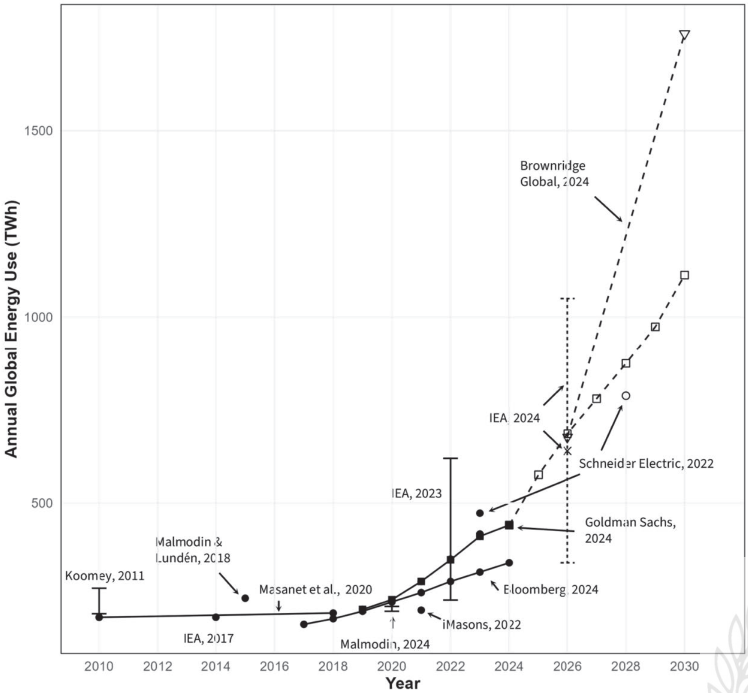

Figure 3. Academic and industry historical estimates of global data center energy use [9]

To mitigate this footprint, tech companies and research institutions are investing in energy-efficient hardware, advanced cooling technologies, and the use of renewable energy. Some data centres now operate in cooler climates to reduce the need for artificial cooling, while others utilise AI to optimise energy usage dynamically. Additionally, carbon-aware computing strategies—where workloads are scheduled during times when cleaner energy is available—are gaining traction. Despite these efforts, the rapid growth of data-intensive technologies means the challenge persists. Addressing the carbon footprint of data infrastructure is critical to aligning digital transformation with global sustainability goals.

The carbon footprint of data centres and high-performance computing (HPC) equipment is an escalating environmental issue due to the increasing global demand for digital services. These facilities utilise substantial quantities of electricity to operate servers, storage systems, and network infrastructure, in addition to powering intensive cooling systems necessary for maintaining appropriate temperatures. Data centres presently constitute approximately 1–2% of global electricity use, but the swift growth of AI, cloud computing, and big

data analytics is anticipated to substantially elevate their energy requirements. High-performance computer systems, employed in scientific research, climate modelling, and intricate simulations, are notably energy-intensive owing to their extensive parallel processing capabilities. When derived from fossil fuels, this energy consumption results in significant carbon emissions. As digital infrastructure expands, mitigating the carbon footprint of data centres and high-performance computing is crucial for reconciling technical advancement with climate sustainability objectives.
The production of computer hardware relies heavily on rare earth minerals, which are essential for manufacturing components such as processors, memory chips, hard drives, and displays. These minerals—including neodymium, lanthanum, and dysprosium—are critical for creating powerful magnets, conductive materials, and other specialised electronic parts. However, the extraction and processing of rare earth elements pose significant environmental and social challenges. Mining operations often result in habitat destruction, soil and water contamination, and the release of toxic byproducts, particularly in countries where environmental regulations are weak or poorly enforced. Additionally, rare earth mining can lead to human rights concerns, including unsafe labour conditions and community displacement. As global demand for electronic devices grows, so does the pressure on rare earth supplies, highlighting the urgent need for more sustainable sourcing practices, recycling of electronic waste, and the development of alternative materials.

Figure 4. Forest devastation by mining operations in Bosnia and Herzegovina [10]

E-waste management refers to the collection, treatment, and recycling of discarded electronic devices such as computers, smartphones, and televisions.

As technology advances rapidly and device lifespans shorten, the volume of electronic waste is growing at an alarming rate. E-waste contains valuable materials like gold, copper, and rare earth elements that can be recovered and reused. However, it also carries hazardous substances such as lead, mercury, and flame retardants, which pose serious risks to human health and the environment if not handled properly. Effective recycling can reduce the need for raw material extraction, lower greenhouse gas emissions, and prevent toxic pollution, making it a critical component of a circular economy.

Despite its importance, e-waste recycling faces numerous challenges. Many countries lack the infrastructure, legislation, or enforcement mechanisms needed for safe and efficient e-waste management. A significant portion of e-waste is exported—often illegally—from wealthier nations to developing countries, where it is dismantled under unsafe conditions by informal workers without protective equipment. Additionally, modern electronic devices are increasingly complex and difficult to disassemble, with manufacturers often prioritising sleek designs over recyclability. Public awareness is also limited, leading to low recycling rates and the accumulation of obsolete devices in households. Addressing these issues requires coordinated global action, including stricter regulations, extended producer responsibility, investment in recycling technologies, and education to encourage responsible consumer behaviour.

Water consumption in chip manufacturing and cooling systems is a significant yet often overlooked contributor to the environmental impact of the IT industry. The production of semiconductors requires extremely clean environments and materials, including ultra-pure water used to rinse and clean silicon wafers during fabrication. A single semiconductor fabrication plant can consume millions of litres of water per day, placing pressure on local water resources—especially in regions already facing water scarcity. If not properly treated, wastewater from these processes can also carry harmful chemicals and heavy metals that pose environmental and health risks when released into the environment.

In addition to manufacturing, water is extensively used in the operation of data centres, where it plays a key role in cooling systems that prevent servers from overheating. Many facilities rely on evaporative cooling, which consumes large volumes of water, contributing further to water stress in some areas. While some companies are adopting more sustainable practices—such as closed-loop water systems or alternative cooling technologies—water use remains a critical environmental challenge in the lifecycle of IT infrastructure. As demand for digital services continues to grow, reducing water consumption and improving water management in both chip production and data centre operations will be essential for minimising the IT sector's overall ecological footprint.

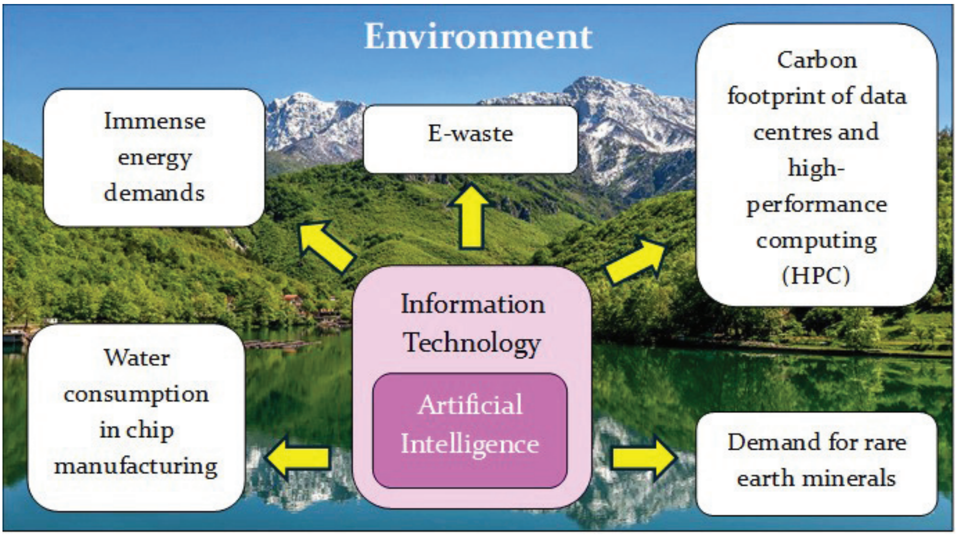

Figure 5. Possible environmental costs of IT and AI

4. Trade-Offs and Unintended Consequences

AI optimisation has the potential to offset, and in some cases even exceed, the energy it consumes—though this depends on how and where it is applied. On one hand, training and deploying large AI models, particularly in deep learning and generative AI, can be extremely energy-intensive, requiring vast computing resources and contributing significantly to carbon emissions. However, AI can also be used to optimise energy efficiency across a wide range of systems, including data centres, power grids, transportation networks, and industrial processes. For example, AI systems have been shown to reduce data centre cooling costs by up to 40% and to improve the efficiency of renewable energy integration into power grids by forecasting supply and demand more accurately [11].

The key to AI offsetting its own energy footprint lies in targeted, efficient deployment and careful system design. Lightweight, energy-efficient models can be used for many applications without incurring large carbon costs, and advancements in hardware and algorithms are continuously reducing the energy required for training and inference. Moreover, when AI is applied in sectors with large energy or emissions footprints—like manufacturing, logistics, or urban planning—the savings it generates can far outweigh its own consumption. Still, to ensure a net-positive environmental impact, the development and use of AI must be guided by sustainability principles, transparency, and lifecycle assessments. In short, while AI can offset its own energy use, whether it actually does sodepends on responsible implementation.

The risk of greenwashing is a growing concern in the tech industry, as companies increasingly promote their environmental credentials without always backing them up with meaningful action. Many tech giants now publish sustainability reports, commit to carbon neutrality, and invest in renewable energy, often framing themselves as leaders in the fight against climate change. While some of these efforts are genuine and measurable, others are criticised for being more about image than substance. For instance, a company might claim to be "carbon neutral" by purchasing carbon offsets rather than reducing actual emissions or highlight small eco-friendly initiatives while continuing unsustainable practices in their supply chains or data centres.

Scrutiny is especially warranted because much of the tech sector's environmental impact is hidden in complex global supply chains, resource extraction for hardware production, and massive energy use in data centres. Additionally, the fast pace of product obsolescence and limited repairability contribute to rising e-waste. True sustainability requires transparent reporting, third-party audits, and systemic changes—not just marketing campaigns or vague commitments. Without clear standards and accountability, the risk of greenwashing remains high, and consumers, investors, and regulators must be vigilant in distinguishing genuine progress from superficial branding.

AI-driven sustainability efforts offer powerful tools to combat climate change and manage natural resources more efficiently, but their prioritisation over social or economic goals raises important ethical concerns. On one hand, addressing environmental challenges is urgent and affects the long-term well-being of all societies, potentially justifying the prioritisation of sustainability. AI can optimise energy systems, reduce emissions, and improve environmental monitoring, contributing significantly to global climate targets. However, if these efforts come at the cost of job losses, increased surveillance, or the exclusion of vulnerable communities, they risk deepening social and economic inequalities.

Ethical AI deployment requires balancing environmental benefits with respect for human rights, equity, and justice. For example, smart city initiatives that reduce energy consumption through AI-based monitoring might infringe on privacy or disproportionately affect lower-income residents. Likewise, AI-driven automation in sustainability sectors could displace workers without adequate retraining or support. Rather than seeing sustainability and social and economic goals as competing priorities, they should be pursued in tandem. Responsible AI should be designed and governed to ensure that environmental benefits do not come at the expense of fairness, inclusivity, and human dignity.

5. Future Directions and Policy Recommendations

The term "Green AI" is an emerging movement that emphasises the development of energy-efficient algorithms and environmentally conscious artificial intelligence systems. As AI models grow in complexity—especially in areas like deep learning and natural language processing—the computational power and energy required to train and run them have skyrocketed. Some large-scale models consume as much energy as several households do in a year, raising serious environmental concerns. In response, researchers and organisations are advocating for "Green AI", which prioritises not only accuracy and performance but also the environmental cost of computation [12].

The goal of Green AI is to reduce the carbon footprint of AI by designing algorithms that are more computationally efficient, using fewer parameters, and requiring less data and training time. Techniques such as model pruning, quantisation, transfer learning, and the use of specialised low-power hardware (like GPUs optimised for efficiency) all contribute to this effort. Additionally, transparency in reporting energy use and emissions associated with training AI models is gaining importance, encouraging accountability and responsible innovation. Green AI represents a critical shift toward sustainable technology development—ensuring that the benefits of AI do not come at an unsustainable cost to the planet.

Sustainable IT practicesthat organisations and technology providers are adopting to reduce their environmental footprint include:

- Carbon-Neutral Cloud Computing:Major cloud service providers like Google Cloud, Microsoft Azure, and AWS are investing in renewable energy and carbon offset projects to power their data centres and achieve carbon neutrality. Some offer tools that allow clients to track the carbon footprint of their cloud usage and make greener choices.
- Circular Economy for Hardware:This approach promotes designing IT hardware for durability, repairability, and recyclability. Companies like Dell and Fairphone are developing modular devices that can be easily upgraded or repaired, and programs for take-back, refurbishing, and responsible recycling of used electronics are growing.
- Energy-Efficient Software and Algorithms:Developers are optimising software to use less computational power, which reduces the energy demand on devices and servers. Lightweight code, efficient data structures, and Green AI techniques help lower the overall environmental impact of digital services.
- Virtualisation and Server Consolidation:By running multiple virtual machines on a single physical server, organisations can significantly

reduce hardware needs and energy consumption in data centres. This practice enhances resource utilisation and decreases electronic waste.

- Sustainable Procurement Policies:Organisations are adopting procurement standards that prioritise eco-friendly products, suppliers with strong environmental practices, and hardware with certifications like Energy Star, EPEAT, or TCO Certified.
- Intelligent Energy Management in IT Operations:Using AI and machine learning, IT systems can dynamically manage power consumption—for example, by adjusting cooling in data centres or powering down idle devices across an enterprise network.

These practices help align digital transformation with environmental sustainability goals while promoting cost savings and long-term operational resilience.

Regulatory frameworks for AI-driven environmental monitoring are emerging to ensure that the use of artificial intelligence in tracking environmental changes is ethical, accurate, and accountable. As AI technologies become integral to monitoring air and water quality, deforestation, wildlife patterns, and climate variables, governments and international bodies are recognising the need for clear standards and oversight. These frameworks aim to ensure data transparency, validate the accuracy of AI models, and prevent misuse or manipulation of environmental data for political or commercial gain.

Some countries and regions have begun incorporating AI into their environmental legislation. For example, the European Union's AI Act [13] includes provisions to regulate high-risk AI systems, which could include those used for environmental monitoring, especially when tied to critical decision-making. The EU Commission has announced it will soon be looking for third-party contractors relating to 'Technical Assistance for AI Safety,' covering the topics of CBRN, cyber offence, loss of control, manipulation, and other AI risks [14]. Additionally, agencies like the U.S. Environmental Protection Agency (EPA) and the UN Environment Programme (UNEP) are exploring the use of AI tools while emphasising the importance of data integrity, privacy, and inclusivity. However, global regulation is still fragmented, and many AI monitoring projects operate without standardised protocols. Strengthening international collaboration and establishing guidelines for ethical AI use in environmental contexts will be crucial for ensuring that these technologies genuinely support sustainability and environmental justice.

6. Conclusion

IT and AI have become powerful tools in environmental protection, enabling real-time monitoring, predictive analytics, and optimisation of resource use. From smart grids and precision agriculture to climate modelling and deforestation tracking, these digital innovations offer unprecedented opportunities to address ecological challenges with greater speed and accuracy. For instance, AI can analyse satellite data to detect illegal logging or predict the spread of wildfires, while IT systems help manage renewable energy distribution and reduce emissions through smart infrastructure. These capabilities demonstrate the potential of digital technologies to contribute meaningfully to environmental sustainability.

However, the same technologies can also contribute to environmental harm if deployed without consideration of their ecological footprint. High energy consumption in data centres, resource-intensive hardware production, and the rapid growth of e-waste are direct consequences of unchecked digital expansion. Moreover, AI models, especially large-scale systems, require significant computing power, often powered by non-renewable energy sources. There is also a risk of greenwashing—where companies overstate the environmental benefits of their digital initiatives—if clear standards and accountability measures are not in place. These tensions highlight the complex dual role of AI and IT, making it essential to view them not as inherently sustainable but as tools that require careful governance.

To balance technological progress with ecological responsibility, an interdisciplinary approach is crucial. Collaboration between technologists, environmental scientists, ethicists, and policymakers can help design digital systems that align with sustainability goals. Recommendations include investing in "Green AI," improving the recyclability of hardware, and developing transparent metrics for environmental impact assessments. Future regulatory frameworks should go beyond data protection and AI ethics to include environmental criteria, such as mandatory sustainability reporting, carbon accounting for digital infrastructure, and lifecycle impact assessments of AI systems. International coordination will also be necessary to ensure that sustainability standards are applied globally and equitably. With the right oversight and cross-sectoral dialogue, AI and IT can evolve from potential threats into essential allies for a sustainable future.

Finally, there is an additional concern not addressed herein. Increased IT usage influences human behaviour and perception, consequently impacting the environment. This issue requires additional observation and analysis.

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Augmented Reality in Industry 4.0/5.0

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Abstract: *As the industry continues to evolve, Augmented Reality (AR) will play a key role in shaping the future of manufacturing. The transition from Industry 4.0 to Industry 5.0 represents a shift from a purely technology-based approach to one that integrates human-centric values, sustainability, and advanced human-machine collaboration. In this evolution, AR is a technology that bridges the gap between the two industrial paradigms. AR is making a difference in the manufacturing sector by improving efficiency, accuracy, and safety. Using a device that supports this technology, engineers and operators have the ability to access information and instructions in real time, reducing the need for hard copy manuals and other types of training materials. AR also enables experts to provide guidance and troubleshoot from any location.*

This paper analyzes AR as one of the most useful techniques for virtualizing the physical world in industry. It also provides descriptions of some of the software packages used in the development of AR systems in manufacturing environments and which have been used in the development of applications for recognizing machine components.

Keywords: *Industry 4.0/5.0,Augmented Reality, Unity, PTC Vuforia*

1. Introduction

Augmented Reality (AR) is a technology that, with the use of appropriate equipment and applications, overlays the visible (real, physical) world with a layer of digital content [1]. This is an auxiliary system used in logistics, maintenance, assembly, etc. (*Assisted Operator*). AR is a direct or indirect representation of the physical environment in the real world that is enhanced/supplemented by adding virtual digital information. AR is an interactive technology in 3D format and combines real and virtual objects. AR aims to help the user by displaying virtual information, not only in the user immediate environment, but also enables any indirect view of the real world environment. AR enhances the user perception and interaction with the real world [2].AR can also be used to augment the user senses through sensory substitution, using audio or visual signals. Virtual objects integrated into the real environment display information that the user cannot directly register with his senses. Information transmitted by virtual objects can e.g. to help the worker when performing activities in the production process [3]. AR can be applied in

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plant maintenance, providing information on the condition of machines, wear of tools, necessary servicing of equipment, etc.

When we talk about AR and its ability to integrate digital information into the real world, there are certain prerequisites that enable this technology (hardware and software conditions) [4,5]. The user, through virtual or augmented reality glassesor the screen of a phone or tablet, sees an image of the real world captured by a camera, on which digital content in the form of text, images or 3D models is added, Figure 1. This additional information has different purposes and can be customized according to the needs or specifics of the industry.

Most advanced AR devices are based on SLAM (*Simultaneous Localization and Mapping*) technology. This technology allows the device to gain a dynamic understanding of the user immediate environment, so that digital elements can be placed in the environment or even generated by the environment in ways that make sense to the observer, Figure 2.Tracking allows the application to understand the position and orientation of the object in space. This can allow more powerful applications to run in more dynamic environments, but it is also the basis for some new user interfaces.While object and image recognition allows an app to present information based on the environment, spatial AR allows users to place digital elements into an AR view of the environment. They may include models, notes, or other types of annotations that remain "anchored" to that position in space for their future reference, and often for other users as well [6,7].

Figure 1. View of digital content on the tablet screen in combination with the real world

Figure 2. Overlays of the digital model with the physical model

2. Physical World Virtualization Technologies

So far, several technologies have been developed that combine the digital and physical worlds in different ways. Each of these technologies uses different methods to create the best user experience in merging the digital and physical worlds [8]. There are four basic technologies that involve the digitization and virtualization of the physical world and they are described below. Each of these technologies offers unique ways of interacting with digital content, adapted to different contexts and applications [9].

2.1. Virtual reality (VR)

VR creates a completely digital environment, separating users from the real world [8–10]. There is no overlap with the environment, but the display is completely digital. Users typically wear virtual reality glasses (such as the *Oculus Quest* and *HTC Vive*) that block out the physical world and replace it with a computer-generated one. The ideal solution for simulations, training and virtual experiences where no real-world context is required. Users interact within the virtual environment, often using motion controllers or hand tracking, which simulate actions in the virtual world.

2.2. Augmented reality (AR)

AR overlays digital information onto the real world, thereby enriching the physical environment with digital content [5–13]. Users can access AR through smartphones, tablets, or AR glasses (such as *Microsoft HoloLens* or *Google Glass*). It is used in smart maintenance, navigation applications, interactive maps, etc. Users see and interact with the real world and enhanced digital elements that are consistent with the physical space.

2.3. Mixed reality (MR)

MR combines elements of both VR and AR, allowing digital and real-world objects to interact in real time [11]. MR glasses (such as *HoloLens 2*) allow users to interact with digital objects as if they were part of the physical world, using advanced sensors and spatial awareness. It is used in collaborative environments, industrial training, medical imaging and architectural design. Users can interact with digital and physical objects that react to each other, enabling more sophisticated applications than AR. The basic prerequisite and difference in relation to AR is the existence of sensors and feedback between digital and real content.

2.4. Extended reality (XR)

XR is an parent term for all immersive technologies, including VR, AR and MR. XR encompasses any technology that combines the digital and physical worlds, and is often applied when talking about the broadest spectrum of digital-physical world integration [12]. Used in a variety of industries, XR describes a range of experiences from fully immersive VR to partially enhanced AR. Interaction depends on the specific technology within XR – it can range from simple overlays in AR to fully immersive VR experiences with the use of 3D touch devices (*Haptic Devices*).

3. Purpose of AR in Production and Industry

In production and industry, AR can be used for a variety of purposes. Below are the areas of application of AR within production and industrial environments.

3.1. Improving the training and skills of employees

AR offers a unique opportunity to revolutionize employees training and skill development in Industry 4.0. By providing interactive and real-time guidance, AR can significantly reduce the learning curve for new hires. Workers can overlay digital instructions, diagrams and simulations with machines at their workplace, allowing them to learn complex tasks more effectively, Figure 3.

Figure 3. Workplace learning with AR applications

3.2. Creation of assembly instructions

AR aids the assembly process in manufacturing by overlaying digital instructions directly onto real-world parts, guiding workers step-by-step. This minimizes errors, as employees can visually follow each stage of assembly with real-time instructions and animations. AR tools can also highlight critical components or areas where precision is key, ensuring accuracy and quality. In addition, AR can display 3D models, making complex parts easier to understand and reducing training time for new assembly workers. Overall, AR increases efficiency, improves quality and enables faster learning curves in the product assembly process, Figure 4.

Figure 4. Interactive assembly instructions that recognize the components

3.3. Identification of parts and equipment

AR improves parts recognition in manufacturing by identifying components in real time and displaying relevant information on the screen, Figure 5. Workers can quickly scan parts with AR devices, which automatically recognize them and display key details such as specifications, part numbers and compatibility. This simplified identification process reduces the possibility of using faulty parts and speeds up assembly and maintenance. In addition, AR provides instant access to spare parts lists, allowing workers to view available inventory, order replacements or find suitable alternatives without leaving their workstation. This improves efficiency and reduces downtime by ensuring the right parts are readily available.

Figure 5. AR application for parts identification

3.4. Enabling remote collaboration - Virtual assistant

AR enables remote collaboration among teams, regardless of geographic location. Through AR-enabled devices, employees can share their views in real time, record objects, and communicate with colleagues, experts, or supervisors, Figure 6.

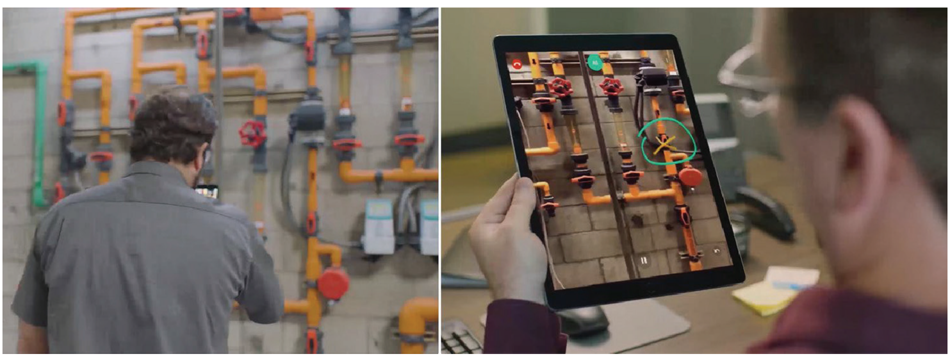

Figure 6.Remote collaboration and expert assistance

Through AR-enabled devices, technicians can receive real-time instructions from experts located in another location. Experts can remotely diagnose problems, provide step-by-step instructions, and even suggest virtual tools within the technician field of view. This capability reduces the need for on-site visits, speeds up maintenance processes, and ensures efficient troubleshooting.

3.5. Improving quality control and inspection

In Industry 4.0, maintaining high quality standards is crucial. AR can improve quality control and inspection processes by overlaying digital information onto physical objects, Figure 7.

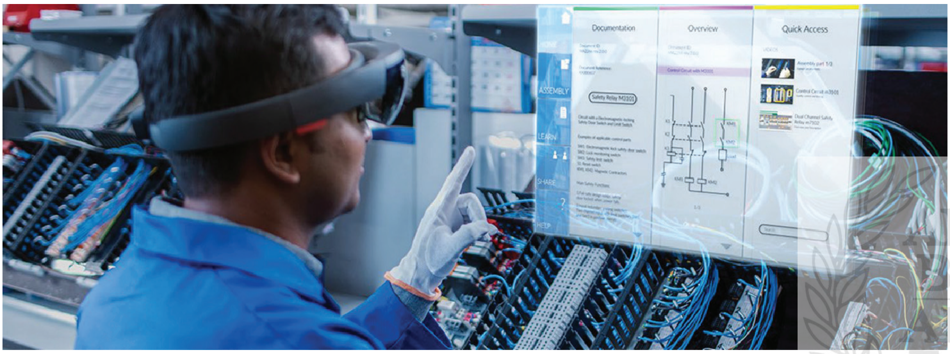

Figure 7. AR procedure for quality control

AR can highlight defects and irregularities in the finished product that might have been missed by the eye, or provide step-by-step inspection instructions and compare real-time data to predefined standards. This technology ensures consistency, accuracy and reduces human error, resulting in improved product quality and customer satisfaction.

3.6. Improving product design and prototyping

AR can revolutionize the product design and prototyping phase in Industry 4.0/5.0. Designers can visualize and manipulate virtual 3D models in realistic environments, allowing them to assess the feasibility, ergonomics and aesthetics of their designs, Figure 8.

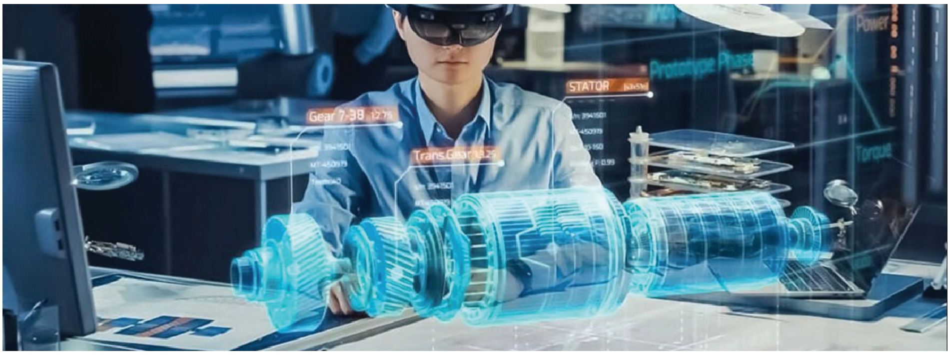

Figure 8. Visualization of the designed part in actual dimensions

AR also enables rapid prototyping, where virtual prototypes can be tested and modified in real time, reducing time to market and development costs. This technology encourages innovation, creativity and accelerates the design iteration process.

3.7. Increasing operator safety

AR can contribute to improving operator safety in manufacturing environments. By overlaying safety instructions, hazard warnings and real-time data on potential risks, AR can help workers navigate their environment more safely. For example, AR can highlight hazardous areas or provide guidance on the proper handling of hazardous materials, Figure 9. This technology promotes a safer work environment, reduces accidents, and reduces the risk of injury.

Figure 9.On-site warning in anindustrial environment

3.8. JIT manufacturing support

Just In Time (JIT) manufacturing is a key principle in Industry 4.0/5.0, aiming to minimize inventory and optimize production efficiency. AR can contribute to JIT manufacturing by providing real-time information on inventory levels, production schedules, and supply chain data. Workers can access this information through AR devices, ensuring they have the right materials at the right time, reducing waste and improving overall production efficiency, Figure 10.

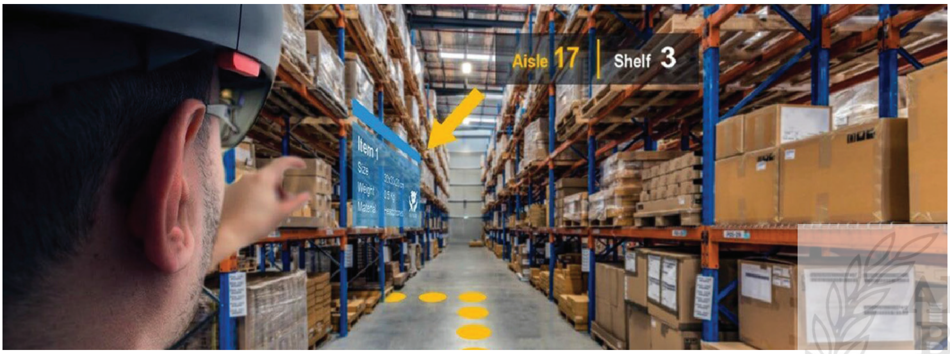

Figure 10.Real-time inventory status

4. Equipment for AR Systems

AR devices usually consist of AR glasses or a transparent screen through which the user looks while displaying applications, a transparent screen onto which the application is projected, or an opaque screen that displays live video content of the user environment supplemented with digital elements [11,12]. This last system, called „passthrough“ is the most common because smartphones and tablets are still the most common AR devices. Passage refers to a built-in camera that transmits a video image of the real world to the device screen.
In addition to the basic hardware requirements of a camera and a screen, more complex AR applications also require sensors for distance detection such as *Time of Flight* – TOF(for *Android* devices) and *Laser Detection and Ranging* – LIDAR (for *iPhone* devices), a gyroscope, and an accelerometer. Also, for remote support functionalities, in real time, an internet connection is necessary [13].
We can state that ready-made mobile phones of the latest generation have all these elements and that there is no obstacle for the mass adoption of these technologies. The quality of these technologies and sensors affect the recognition process in AR applications as follows:

- ***Camera*** plays a significant role in the accuracy and reliability of object recognition in AR applications. Higher-resolution cameras with better image sensors can capture more detailed and clearer images, which can improve object detection and target tracking. Cameras with features such as autofocus, optical image stabilization, and low-light capabilities can also improve the overall AR experience, providing better image quality in a variety of lighting conditions.
- ***Sensors*** used in AR applications are divided into gyroscopes, accelerometers and magnetometers for tracking the orientation and movement of the device. These sensors help determine the position and alignment of virtual objects relative to their real-world environment. The accuracy and responsiveness of these sensors can affect the stability and accuracy of object tracking in AR. Higher quality sensors can provide more reliable data, resulting in smoother and more accurate AR experiences.

- ***Operating system*** of the device may affect the performance and compatibility of AR applications. Different OS versions may have different levels of support for AR functions and API (*Application Programming Interface*) i.e. functionality of the user system. For example, Apple OS has *ARKit*, a framework that provides advanced AR capabilities, while Android has *ARCore*, a similar framework. Availability and functionality of these frameworks may vary depending on OS version and device compatibility. It is important to consider the specific requirements and limitations of the AR framework being used and to ensure compatibility with the OS of the target devices.

For the best AR experience, generally it is recommended to use devices with top quality cameras, reliable sensors, and the latest operating systems.

5. Application of Unity And PTC Vuforia Software Packages in AR

In the domain of AR for industrial applications, the company PTC has imposed itself with its Vuforia software. PTC is known for its Creo (*CAD/CAM*) and OnShape (*Cloud CAD*) software. Vuforia has several subvariants, from a stand-alone version called Vuforia Studio, which is a commercial solution intended for large businesses, to a free version. This is, in fact, an upgrade to the Unity environment, which is intended for creating 2D and 3D computer games and virtual worlds.

5.1. Unity development platform

Unity Engine is a powerful and versatile multi-platform game engine widely used for developing interactive 2D, 3D, VR and AR applications [14]. Unity provides an intuitive development environment with a wide set of tools, including a visual editor, a robust environment for physics and kinematic simulations, and support for the C# programming language. When integrated with the Vuforia Engine, Unity extends its AR capabilities, allowing developers to create applications that recognize and interact with real-world objects, Figure 11.

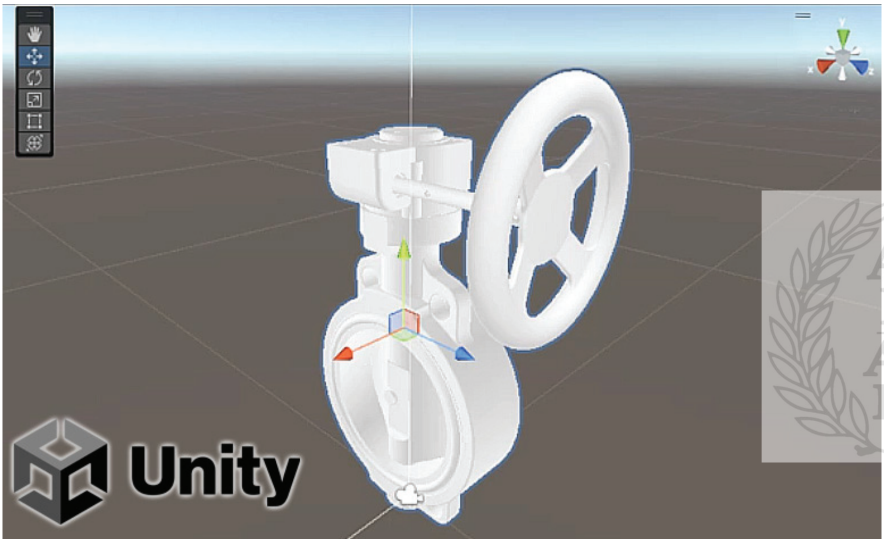

Figure 11. Development of the Unity AR application solution for valve recognition

The Unity environment enables the development of an AR application software solution that can be used in the recognition of machine components. This solution can be adapted to different devices and operating systems. One of the main features of Unity is the development of projects for different platforms. Projects created in this environment can be executed on a total of 27 different platforms [14].

5.2. Vuforia software package

PTC Vuforia is an advanced AR platform that uses a camera to identify and track images, objects and spatial features [15]. Developers can leverage Unity rendering and scene management tools along with Vuforia recognition and tracking capabilities, enabling the precise overlay of virtual elements onto physical objects in applications such as industrial model recognition and user guidance. Vuforia is a software platform that allows developers to create AR applications for mobile devices and AR glasses. Figure 12 shows the application of AR technology in the recognition of machine components of valves. The ultimate goal is easier identification of parts, assemblies and products in large factories and production facilities. In this way, easier maintenance of machines, devices and equipment is ensured, as well as more efficient replacement of parts.

Figure 12. Application of the Vuforia AR application in the recognition of machine components

Vuforia supports tools for creating and managing different types of AR content on different platforms (*Android, iOS* and *Microsoft*). During virtualization, several different technologies are used for space recognition and positioning of virtual content in the real environment. These technologies include: positioning using 2D graphics – *Image Targets*, positioning using barcodes and QR codes – *Barcode Scanner*, positioning using specially designed graphic targets – *VuMarks*, positioning using graphic targets in the shape of cylinders – *Cylinder Targets*, positioning using graphic targets in the shape of a box - Multi-Targets, positioning using 3D model detection - Model Targets, positioning using plane detection using the phone distance sensor – *Ground Plane* and positioning using space detection – *Area Targets*.

6. Conclusion

AR is ready to revolutionize the manufacturing sector in Industry 4.0/5.0. It upgrades production processes and practices. Its applications in worker training, manufacturing processes, quality control, remote collaboration and product design are transforming traditional manufacturing practices. Using AR companies can improve productivity, reduce costs, improve product quality and drive innovation. It is already realistic to expect that a solution will be found to connect ERP, MES, SCADA, PLC and AR applications in order to obtain all information in real time directly in the factory on a portable device such as a tablet or phone. Such a solution will contribute to a faster response to changes in technological parameters, preventive and emergency maintenance, connection to the warehouse of spare parts, as well as relevant information about suppliers and delivery dates.

Bringing new engineers and operators into industrial processes with AR applications will lead to faster onboarding as well as a better understanding of the manufacturing process and the equipment that is handled and maintained. A digital twin of the factory in a device that fits in your pocket with complete information about every piece of equipment is the ultimate goal of such solutions.

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Coexistence and Integration of Artificial Intelligence and Humans in Traffic Engineering

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Abstract: *Traffic engineering is experiencing a significant transformation with the integration of Artificial Intelligence. AI-driven systems provide real-time traffic and transport monitoring, predictive analytics, and autonomous control, improving efficiency, safety, and sustainability. However, human intelligence remains essential for supervision, regulation, and ethical considerations. The coexistence and integration of AI and human intelligence in traffic engineering create a hybrid approach that maximizes strengths while minimizing weaknesses. A balanced coexistence between AI and human expertise should lead to smarter, safer, more sustainable, and more adaptable traffic systems. This paper explores the coexistence of AI in traffic engineering and the role of human engineers guided by artificial intelligence.*

Keywords: *AI, Coexistence, Integration, Humans, Traffic Engineering*

1. Introduction

The rise of automation and artificial intelligence (AI) has sparked conversations about the future of work. Will robots completely replace humans? While technology will undoubtedly reshape the workplace landscape, the reality is far more nuanced. The future belongs to a powerful combination - the seamless integration of human skills and technological progress. The machines excel at processing vast amounts of data and handling repetitive tasks with unparalleled speed and precision. However, they need more creativity, critical thinking, and social intelligence, essential for success in the coming years. That's where people come in - the ability to think creatively, solve complex problems, collaborate effectively, and navigate interpersonal dynamics remains irreplaceable. Industry 4.0 technologies, such as automation, AI, IoT, and robotics, can be integrated with human labour to create synergies that advance productivity, innovation, and sustainability. Promoting the understanding and acceptance of Industry 5.0, which emphasizes the importance of humanizing technology, and emphasizes the integration of humans and AI, where humans and robots work together in a harmonious environment, leveraging the strengths

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of both parties to achieve better results. Traffic engineering is undergoing a significant transformation with the integration of Artificial Intelligence (AI). AI-driven systems offer real-time traffic monitoring, predictive analytics, and autonomous control, enhancing efficiency and safety. However, human expertise remains essential in decision-making, ethical considerations, and system oversight. The coexistence and integration of AI and human intelligence in traffic engineering generate a hybrid approach that maximizes strengths while mitigating weaknesses. The coexistence and integration of artificial intelligence (AI) and humans in traffic engineering is a transformative development reshaping how transportation systems are planned, operated, and maintained.

2. Applications for AI in Traffic Engineering

Artificial Intelligence (AI) has emerged as a transformative force in traffic engineering, offering advanced capabilities for automation, prediction, and optimization. The integration of AI into traffic systems supports smarter decision-making, enhances operational efficiency, and improves safety and sustainability. Artificial Intelligence (AI) continues to revolutionize traffic engineering by enabling more efficient, safe, and adaptive transportation systems. Recent developments have accelerated the deployment of AI-powered tools in multiple domains of traffic management and planning.

2.1. Traffic Flow Optimization and Management

2.1.1 Adaptive Traffic Signal Control

AI-driven systems use real-time traffic data to dynamically adjust signal timings. Reinforcement learning algorithms can optimize traffic light sequences to minimize delays and congestion. AI-driven adaptive traffic signal control systems, such as Pittsburgh's Surtrac [10], dynamically adjust traffic lights based on real-time data from sensors and connected vehicles. Reinforcement learning algorithms optimize signal timings to reduce congestion and emissions. Similar systems have been implemented in cities like Los Angeles and Hangzhou, China, demonstrating significant travel time savings [12].

2.1.2 Congestion Prediction

Machine learning models analyze historical and real-time traffic data to forecast congestion patterns, enabling proactive traffic rerouting and management. AI models such as Long Short-Term Memory (LSTM) neural networks predict traffic volumes and travel demand with high accuracy by analyzing large-scale spatiotemporal data [9]. These forecasts aid in proactive traffic control and transit scheduling. Advanced AI can also incorporate weather, events, and socio-economic variables to improve predictions [11].

2.1.3 Incident Detection and Response

Computer vision and sensor data can automatically detect traffic incidents (e.g., accidents, stalled vehicles) and alert relevant authorities to rapid response. Computer vision models powered by deep learning enable rapid and accurate incident detection on highways and urban roads. For example, Singapore's Land Transport Authority uses AI-enhanced video analytics to reduce incident detection time by over 50% [17]. Emerging technologies involve integrating social media feeds and connected vehicle alerts to improve situational awareness [13].

2.2 Intelligent Transportation Systems (ITS)

AI applications in systems Intelligent Transportation Systems (ITS) use for:
- Integrated Traffic Control Centres: AI enhances the capabilities of ITS control centres by automating data processing and providing decision support tools.
- Smart Parking Systems: AI applications can predict parking availability and guide drivers, reducing traffic circling and emissions.
- Dynamic Road Pricing: AI optimizes toll pricing based on real-time traffic demand, encouraging more balanced road usage and reducing peak-hour congestion.

2.3. Infrastructure Maintenance and Asset Management

AI applications in infrastructure maintenance and asset management used for:
- Predictive Maintenance: AI algorithms predict infrastructure degradation using data from sensors, drones, and maintenance logs. This allows for timely and cost-effective repairs.
- Automated Inspections: Drones equipped with AI-powered image recognition systems conduct inspections of roads, bridges, and tunnels, identifying cracks, corrosion, and other defects.

Predictive maintenance uses AI to analyze sensor data from roads, bridges, and signals to forecast asset degradation and schedule timely repairs. For example, the city of Amsterdam employs AI analytics to monitor pavement conditions and optimize maintenance workflows [2]. This approach reduces costs and extends infrastructure lifespan.

2.4. Autonomous and Connected Vehicles

AI applications in autonomous and connected vehicles are used for:

- Navigation and Path Planning: AI guides autonomous vehicles (AVs) in real-time, enabling them to interpret road conditions, obey traffic rules, and avoid obstacles.
- Vehicle-to-Everything (V2X) Communication: AI processes information exchanged between vehicles, traffic lights, pedestrians, and infrastructure to coordinate movement and enhance safety.
- Mixed Traffic Management: AI facilitates the coexistence of AVs and human-driven vehicles, optimizing traffic flow and minimizing disruption.

AI algorithms enable perception, localization, path planning, and decision-making for autonomous vehicles (AVs). In Phoenix, Waymo's fleet demonstrates AI-human collaboration in managing AV operations safely in mixed-traffic environments [4]. AI also supports vehicle-to-everything (V2X) communication, improving coordination between AVs and infrastructure for smoother traffic flows [5].

2.5. Public Transportation Optimization

AI applications for public transportation optimization used for:

- Demand Forecasting: AI models predict passenger demand based on time of day, weather, events, and historical data, helping transit agencies allocate resources efficiently.
- Route and Schedule Optimization: AI continuously analyzes performance data to adjust bus and train schedules, reduce waiting times, and improve service reliability.
- Passenger Flow Analysis: Computer vision and sensor data help analyze passenger movements at stations, improving layout and reducing bottlenecks.

AI systems in cities like Helsinki use real-time passenger data and traffic conditions to optimize bus routes and schedules, enhancing service reliability and rider satisfaction [6]. Emerging applications include AI-powered demand-responsive transit (DRT) that dynamically matches vehicle deployment with passenger requests, increasing efficiency [1].

2.6. Pedestrian and Cyclist Safety

AI applications for pedestrian and cyclist safety are used for:

- Smart Crosswalks: AI-enabled crosswalks detect pedestrian presence and adjust traffic signals accordingly.
- Collision Avoidance Systems: AI in vehicles and infrastructure can predict and prevent potential conflicts between vehicles, pedestrians, and cyclists.

2.7. Environmental Monitoring and Control

AI applications for environmental monitoring and control use for:

- Emission Tracking: AI systems monitor vehicle emissions in real time and recommend adjustments in traffic control to reduce pollution hotspots.
- Green Wave Systems: AI synchronizes traffic signals to create a continuous flow for vehicles, reducing stops and minimizing fuel consumption.

AI-based traffic management systems minimize vehicle idling and optimize flow to reduce carbon emissions. Cities like Barcelona leverage AI integrated with IoT sensors and environmental monitoring to improve air quality and promote sustainable mobility [14]. Additionally, AI can help design low-emission zones and promote electric vehicle (EV) usage through intelligent routing [8].
The applications of AI in traffic engineering are diverse and rapidly advancing. By combining large-scale data analytics, machine learning, and human expertise, AI enables adaptive, safe, and environmentally conscious traffic systems. Continued innovation and interdisciplinary collaboration will drive further integration of AI technologies into the fabric of urban mobility.

3. Human Roles In AI-Augmented Traffic Systems

As Artificial Intelligence (AI) becomes increasingly integrated into traffic engineering, the role of humans remains crucial in ensuring system effectiveness, safety, and ethical operation. AI-augmented traffic systems combine automated data processing and decision-making with human oversight, judgment, and intervention. Despite the rapid advancements and deployment of Artificial Intelligence (AI) technologies in traffic engineering, human involvement remains indispensable. AI systems, while powerful in data processing and automation, require human oversight, interpretation, and ethical governance to function effectively and safely. Basic characteristics of human roles in AI-augmented traffic systems:

- Traffic engineers remain central to the design, operation, and evaluation of AI-driven traffic management systems.
- Operators monitor AI systems in real-time.

- The ethical and legal frameworks guiding AI in traffic systems are crafted by policymakers and regulatory bodies.
- Continuous improvement of AI applications depends on the work of researchers and developers.
- The acceptance and success of AI-augmented traffic systems depend on the broader public, including drivers, pedestrians, and local communities.

Table 1. Role and responsibilities of human roles in AI-augmented traffic systems

Role	Responsibilities
Traffic Engineers and Analysts	● Interpretation of AI-generated insights and translate them into practical traffic control strategies. ● Validation and calibration of AI models to ensure they align with real-world conditions and engineering principles. ● Identification and addressing anomalies or errors in AI outputs that automated systems might overlook. ● Developing and implementing system improvements based on AI performance feedback.
Operators and System Supervisors	● Managing exceptions, such as system malfunctions, unexpected traffic events, or conditions outside the AI's training data. ● Intervention manually when necessary to prevent or mitigate traffic disruptions or safety hazards. ● Coordination responses with emergency services, maintenance crews, and other stakeholders during incidents.
Policy Makers and Regulators	● Establishing safety standards and operational guidelines for AI deployment in public infrastructure. ● Addressing issues related to data privacy, security, and algorithmic bias. ● Promote transparency and accountability to foster public trust in AI-enhanced traffic systems. ● Facilitate public engagement and stakeholder consultations to align AI applications with societal values.
Researchers and Developers	● Innovation of new algorithms and technologies to enhance system capabilities. ● Conduct rigorous testing and validation to ensure AI reliability and robustness. ● Collaboration with traffic professionals to tailor AI solutions to specific urban contexts.

Public Users and Community Stakeholders	• Providing valuable feedback on system performance and user experience. • Adaptation behaviours in response to AI-driven traffic management measures. • Engaging in awareness campaigns and educational initiatives about AI's role and benefits.

In AI-augmented traffic engineering, humans serve as the essential architects, overseers, and ethical stewards of technology. This human-AI partnership ensures that automated systems are effectively integrated, responsive to dynamic conditions, and aligned with societal goals, ultimately enhancing traffic safety, efficiency, and sustainability.

4. Human Role In AI-driven Traffic Engineering

While Artificial Intelligence (AI) has revolutionized traffic engineering by enabling automated, data-driven decision-making, the role of humans remains fundamental to the successful implementation, operation, and governance of these systems. AI functions as a powerful tool that augments human expertise rather than replacing it. As Artificial Intelligence (AI) becomes increasingly integrated into traffic engineering, human involvement remains indispensable to ensure system effectiveness, safety, and ethical governance. AI-augmented traffic systems blend automated data processing and decision-making with human oversight, judgment, and intervention. The human role in AI-driven traffic engineering encompasses multiple dimensions.

4.1. Strategic Oversight and Decision-Making

Human operators continuously monitor AI-driven traffic management systems to ensure smooth operation and quickly identify anomalies or system failures. By reviewing real-time dashboards and alerts, operators can detect false positives, malfunctions, or unforeseen traffic events that AI algorithms may not fully understand. Humans provide critical judgment and contextual understanding that AI systems alone cannot replicate. Traffic engineers and planners:

- Interpretation of AI outputs within the broader socio-economic and environmental context.
- Making strategic decisions on traffic policies, infrastructure investments, and system design.
- Balanced AI recommendations with public safety, equity, and ethical considerations.

Human operators continuously monitor AI-driven traffic management platforms to verify system outputs and identify anomalies. For instance, in Singapore's AI-assisted incident detection system, operators validate AI-generated alerts before dispatching emergency responses, reducing false positives and improving reliability [7]. Despite the autonomy of AI traffic control algorithms, human experts retain authority to override AI decisions when context demands. In Pittsburgh's Surtrac system, traffic engineers intervene during special events or roadworks to adjust system behavior beyond AI recommendations [23]. This ensures decisions remain sensitive to real-world complexities.

4.2. System Monitoring and Intervention

Although AI systems can recommend or execute traffic control actions autonomously, human experts retain the authority to override AI decisions when necessary. In complex or ambiguous scenarios, such as emergencies, roadworks, or unusual traffic patterns, human judgment is essential to assess context, apply ethical considerations, and coordinate with other agencies. Traffic control operators continuously supervise AI-enabled traffic management systems to:

- Detecting and responding to irregularities or system failures.
- Overriding or adjusting AI-driven controls during emergencies or unexpected traffic events.
- Ensuring smooth interaction between AI automation and human-operated interventions.

4.3. Model Development and Validation

Traffic engineers and data scientists collaborate to design, configure, and fine-tune AI algorithms and models based on evolving traffic patterns and urban development. Human expertise guides model training, validation, and updates to improve AI accuracy and relevance, ensuring that system performance adapts over time. Humans develop, train, and refine AI algorithms by:

- Providing domain expertise to select relevant data features and design model architecture.
- Validating AI predictions against real-world scenarios to ensure reliability and accuracy.
- Addressing biases, data quality issues, and limitations in AI models.

Traffic engineers and data scientists collaborate to develop, calibrate, and refine AI models. Human expertise guides training data selection and parameter tuning to maintain AI system accuracy. The Helsinki public transit AI system benefits from planners' input to tailor demand forecasting models to socio-economic factors [16].

4.4. Ethical and Regulatory Governance

Humans hold responsibility for ethical considerations, legal compliance, and public transparency in AI-augmented traffic systems. This includes ensuring data privacy, avoiding biased decision-making, and communicating AI capabilities and limitations to stakeholders and the public. Policymakers, regulators, and ethicists establish frameworks to:

- Defining acceptable uses of AI in public infrastructure.
- Ensuring data privacy and security in AI-driven traffic systems.
- Promoting transparency, fairness, and accountability of AI algorithms.
- Engaging with stakeholders to foster trust and social acceptance.

Humans are responsible for the ethical oversight and legal compliance of AI applications. This includes protecting privacy, mitigating bias, and ensuring transparency. Johnson et al. (2021) [4] emphasize that human supervision in autonomous vehicle operations is critical to upholding safety and ethical standards.

4.5. Public Engagement and Education

Human roles extend to engaging with the public and policymakers to foster trust and understanding of AI integration in traffic systems. Educating users about AI benefits and limitations, addressing concerns, and incorporating community feedback helps to improve acceptance and cooperation. The broader public plays a key role by:

- Adapting behaviours to AI-influenced traffic controls and guidelines.
- Providing feedback that informs system improvements.
- Participating in educational efforts to increase awareness of AI benefits and limitations.

Human roles extend to educating and engaging with the public to foster trust in AI-augmented traffic systems. Barcelona's smart city project includes community feedback loops to incorporate citizen concerns into AI tuning and policy-making [14].

4.6. Emergency and Incident Management

During incidents such as accidents or natural disasters, human operators coordinate multi-agency responses supported by AI data. Humans interpret AI-generated insights alongside situational awareness to prioritize actions, allocate resources, and manage communication effectively. During traffic incidents, human operators coordinate multi-agency responses using AI-generated situational awareness. The hybrid approach in Singapore enables rapid verification and action, demonstrating how human-AI synergy improves incident outcomes [17]. Humans and AI function as complementary partners in traffic engineering. While AI offers data-driven speed and automation, humans provide critical oversight, contextual understanding, and ethical governance. Maintaining active human roles in AI-augmented traffic systems ensures resilience, safety, and public confidence in emerging intelligent transportation solutions.

5. Benefits of Integrating AI and Humans in Traffic Engineering

The integration of Artificial Intelligence (AI) with human expertise in traffic engineering offers significant advantages that enhance the efficiency, safety, and sustainability of transportation systems. Combining AI's computational power and real-time data processing with human judgment and ethical oversight leads to a more robust and adaptive traffic management ecosystem. This human-AI collaboration enhances operational efficiency, decision-making quality, and public trust, among other benefits.

5.1. Enhanced efficiency and traffic flow

AI systems can analyze vast amounts of data to optimize traffic signals, predict congestion, and dynamically manage traffic flows. When integrated with human oversight, these systems can adapt to unexpected conditions and fine-tune control strategies, resulting in:

- Reduced travel times and congestion.
- Improved vehicle throughput at intersections.
- Better utilization of existing infrastructure.

AI automates routine tasks such as real-time traffic signal adjustment and incident detection, reducing response times and operational costs. Humans monitor these automated processes, ready to intervene in complex or unexpected situations. This collaboration results in faster, more accurate responses to dynamic traffic conditions, optimizing flow and reducing congestion [10].

5.2. Improved safety

AI technologies facilitate the rapid detection of incidents such as accidents or hazardous conditions using sensors and computer vision. Human operators can then verify and coordinate timely responses. This synergy leads to:

- Faster incident detection and response.

- Enhanced pedestrian and cyclist safety through AI-enabled monitoring.
- Reduced accident rates due to predictive analytics and preventive measures.

Combining AI's precision in detecting anomalies and predicting hazardous scenarios with human oversight enhances overall safety. Humans provide critical judgment in ambiguous or rare events where AI might lack sufficient training data, ensuring ethical and cautious intervention [7].

5.3. Environmental Benefits

Optimized traffic flow reduces idling and stop-and-go driving, which in turn lowers vehicle emissions. The collaboration between AI's optimization capabilities and human-led environmental policies results in:

- Decreased air pollution and greenhouse gas emissions.
- Promotion of sustainable transport modes through AI-enhanced public transit planning.
- Implementation of dynamic traffic control strategies aligned with environmental goals.

Human expertise guides the continuous training, tuning, and adaptation of AI models to changing urban environments and traffic patterns. This iterative process enables traffic systems to scale effectively while maintaining performance, and accommodating new technologies, regulations, and societal needs [16].

5.4. Cost Savings and Resource Optimization

Predictive maintenance powered by AI, combined with human expertise in infrastructure management, enables:

- Early identification of maintenance needs reduces repair costs.
- Efficient allocation of resources based on AI-driven demand forecasting.
- Prolonged infrastructure lifespan and reduced downtime.

The hybrid system improves the allocation of human and technical resources by automating routine monitoring and analysis, allowing human experts to focus on strategic planning, complex problem-solving, and emergency response. This leads to better use of limited personnel and infrastructure assets [10].

5.5. Ethical and Context-Aware Decision-Making

Humans provide essential ethical judgment, ensuring that AI-driven decisions respect social norms and equity. This integration:

- Mitigates biases in AI algorithms.

- Ensures transparency and accountability in traffic management.
- Aligns technological interventions with public values and legal frameworks.

Human involvement ensures ethical considerations, legal compliance, and transparency in AI deployment. Humans are accountable for decisions impacting public safety and privacy, helping to address concerns around bias, fairness, and data security [14]. AI systems process vast amounts of data rapidly, identifying patterns and generating insights beyond human capability. However, humans bring contextual understanding, intuition, and ethical judgment. The integration allows for improved decision-making where AI recommendations are validated and contextualized by human experts, leading to more reliable and balanced traffic management [15].

5.6. Enhanced Public Trust and Acceptance

Involving humans in oversight, communication, and policy development fosters trust in AI systems, facilitating:
- Greater public acceptance of AI-driven traffic solutions.
- Improved user compliance and cooperation.
- Continuous feedback loops for system improvement.

Active human roles in monitoring and communicating AI system operations help build public trust. Transparent collaboration between AI and humans reassures stakeholders about system reliability and responsiveness, fostering greater acceptance of intelligent traffic solutions [15, 23].

The fusion of AI capabilities with human expertise creates a synergistic relationship that maximizes the strengths of both. This integration leads to more intelligent, safe, sustainable, and equitable traffic engineering solutions capable of meeting the demands of modern urban mobility.

6. Challenges and Considerations in AI-Human Integration in Traffic Engineering

While the integration of Artificial Intelligence (AI) with human expertise holds immense promise for advancing traffic engineering, it also presents several challenges and considerations that must be carefully addressed to ensure effective, ethical, and sustainable deployment. The integration of AI with human elements in traffic engineering brings notable advancements but also introduces a range of complex challenges that must be carefully managed. These challenges span ethical, technological, operational, and social dimensions, underscoring the need for deliberate planning and governance.

6.1. Ethical and Social Issues

AI systems in traffic engineering often rely on large datasets for training and operation. However, these datasets may reflect existing societal biases, leading to discriminatory outcomes, such as uneven enforcement or resource allocation across different neighbourhoods or demographic groups. Ensuring fairness in AI decision-making is essential to prevent systemic inequalities. Additionally, the widespread deployment of AI requires continuous data collection from road users, raising concerns about privacy and surveillance. There must be clear policies for data governance, including anonymization, data ownership, and user consent.

Table 2. Ethical and social issues

Issue	Description
Bias and Fairness	AI algorithms can inherit biases from training data, potentially leading to unfair or discriminatory outcomes in traffic management, such as disproportionate enforcement or neglect of underserved areas.
Privacy Concerns	Extensive data collection, including video surveillance and vehicle tracking, raises significant privacy issues. Balancing data utility with individual rights is a complex ethical challenge.
Transparency and Accountability	Ensuring AI decisions are explainable and auditable is crucial for maintaining public trust and enabling human operators to effectively oversee AI systems.

6.2. Technological and Operational Challenges

The performance of AI applications heavily depends on the availability of high-quality, real-time data.

Table 3. Technological and operational challenges

Challenge	Description
Data Quality and Availability	AI systems require large volumes of accurate, timely, and comprehensive data. Incomplete, noisy, or biased data can degrade AI performance.
System Integration	Incorporating AI into existing traffic infrastructure often requires costly upgrades and interoperability solutions to bridge legacy and modern systems.

Real-Time Processing Demands	AI algorithms for traffic management must operate with low latency and high reliability, necessitating robust hardware and communication networks.

Many traffic systems still operate with outdated infrastructure and limited sensor networks, which hinders effective AI deployment. Integrating AI into legacy systems presents challenges in interoperability, standardization, and scalability. Furthermore, AI models require regular maintenance, retraining, and validation to remain accurate over time. This operational demand may strain resources and necessitate new roles within transportation agencies, such as data scientists and AI system specialists.

6.3. Human Factors

A significant challenge is building trust and acceptance among stakeholders—traffic engineers, operators, policymakers, and the public. AI decisions must be explainable and transparent to enable human oversight and meaningful intervention. Without a sufficient understanding of AI's capabilities and limitations, operators may underutilize or overly rely on automated systems. Organizational change is also required. Public institutions must adapt workflows, invest in capacity building, and promote interdisciplinary collaboration to ensure effective human-AI integration.

Table 4. Human factors

Key Area	Details
Trust and Acceptance	Operators and the public must trust AI systems for them to be effective. Lack of transparency, unpredictability, or perceived loss of control can lead to resistance.
Skill Gaps	Traffic engineers and operators need training to understand AI tools, interpret outputs, and intervene when necessary, creating a demand for ongoing education and capacity building.
Human-AI Interaction	Designing intuitive interfaces that facilitate effective human-AI collaboration is critical to avoid operator overload or errors.

6.4. Regulatory and Governance Considerations

The rapid pace of AI development has outstripped the evolution of regulatory frameworks. Uncertainty remains around liability in cases of failure or harm caused by AI-driven systems, especially in mixed environments with both human and autonomous agents. Establishing clear guidelines for responsibility and accountability is crucial for safe and lawful AI deployment in traffic contexts.

Table 5. Regulatory and Governance Considerations

Issue	Description
Legal and Liability Issues	Defining responsibility when AI systems fail or cause accidents is legally complex and require clear frameworks.
Standards and Compliance	The absence of universally accepted standards for AI in traffic systems can hinder interoperability and safety assurance.
Policy Development	Dynamic and evolving AI technologies necessitate adaptable regulatory policies that balance innovation with public protection.

6.5. Socioeconomic and Equity Concerns

While the integration of Artificial Intelligence (AI) into traffic engineering presents numerous benefits, it also raises critical concerns related to socioeconomic equity, accessibility, and justice. Without deliberate planning and inclusive governance, AI-enhanced traffic systems risk exacerbating existing inequalities in urban mobility.

Table 6. Socioeconomic and Equity Concerns

Issue	Description
Digital Divide	Disparities in access to AI-enabled technologies may exacerbate existing inequalities in mobility and service quality.
Impact on Employment	Automation may alter workforce requirements, raising concerns about job displacement and the need for workforce transition strategies.

Addressing socioeconomic and equity concerns in AI-human integration is essential for building just and inclusive transportation systems. Planners, engineers, and policymakers must adopt proactive strategies to mitigate algorithmic bias, bridge data and access gaps, and engage diverse communities in the governance of AI-enhanced mobility. Equity must be embedded not as an afterthought but as a foundational principle in the design of future traffic systems.

7. Future Directions for AI-Human Integration in Traffic Engineering

As Artificial Intelligence (AI) continues to evolve and become increasingly integrated into traffic engineering, the future promises deeper and more sophisticated collaboration between AI systems and human professionals. Emerging trends and research directions highlight key areas that will shape the next generation of traffic management solutions. As the field of traffic engineering continues to evolve, the future of AI-human integration promises more intelligent, adaptive, and human-centred transportation systems. Strategic development in both technology and governance will be essential to fully leverage the benefits of this integration while managing its complexities. The integration of Artificial Intelligence (AI) with human expertise in traffic engineering is poised to transform how transportation systems are designed, managed, and evolved. Future directions emphasize not only technical innovation but also the institutional and ethical frameworks necessary for sustainable, trustworthy, and equitable AI deployment. Several key directions are expected to shape the next phase of this evolution.

7.1. Human in the Loop AI Systems

Future traffic systems will increasingly implement *human-in-the-loop* (HITL) AI frameworks, where humans remain actively engaged in the decision-making cycle. These systems will combine the speed and pattern recognition of AI with human ethical reasoning and contextual awareness. HITL models will be particularly valuable in high-stakes situations such as traffic incident management, emergency evacuations, and the regulation of mixed traffic with autonomous and human-driven vehicles. Emerging AI systems in traffic engineering will adopt *human-in-the-loop* architectures, where human operators remain central in monitoring, interpreting, and validating AI decisions. These hybrid systems are crucial for maintaining safety in edge-case scenarios and ensuring ethical decision-making in high-stakes contexts [24]. HITL systems will be vital in managing autonomous vehicle interactions, infrastructure control, and real-time emergency response.

7.2. Development of Digital Twins for Traffic Systems

The adoption of digital twins- virtual replicas of physical traffic systems, will allow for real-time monitoring, simulation, and forecasting. By integrating AI with high-resolution traffic data, digital twins can test policy scenarios, simulate infrastructure changes, and improve the accuracy of predictive models. Human operators and planners will use these systems to validate AI recommendations and explore intervention strategies in a risk-free environment. The use of digital twins—real-time, data-driven virtual representations of physical traffic networks facilitates advanced modelling and scenario testing [25]. These platforms will enable human planners to simulate traffic interventions, forecast congestion outcomes, and refine AI model behaviour under controlled environments, enhancing both system robustness and human oversight.

7.3. Explainable and Transparent AI

The adoption of digital twins—virtual replicas of physical traffic systems—will allow for real-time monitoring, simulation, and forecasting. By integrating AI with high-resolution traffic data, digital twins can test policy scenarios, simulate infrastructure changes, and improve the accuracy of predictive models. Human operators and planners will use these systems to validate AI recommendations and explore intervention strategies in a risk-free environment. To foster trust and accountability, traffic AI systems must be explainable and interpretable. Explainable AI (XAI) techniques will provide insights into algorithmic decisions, allowing traffic engineers and policymakers to understand and contest AI outputs when necessary [28]. Transparency in AI logic is also critical for public trust, especially in decisions affecting urban mobility and surveillance.

7.4 Interdisciplinary Collaboration and Education

The future of AI-human collaboration in traffic engineering will require closer interdisciplinary cooperation across fields such as computer science, urban planning, psychology, and law. Training programs for engineers and transportation professionals will increasingly emphasize AI literacy, ethical considerations, and collaborative problem-solving. Public sector organizations will also need to invest in continuous professional development to stay current with emerging technologies. As AI systems become embedded in public infrastructure, transportation professionals must be equipped with cross-disciplinary knowledge, blending traffic engineering, data science, ethics, and law. Educational institutions and government agencies must invest in AI literacy programs to prepare the workforce for collaborative decision-making in AI-augmented environments [26].

7.5 Robust Governance and Regulatory Frameworks

As AI continues to assume more critical functions in transportation systems, robust governance models will be needed to address accountability, liability, safety, and ethical concerns. International and national guidelines should standardize practices for data use, risk assessment, performance auditing, and public engagement. Adaptive regulatory frameworks will also support innovation while ensuring system safety and equity. The rapid adoption of AI in traffic systems necessitates responsive and adaptive governance models. Regulations must address liability, data privacy, algorithmic bias, and interoperability between AI platforms [29]. International cooperation on AI standards as those proposed by ISO and IEEE, will help harmonize practices and prevent fragmented development across jurisdictions.

7.6 Integration with Sustainable Urban Mobility Goals

AI-human systems will play a pivotal role in supporting broader sustainability goals, such as reducing greenhouse gas emissions, improving public transit efficiency, and enhancing multimodal transport systems. Future AI tools will prioritize not only traffic flow but also environmental performance, social equity, and public health outcomes. Human planners will be instrumental in aligning AI applications with long-term policy visions for sustainable urban mobility. Future AI-human collaborations will align with sustainable urban mobility goals, such as emissions reduction, multimodal integration, and equitable access to transport services. AI systems should optimize not only for flow efficiency but also for social and environmental outcomes. Human oversight ensures that marginalized communities are not excluded from data-driven decision processes [30].

7.7 Ethical AI by Design

Future AI systems will be developed with embedded ethical principles from the outset. This includes fairness in algorithm design, privacy-preserving data methods, and inclusive stakeholder participation. Engineers and designers will collaborate with ethicists and community representatives to ensure AI systems serve the public interest and respect social values. A shift toward *ethics by design* in AI development will embed fairness, accountability, and inclusivity into traffic engineering tools from the outset. Co-design methodologies involving community stakeholders, policymakers, and technologists will ensure that AI systems reflect diverse societal needs and values [27].

8. Future Outlook for AI-Human Integration in Traffic Engineering

The integration of Artificial Intelligence (AI) and human expertise in traffic engineering is poised to fundamentally transform urban mobility over the coming decades. As both technology and societal needs evolve, the future outlook reflects a dynamic interplay between increasingly capable AI systems and indispensable human judgment, collaboration, and governance. The integration of Artificial Intelligence (AI) with human decision-making in traffic engineering is not merely a technical transition, it represents a foundational shift in how mobility systems are conceptualized, governed, and optimized. As urban environments become increasingly complex and data-rich, the partnership between human insight and machine intelligence will become central to the design of responsive, sustainable, and inclusive transportation systems.

8.1 Toward Collaborative Intelligence

Future traffic systems will emphasize *collaborative intelligence*, where AI augments rather than replaces human roles. This paradigm shift envisions engineers, planners, and policymakers working in synergy with AI tools to co-create adaptive strategies that are both efficient and ethically grounded. AI will handle large-scale data analysis, pattern recognition, and real-time control, while humans will contribute contextual understanding, value-based judgment, and strategic vision. The concept of *collaborative intelligence* emphasizes leveraging the complementary strengths of AI and human judgment. AI excels at processing large-scale real-time data and identifying spatiotemporal traffic patterns, while humans bring contextual awareness, ethical reasoning, and adaptive decision-making [37]. Future traffic control systems will increasingly implement human-in-the-loop (HITL) AI architectures, where engineers intervene in high-stakes decisions such as emergency routing, infrastructure failure management, and conflict resolution in mixed traffic environments [40].

8.2 Urban Transformation and Smart City Integration

AI-human integration will increasingly be embedded within the broader *smart city* ecosystem, linking transportation with energy management, urban planning, and public services. Integrated data platforms and cross-sectoral AI models will enable holistic optimization of urban systems. Human oversight will be essential in mediating trade-offs among competing urban priorities, such as speed versus safety, or access versus cost. Traffic engineering will not evolve in isolation but as a core component of interconnected smart city infrastructures. AI-human collaboration will support *cross-domain interoperability* between traffic systems, energy grids, environmental monitoring, and public safety. Digital twins and cyber-physical systems will simulate city-wide mobility scenarios, supporting dynamic interventions [25]. Cities like Helsinki and Amsterdam have begun deploying such frameworks to enhance system responsiveness and environmental sustainability.

8.3 Decentralized and Participatory Governance Models

As traffic systems become more autonomous and algorithm-driven, questions of governance will gain prominence. The future outlook points toward more *decentralized* and *participatory* models of oversight, where communities and local governments are empowered to shape AI applications. Open-data initiatives, algorithmic transparency, and stakeholder engagement will become standard elements of traffic AI governance. AI-driven traffic systems must be governed transparently and inclusively. Future governance models will emphasize *algorithmic accountability*, open data policies, and decentralized decision-making. Technologies such as federated learning allow local authorities to train AI models without centralized data aggregation, addressing privacy concerns while enabling localized optimization [39]. Public dashboards and explainable AI tools will enhance civic engagement and trust in autonomous systems.

8.4 Resilience and Crisis Preparedness

Climate change, pandemics, and geopolitical disruptions are reshaping how cities plan for uncertainty. AI-human systems will be central to building *resilient* traffic networks that can adapt quickly to shocks and disruptions. By simulating extreme scenarios and enabling fast reconfiguration of services, these systems will help ensure continuity of mobility and accessibility even under stress. AI-human systems can bolster infrastructure resilience by enabling *anticipatory responses* to disruptions, including natural disasters, cyber-attacks, or pandemics. For instance, AI models trained on historical disaster data can recommend rerouting strategies or deploy adaptive signal controls during evacuations, while humans monitor and adjust plans in real-time [42]. Post-disruption, engineers can use AI-generated diagnostics to prioritize repairs and resource allocation efficiently.

8.5 Ethical and Social Equity Considerations

Looking ahead, the ethical landscape of AI in traffic engineering will remain a dynamic and critical field of inquiry. Future systems must address disparities in access, avoid algorithmic bias, and support equitable outcomes. Human involvement will be necessary to embed social values into technical systems and to ensure that AI supports, rather than undermines, inclusivity and justice. Ensuring *ethical alignment* and social equity is a cornerstone of future integration strategies. AI systems must avoid reproducing existing biases, such as unequal surveillance or service allocation in marginalized communities [41, 43]. Regulatory frameworks should mandate impact assessments and fairness audits of mobility algorithms. Furthermore, inclusive data governance involving community stakeholders can ensure diverse representation in model training and policy design.

8.6 Technological Evolution and Continuous Learning

Finally, the future will be shaped by ongoing advancements in AI capabilities, such as self-learning algorithms, edge computing, and federated learning, which will reduce data dependency and enhance local decision-making. Human-AI teams will need to engage in *continuous learning*, updating models, frameworks, and skills to remain effective in fast-evolving urban and technological landscapes. The dynamic nature of urban mobility demands *lifelong learning* by both AI systems and human operators. AI systems will incorporate online learning techniques and reinforcement learning to refine decision policies over time. Concurrently, transport professionals must be equipped with interdisciplinary skills in AI ethics, data science, and urban planning to effectively collaborate with these systems [38]. Capacity-building programs and academic-industry partnerships will play a key role in workforce adaptation.

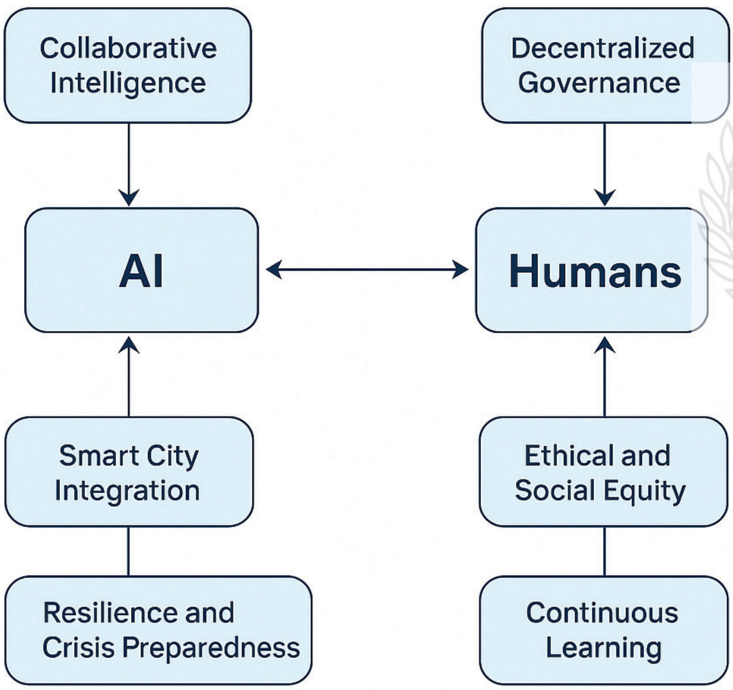

Figure 1. Future outlook for AI-human integration in traffic engineering

9. Case Studies AI-Human Integration in Traffic Engineering

Real-world implementations of AI-human integration in traffic engineering demonstrate the practical benefits, challenges, and lessons learned from combining artificial intelligence with human expertise. The following case studies highlight diverse approaches and outcomes across different urban contexts.

9.1. Adaptive Traffic Signal Control in Pittsburgh, USA

Pittsburgh's Surtrac (Scalable Urban Traffic Control) system represents a pioneering example of AI-human collaboration in urban traffic management. Developed by researchers at Carnegie Mellon University, Surtrac utilizes real-time data from roadway sensors, cameras, and connected vehicles to dynamically optimize traffic signal timings at intersections. The AI algorithms predict traffic flows and adjust signals locally while coordinating with neighbouring intersections to improve overall network efficiency.

Traffic engineers and operators continuously monitor Surtrac's performance through interactive dashboards that visualize traffic patterns, signal timings, and system alerts. Human operators can override AI controls in case of unusual traffic incidents, roadworks, or events. Additionally, engineers update the system's parameters and machine learning models based on evolving traffic conditions and seasonal variations.

Outcomes and Impact:
- Reduction in average travel times by approximately 25%, leading to smoother traffic flows.
- Emissions and fuel consumption dropped by an estimated 21%, contributing to environmental sustainability.
- Increased safety due to reduced vehicle idling and abrupt stops.
- The system's transparent design and operator involvement enhanced trust and facilitated smooth adoption by local traffic authorities.

Pittsburgh's Surtrac system leverages real-time sensor data and AI algorithms to optimize traffic signal timings at intersections dynamically. Human traffic engineers continuously monitor the system, intervening as necessary and refining operational parameters to adapt to evolving traffic conditions. This collaboration has led to a 25% reduction in travel time and a 21% decrease in emissions [35].

9.2. AI-assisted Incident Detection in Singapore

Singapore's Land Transport Authority (LTA) has integrated AI-powered video analytics into its expressway management to enhance rapid incident detection and response. Cameras installed along key expressways feed continuous video streams to AI systems that employ computer vision and deep learning techniques to identify accidents, stalled vehicles, and debris on roadways.

Once AI flags a potential incident, human operators at the Traffic Management Centre verify the alerts via video feeds and coordinate immediate responses with emergency services and road maintenance teams. This human verification is crucial to filter out false positives caused by environmental factors such as shadows, weather, or camera malfunctions.

Outcomes and Impact:

- Incident detection time was reduced by more than 50%, enabling quicker dispatch of response teams.
- Faster incident clearance minimized secondary crashes and congestion ripple effects.
- The hybrid system improved overall traffic safety and commuter satisfaction.
- Human oversight ensured reliability and maintained public confidence in AI monitoring.

Singapore's Land Transport Authority integrates AI-powered video analytics for rapid incident detection on expressways. While AI flags potential incidents, human operators verify these alerts before coordinating emergency responses. This hybrid approach has halved incident detection times and improved overall traffic safety [7].

9.3. Smart Public Transit Management in Helsinki, Finland

Helsinki's public transit system integrates AI-driven analytics with human planning to optimize routes, schedules, and resource allocation dynamically. Using data from passenger counts, vehicle locations, and traffic conditions, AI models predict demand patterns and potential delays.
Transit planners and operators analyze AI-generated insights to make informed decisions on adjusting service frequency, rerouting buses during disruptions, and managing fleet deployment. Human judgment ensures that AI recommendations consider socio-economic factors, community needs, and long-term urban mobility strategies.

Outcomes and Impact:
- Improved service reliability and punctuality, with fewer delays and missed connections.
- Increased passenger satisfaction due to more responsive and flexible service.
- Efficient use of fleet resources, reducing operational costs.
- Maintained equity in service provision, ensuring vulnerable populations are not underserved.

Helsinki employs AI-driven demand forecasting to optimize transit routes and schedules. Human planners interpret AI insights to adjust service deployment, ensuring reliability and equitable service distribution. This AI-human integration has enhanced punctuality and passenger satisfaction while reducing operational costs [6].

9.4. Autonomous Vehicle Integration in Phoenix, USA

Waymo operates one of the largest commercial autonomous vehicle (AV) fleets in Phoenix, navigating complex urban environments that include human drivers, pedestrians, and cyclists. While AI powers vehicle perception and decision-making, human safety drivers and remote operators oversee operations to manage edge cases and intervene if necessary.

Safety drivers remain ready to take control in unforeseen situations, while remote operators provide assistance during complex manoeuvres or technical anomalies. Human teams analyze AV performance data to continually improve algorithms and ensure compliance with local traffic regulations.

Outcomes and Impact:
- Demonstrated safe and reliable autonomous driving with a growing number of miles driven without incident.
- Validated the importance of human-AI teamwork in managing unpredictable urban conditions.
- Provided critical data for advancing AV technology and regulatory frameworks.
- Enhanced public awareness and trust through transparent reporting and safety measures.

Waymo's autonomous fleet in Phoenix operates under continuous human oversight, with safety drivers ready to intervene and remote operators assisting in complex scenarios. This collaboration has demonstrated high safety performance and provided critical data for improving autonomous driving algorithms [4].

9.5. AI-enhanced Traffic Management in Barcelona, Spain

Barcelona's smart city initiative incorporates AI systems to manage traffic signals, parking, and pedestrian flows, working in conjunction with human operators. AI integrates data from IoT sensors, mobile apps, and social media to provide real-time situational awareness.

City traffic managers use AI dashboards to monitor traffic conditions, predict congestion, and coordinate responses to special events or emergencies. Humans adjust AI parameters and enforce policies to balance traffic efficiency with urban livability and environmental goals.

Outcomes and Impact:
- Reduced congestion and improved air quality in key urban zones.
- Increased adaptability during events and disruptions through proactive human-AI collaboration.
- Fostered community engagement by integrating citizen feedback into AI system tuning.
- Set a model for scalable AI-human traffic management in dense metropolitan areas.

Barcelona's smart city traffic management uses AI to analyze data from IoT devices, social media, and mobile apps. Human operators adjust AI parameters and enforce policies to optimize traffic flow and environmental outcomes. This system has successfully reduced congestion and improved air quality in urban areas [14].

10. Conclusion

Increasing urbanization and mobility demands require smarter, more adaptive traffic systems. AI technologies bring automation, predictive analytics, and real-time decision-making capabilities. Rather than replacing humans, AI is designed to augment human decision-making and operational efficiency.
The human role in AI-driven traffic engineering is multifaceted, blending technical expertise, ethical stewardship, and social engagement. This partnership between human intelligence and artificial intelligence is essential for creating adaptive, resilient, and equitable traffic systems that effectively respond to evolving urban mobility challenges.
The future of AI-human integration in traffic engineering is marked by collaborative intelligence, where machines enhance human capabilities without supplanting them. Advances in technology, governance, and human factors will

collectively shape resilient, efficient, and socially responsible traffic systems that adapt seamlessly to the complexities of urban mobility.

The future of AI-human integration in traffic engineering lies in developing systems that balance technological intelligence with human insight and responsibility. By advancing HITL models, digital twin environments, explainable AI, and inclusive governance, the field can move toward more adaptive, ethical, and resilient traffic systems that meet the demands of 21st-century urban life.

The trajectory of AI-human integration in traffic engineering envisions collaborative, transparent, and sustainable systems. Central to this evolution is the embedding of human judgment, ethical safeguards, and institutional capacity within advanced AI infrastructures. This dual-centred approach offers a resilient pathway for navigating the complex demands of modern transportation systems.

AI's integration into traffic engineering must be balanced with human insight to create effective and ethical systems. The synergy between AI technologies and human professionals offers the potential to revolutionize traffic engineering, making transportation systems more responsive, sustainable, and inclusive.

The integration of AI and humans in traffic engineering combines the computational power of machines with human contextual intelligence and ethical judgment. This collaboration enhances operational efficiency, safety, adaptability, and public trust, paving the way for smarter and more resilient traffic management systems.

A balanced coexistence between AI and human expertise should lead to smarter, safer, sustainable, and more adaptable traffic systems.

AI is not a replacement for human roles in traffic engineering but a powerful partner. The future of traffic systems lies in creating synergies between AI capabilities and human judgment to achieve safer, more efficient, and sustainable mobility.

The integration of AI in traffic engineering marks a pivotal evolution in transportation systems, offering advanced tools for real-time management, predictive analytics, and automation.

AI systems are vulnerable to cyber threats, including data breaches, model manipulation, and infrastructure sabotage. As traffic control systems become more connected, they also become more exposed to potential attacks. Ensuring robust cybersecurity protocols and contingency planning is vital to maintaining operational resilience.

Addressing the challenges of AI-human integrationrequires a multidisciplinary approach involving engineers, data scientists, ethicists, policymakers, and the public. Proactive governance, transparent AI development, and inclusive stakeholder engagement are essential to harness the full potential of AI-human integration in traffic engineering while mitigating risks.

The future of AI-human integration in traffic engineering envisions a synergistic relationship where technological innovation and human insight coalesce to address complex mobility challenges. By fostering adaptive collaboration, ethical stewardship, and inclusive design, this integration promises to create resilient, efficient, and people-centred transportation systems for the cities of tomorrow. As cities face mounting pressures from urbanization, climate change, and technological disruption, the co-evolution of artificial and human intelligence will be key to creating traffic systems that are not only efficient but also ethical, resilient, and adaptive. Realizing this vision will require sustained investment in education, regulation, cross-sector collaboration, and public trust.

Case studies presented in this paper illustrate that successful AI-human integration in traffic engineering relies on complementary roles. AI excels in data processing and automation, while humans contribute oversight, ethical judgment, and contextual understanding. Effective interfaces, training, and governance are essential to maximize system benefits and public acceptance.

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Mathematical Modeling Behind Recurrent Neural Networks

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Abstract: *Picture this: a world where machines can decode the intricate rhythms of the human body, tracing electrical patterns from the brain and heart to uncover hidden signs of disease. Artificial intelligence has brought this vision closer to reality, transforming electroencephalography (EEG) and electrocardiography (ECG) analysis into a sophisticated fusion of data science and medicine. Yet, the journey is far from complete. Biomedical signals are notoriously complex—drenched in noise, prone to variability, and demanding meticulous preprocessing before they reveal their secrets. This review embarks on a deep dive into the essential preprocessing and feature engineering techniques that refine raw EEG and ECG data, making them suitable for intelligent analysis. From signal filtering to wavelet transformations, each step in the pipeline plays a crucial role in shaping AI's ability to detect meaningful patterns. Particular attention is given to recurrent neural networks (RNNs), which excel in capturing the temporal dependencies hidden within these signals but come with their own set of computational hurdles. Beyond technical refinement, the discussion extends into the future—how can multimodal AI enhance clinical diagnostics?*

Keywords: *deep learning, artificial intelligence, recurrent neural network, biomedical engineering*

1. Introduction

With new technologies on the rise, AI is redefining how clinical diagnostics interprets and utilizes patient information, offering tools that process data with extraordinary precision and speed. Diagnostic techniques (with previously mentioned EEG and ECG included) have traditionally required extensive manual analysis, relying on clinicians to carefully scrutinize signal patterns. While effective, these methods were timeconsuming and constrained by the natural limitations of human capacity. AI completely transforms this approach. By leveraging advanced algorithmic systems, it not only accelerates data processing but also identifies relationships and subtle variations within complex signals that might otherwise go unnoticed. These capabilities allow AI to convert disorganized inputs into meaningful clinical evaluations, enabling healthcare providers to act with greater confidence and efficiency [1-4].

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Beyond speeding up diagnostics, AI introduces a proactive element to healthcare. Traditional systems often waited for symptoms to emerge before action could be taken. Now, AI anticipates potential risks by analyzing patterns that signal disease development at earlier stages. For instance, it can detect inconsistencies in heart rhythms that indicate cardiac conditions before they worsen. Similarly, AI applied to EEG studies highlights neural irregularities that may suggest cognitive decline or seizure risks. This early detection empowers clinicians to intervene sooner, creating opportunities for personalized care within preventative medicine, which reduces longterm health risks [5, 6].
What sets AI apart is its ability to evolve. Unlike rigid diagnostic frameworks, AI continuously learns from new datasets, adapting its methods to suit diverse medical contexts. This adaptability is especially critical in complex cases where traditional approaches struggle to interpret atypical signals. For example, AI has proven effective at decoding uncommon variations in neural or cardiac data where established norms may not apply. By doing so, it bridges the gap between raw information and actionable decisions, elevating diagnostics to a new level of precision and reliability. As AI becomes more integrated into healthcare, it transcends its role as a support tool to become a collaborative partner, shaping the future of personalized medicine [5].

2. Artificial Intelligence in Clinical Diagnostics

Artificial intelligence has introduced an unprecedented level of sophistication to diagnostic medicine, seamlessly blending efficiency with precision. By processing vast and complex datasets, AI can uncover patterns and relationships that often escape even the most seasoned clinicians. In cardiology, for instance, AI systems analyze the nuanced changes in electrocardiogram waveforms, pinpointing subtle irregularities that might signal early signs of heart failure or arrhythmias.

Table 2.1. The entire concept of artificial intelligence getting along with traditional diagnostics

Comparison of AI vs. Traditional Diagnostics	AI-Powered Diagnostics	Traditional Diagnostics
Data Analysis Speed	Real-time, automated	Time-intensive, manual
Accuracy	High, with predictive capabilities	Variable, dependent on clinician skill
Scalability	Handles large datasets simultaneously	Limited by human capacity
Personalization	Tailored insights to individual patient data	Generalized recommendations

In the field of neurology, AI elevates the interpretation of electroencephalograms by decoding intricate neural activity, aiding in the timely diagnosis of epilepsy or the progression of cognitive impairments [4, 5, 7]. Beyond its ability to identify abnormalities, AI provides a predictive edge, enabling physicians to anticipate patient trajectories and make informed decisions regarding personalized treatment plans. While its potential to revolutionize diagnostics is undeniable, the integration of AI is not without challenges. Ensuring that algorithms are transparent and trained on diverse datasets remains critical to avoiding biases and achieving equitable healthcare outcomes [5, 6]. Yet, even with these obstacles, AI continues to redefine the boundaries of what diagnostic medicine can achieve.

2.1. EEG and ECG Inclusion

The application of artificial intelligence in electrocardiography has fundamentally transformed the scope and efficiency of cardiac diagnostics. By automating routine processes, AI enables clinicians to focus on interpreting complex cases rather than being bogged down by repetitive analyses. For example, AI systems can detect myocardial infarctions and arrhythmias with remarkable accuracy, allowing for early intervention and better outcomes. Beyond detecting immediate concerns, AI excels in predictive capabilities, using historical ECG data to assess the risk of conditions such as stroke or sudden cardiac arrest. This predictive layer empowers healthcare providers to implement preventative strategies, reducing mortality rates and improving quality of life for patients [8]. On top of that, AI significantly enhances workflow efficiency by processing large volumes of ECG data rapidly, freeing up clinicians to concentrate on nuanced decision-making for their patients [8, 9]. As AI becomes an integral part of cardiology, it is essential to ensure that it complements human expertise, fostering collaboration between cutting-edge technology and clinical judgment. Balancing this partnership will be key to unlocking the full potential of AI in revolutionizing ECG diagnostics.

Electroencephalography, a cornerstone in neurological diagnostics, has undergone a transformative evolution with the integration of artificial intelligence. Historically, interpreting EEG signals was a painstaking process, requiring specialists to manually sift through waveforms in search of meaningful patterns. This approach, while valuable, was inherently limited by human effort and the potential for oversight. Artificial intelligence, however, has revolutionized EEG analysis by automating many aspects of interpretation. AI systems excel at identifying subtle, yet critical, anomalies in neural activity that might go undetected by traditional methods. For example, algorithms are capable of pinpointing epileptiform discharges in real-time, drastically reducing the time to diagnosis and increasing accuracy [10].

Beyond epilepsy, AI-driven EEG applications extend to broader areas of brain health. In sleep studies, for instance, AI tools analyze intricate neural oscillations to identify irregularities in sleep architecture, enabling the diagnosis of conditions like insomnia or sleep apnea. In the context of cognitive health, AI leverages EEG data to track changes in brain function associated with neurodegenerative diseases such as
Alzheimer's or Parkinson's. These systems are not only capable of detecting existing conditions but also of identifying subtle precursors, allowing clinicians to intervene earlier than ever before. Such applications demonstrate AI's potential to shift EEG from a diagnostic tool to a predictive instrument that actively shapes treatment strategies. A particularly groundbreaking aspect of AI in EEG diagnostics is its ability to visualize and analyze neural connectivity. By mapping the interactions between different regions of the brain, AI uncovers how these regions communicate during normal and pathological states. For example, connectivity maps may reveal disruptions in neural networks associated with disorders such as autism spectrum disorder or traumatic brain injury. This deeper layer of analysis provides clinicians with insights that were previously inaccessible, paving the way for precision therapies tailored to the unique neural profiles of individual patients [11].
Integrating artificial intelligence into EEG workflows has also made these systems more adaptable to clinical realities. Unlike traditional methods, which rely on static protocols, AI algorithms learn and improve continuously, refining their performance with every dataset they encounter. This adaptability is particularly valuable in complex cases, such as atypical seizure presentations or rare cognitive disorders, where traditional EEG analysis might falter. By bridging the gap between raw neural data and actionable insights, AI enhances the reliability of EEG diagnostics while expanding its scope. As these technologies continue to advance, they are redefining how we understand and treat neurological conditions, enabling a future where personalized and predictive care is the norm [12].

2.2. Ethics Above All

As artificial intelligence gains traction in medical diagnostics, it comes with it a slew of new difficulties that must be addressed. One key worry is the fairness and inclusion of the datasets used to train AI models. If the training data is insufficiently diverse, the resulting algorithms may struggle to generalize across populations, potentially leading to incorrect diagnoses for underrepresented groups. This bias can unintentionally cause gaps in healthcare access and quality, underlining the importance of data that captures the whole range of human variability [13].

Another major concern is the protection of patients' privacy. Medical records are among the most sensitive types of personal information, and incorporating AI into diagnosis creates additional dangers. Because these systems handle large volumes of patient data, effective cybersecurity measures are required to prevent breaches and illegal access. Ensuring compliance with privacy standards, such as HIPAA or GDPR, has become an essential component of designing reliable AI systems. Beyond privacy concerns, the "black box" aspect of some AI models poses a hurdle for therapists. If the logic behind a diagnosis or prediction is unclear, clinicians may lose trust in the system, making it harder to defend AI-generated suggestions to their patients. This lack of openness may diminish trust in AI as a diagnostic tool [12].

Addressing these issues requires a coordinated effort involving researchers, developers, physicians, and policymakers. Developers must create AI systems that prioritize interpretability, allowing users to comprehend and confirm decision-making processes. Meanwhile, clinicians must have the required skills and training to successfully integrate AI tools into their workflows. Finally, healthcare policymakers must develop clear standards for using AI responsibly and ethically. By addressing these concerns head on, we can create a future in which AI-driven diagnoses are egalitarian and secure, while also driving trust and creativity [14].

AI in combination with clinical diagnostics aims for transformative advancements in patient care. Wearable devices equipped with biosensors are among the most promising developments, offering continuous monitoring of vital physiological signals. These AI-powered technologies hold the potential to detect early warnings of health issues before symptoms become clinically apparent. For example, wearable ECG devices integrated with AI could track subtle arrhythmic patterns, identifying early signs of cardiac stress that might otherwise be missed during routine checkups. Similarly, continuous EEG monitoring via portable devices could provide insights into abnormal neural activity, such as early seizure indicators or cognitive decline, enabling clinicians to intervene proactively [15, 16]. Such real-time monitoring could shift the paradigm from reactive to preventative care, empowering both patients and healthcare providers to act before conditions escalate.

Beyond wearable technologies, AI’s ability to integrate data from multiple diagnostic modalities offers unprecedented opportunities for precision medicine. By combining information from ECG, EEG, imaging technologies, genetic profiles, and even blood biomarkers, AI systems can provide a comprehensive view of a patient’s health. For instance, AI could analyze EEG data alongside structural brain imaging to identify not only epilepsy but also underlying abnormalities that may guide surgical interventions. Similarly, integrating cardiac biomarkers with AI-enhanced ECG interpretations could identify stress patterns indicative of heart failure, informing personalized treatment strategies tailored to each patient's unique needs [16]. This multimodal approach has the potential to address complex medical conditions with unparalleled accuracy and depth.

Equally significant is the evolution of human-AI collaboration in diagnostics. The future of AI will likely emphasize transparency, with systems designed to explain their reasoning and outputs clearly to clinicians. This interpretability will enable healthcare professionals to validate AI-generated insights, fostering trust and ensuring that these tools enhance rather than replace clinical expertise. Such transparency is critical in high-stakes settings, such as cardiac surgeries or neurodegenerative disease management, where the implications of diagnostic decisions are profound [17]. By augmenting human intuition with computational precision, AI can transform diagnostics into a collaborative process where machines and clinicians work seamlessly to improve patient outcomes.

Table 2.2. Examples of trends in the utility of AI in EEG and ECG devices and algorithms along with its possible outcome

Emerging Trends in AI Diagnostics	Examples	Impact
Continuous Monitoring via Wearables	Smartwatches with ECG/EEG sensors	Real-time anomaly detection and early interventions
Multimodal Diagnostic Systems	Combining imaging, blood tests, and EEG/ECG data	Comprehensive patient health assessments
Personalized AI Models	Algorithms tailored to individual genetic and health data	Precision medicine and targeted treatment plans

The ultimate promise of AI in diagnostics lies not just in its ability to improve accuracy, but in its capacity to revolutionize how healthcare is delivered. With its applications in real-time monitoring, data integration, and decision support, AI is steering healthcare toward a model that is more proactive, patient-centered, and personalized. This evolution ensures that care will not only address current conditions but also anticipate and prevent future risks, offering patients a higher quality of life and clinicians a more effective set of tools to manage complex medical challenges [14].

3. Diving Into the Complexity of Neural Networks

Neural networks represent the magical web of modern artificial intelligence, and they are computational frameworks inspired by the brain's ability to process and interpret information. These models consist of layers of interconnected processing units, referred to as artificial neurons, which collaborate to analyze data and uncover patterns that are often invisible to traditional analytical techniques. Unlike static rule-based approaches, neural networks dynamically adapt to the data they encounter, making them particularly valuable for complex applications such as speech processing, autonomous decision-making, and biomedical signal analysis [18].

The underlying strength of neural networks lies in their iterative learning process. Each connection between neurons is associated with adjustable parameters, namely weights and biases, which determine the influence of one neuron on another. As data flows through the network, the prediction errors—quantified by a loss function—serve as feedback for fine-tuning these parameters. This adjustment process, guided by optimization algorithms like gradient descent, allows the network to progressively refine its outputs with each iteration. Over time, the network evolves from producing rudimentary predictions to achieving a high level of accuracy, capable of interpreting raw, unstructured data with remarkable precision [19].

One of the most striking advantages of neural networks is their ability to model nonlinear, highly intricate relationships in data. This is in stark contrast to traditional techniques, which rely on fixed equations and predetermined assumptions. Neural networks autonomously learn to extract meaningful patterns directly from the data, which has enabled specialized architectures to emerge. For instance, convolutional neural networks are designed to analyze spatial features, making them indispensable in image-processing tasks. Similarly, recurrent neural networks excel at capturing temporal dependencies in sequential data, such as time-series signals or language patterns. These architectural advancements have significantly extended the capabilities of neural networks, enabling their adoption in domains that demand rigorous precision, such as medical diagnostics, robotics, and engineering. Today, neural networks stand as an essential tool in the pursuit of innovative, data-driven solutions to complex challenges [19].

3.1. Following the Steps of Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are a specialized type of neural network uniquely suited for processing data that unfolds over time. Unlike traditional neural networks, which process inputs independently, RNNs are designed to handle sequential information by maintaining a form of memory that allows them to link previous inputs with current data. This temporal dependency makes RNNs particularly effective in tasks such as time-series forecasting, natural language processing, and biomedical signal analysis, where understanding the relationships between events or data points in sequence is crucial [19].

The defining feature of RNNs is their ability to process inputs in a way that mirrors the sequential nature of many real-world phenomena. Each input is not treated in isolation; instead, the network uses its internal states to store and recall information from prior steps. This capability enables RNNs to interpret data contextually, making sense of patterns that only emerge when considering the progression of inputs over time. For instance, in analyzing an electrocardiogram, an RNN can detect subtle changes in heart rhythms by linking one heartbeat to the next. Similarly, in EEG data, it can identify trends in brainwave activity that might indicate neural irregularities. Training an RNN involves iteratively improving its parameters to ensure the network can accurately predict outcomes based on sequences of input data. The learning process hinges on adjusting the weights that govern how inputs and internal states influence the network's predictions. However, traditional RNNs are known to encounter challenges when working with long sequences. Specifically, they may struggle with what is known as the vanishing gradient problem, where the mathematical signals that guide learning diminish over time, hindering the network's ability to retain long-term dependencies. This limitation has spurred the development of more advanced architectures, such as Long Short-Term Memory (LSTM)networks and Gated Recurrent Units (GRUs). These models introduce mechanisms to control the flow of information, allowing the network to selectively retain or forget specific details as needed, significantly improving performance in complex scenarios [20].

RNNs have been transformative in biomedical engineering, where the analysis of sequential data is essential. For example, they have been used to predict cardiac events by analyzing the sequential patterns in ECG data, identifying anomalies that might signal arrhythmias. Similarly, in EEG analysis, RNNs have been leveraged to detect epileptic seizures by interpreting changes in brainwave patterns over time. Beyond diagnostics, RNNs play a pivotal role in predictive healthcare by analyzing patient data to foresee potential complications, enabling earlier interventions and personalized care strategies [20].

By introducing a new paradigm for processing temporal data, RNNs have unlocked possibilities across numerous domains, particularly in healthcare, where the ability to model dynamic processes is critical. Their continued evolution and integration with other advanced architectures promise to further expand their applicability, making them indispensable in advancing data-driven solutions for complex, time-dependent challenges.

3.2. The Mathematical logic Behind Recurrent Neural Networks

The structure of recurrent neural networks and their complex nature allow them to process sequential data such as language, time-series signals, and data, as well as audio records, where the order of inputs significantly impacts the output. Beginning with the hidden state dynamics, the primary equation represents the computation of the hidden state $\boldsymbol{h_t}$ which serves as the memory of the network at time $\boldsymbol{t}$. The hidden state is determined by combining the current input vector $\boldsymbol{x_t}$ and the previous hidden state $\boldsymbol{h_{t-1}}$. The weights $\boldsymbol{W_{xh}}$ control how the input $\boldsymbol{x_t}$ influences the hidden state, while $\boldsymbol{W_{hh}}$ governs the recurrent connections that link $\boldsymbol{h_{t-1}}$ to $\boldsymbol{h_t}$. The bias term $\boldsymbol{h_t}$helps shift the activation function, ensuring the network does not get stuck in suboptimal configurations. Finally, the **Tanh** function introduces non-linearity, enabling the network to model complex relationships in the data [19]:

$$\boldsymbol{h_t} = \mathbf{tanh}(\boldsymbol{W_{xh}} + \boldsymbol{W_{hh}}\boldsymbol{h_t} \boldsymbol{-1} + \boldsymbol{b_h})$$

The recursive nature of this equation allows RNNs to maintain information from prior time steps, making them well-suited for sequential data. For example, in a biomedical application like analyzing ECG signals, this memory enables the RNN to track the progression of cardiac patterns over time [20].
The output, annotated as $\boldsymbol{y_t}$at a time step $\boldsymbol{t}$ is derived from the hidden state $\boldsymbol{h_t}$ using a weight matrix $\boldsymbol{W_{hy}}$and a bias term $\boldsymbol{b_y}$. This equation ensures that the information stored in the hidden state is translated into a format suitable for the specific task, such as predicting a numerical value or classifying an event.
Technically said, $\boldsymbol{y_t}$ could represent a prediction of whether a patient's heart rhythm is normal or indicative of an anomaly. The parameters $\boldsymbol{W_{hy}}$ and $\boldsymbol{b_y}$ are learned during the training process to optimize the network's predictive accuracy [19]:

$$\boldsymbol{y_t} = \boldsymbol{W_{hy}}\boldsymbol{h_t} + \boldsymbol{b_y}$$

The loss function is annotated as J and it quantifies the discrepancy between the predicted outputs $\hat{\boldsymbol{y_t}}$ and the true labels $\boldsymbol{y_t}$over a sequence of length *T*. The summation ensures that the network learns to minimize the cumulative error across all time steps in the sequence. The choice of the loss function □ depends on the specific task. For example, the mean squared error MSE is used for regression tasks where the outputs are continuous, while the cross-entropy loss is applied in classification tasks and it serves to measure the divergence betweenpredicted probabilities and true labels.

By minimizing $\boldsymbol{J}$, the network learns to generate outputs that closely match the ground truth, improving its performance over time [19]:

$$\boldsymbol{J} = \sum_{t=1}^{T} \mathcal{L}(\boldsymbol{y_t}, \widehat{\boldsymbol{y}}_t)$$

Backpropagation Through Time **(BTT)** whose weight matrix is given by:

$$\frac{\partial \boldsymbol{J}}{\partial \boldsymbol{W}} = \sum_{t=1}^{T} \frac{\partial \boldsymbol{J}}{\partial \boldsymbol{ht}} \times \frac{\partial \boldsymbol{ht}}{\partial \boldsymbol{W}}$$

represent the gradients of the loss function concerning its model parameters. The parameters are computed using this method which involves a process called unrolling of the RNN across time steps, so the gradients are computed for each parameter. The gradients are then finally summoned to update the neural parameters. Despite its beautiful architecture, BPTTs are computationally problematic and very intensive – they are susceptible to the problem of vanishing gradient, where gradients are shrinking and become way too small to execute updates in the long run. This is the main reason why GRUs and LSTMs were developed in order to address this issue, as advanced RNN architectures [19]:

Long Short-Term Memory (LSTM) networks help avoid gradient issues via gating mechanisms which help regulate the flow of information throughout the networks. Getting to know the core computations in LSTM is crucial in order to understand the importance of LSTM integration, and they consist of:
Forget gate which determines what information is going to get discarded:

$$\boldsymbol{f_t} = \boldsymbol{\sigma}(\boldsymbol{W_f} \times [\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_f})$$

Input Gate that decides what information should be added:

$$\boldsymbol{i_t} = \boldsymbol{\sigma}(\boldsymbol{W_i} \times [\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_i})$$

Output gate that controls the information that the neural network yields:

$$\boldsymbol{o_t} = \boldsymbol{\sigma}(\boldsymbol{W_o} \times [\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_o})$$

The sigmoid annotation here represents the activation function that controls the output of the network.

The cell state update equation shows how the cell state $\boldsymbol{c_t}$ in the LSTM network gets updated by each step, while the forget gate helps the network determine how much of the previous cell state is held back ($\boldsymbol{c_{t-1}}$). The input gate ($\boldsymbol{i_t}$) determines the quantity of new information $\tilde{\boldsymbol{c}}_t$ that gets incorporated. There is also an element-wise multiplication ($\odot$) in charge of ensuring that all operations are performed independently for each one of the cell units within the network.

$$\boldsymbol{c_t} = \boldsymbol{f_t} \odot \boldsymbol{c_{t-1}} + \boldsymbol{i_t} \odot \tilde{\boldsymbol{c}}_t$$

LSTMs are there to help us solve the vanishing gradient successfully – by maintaining the consistency of the cell state and storing our information over long sequences. This is the exact reason why LSTMs are so effective for tasks like EEG and ECG analysis, where they can capture long-term dependencies and are therefore crucial for identifying irregularities in any irregularities present [20]:

LSTM Hidden State Update is computed using the current cell state and the output gate, and it controls how much of the cell state gets exposed to the remaining parts of our network. Tanh function (non-linear activation function) is there to secure the bounded output remains and stabilize the learning process of the network, as observed in the equation below.

$$\boldsymbol{h_t} = \boldsymbol{o_t} \odot \tanh(\boldsymbol{c_t})$$

Table 3.1. Key mathematical differences that stand on the foundation of RNN and LSTM architectures

Feature	RNN	LSTM
Memory Retention	Short-term memory via hidden states	Long-term memory via cell states
Activation Function	Typically, Tanh but sometimes ReLU	Includes Tanh sigmoid, and gating functions
Vanishing Gradients	Susceptible	Controlled through gating mechanisms
Architecture	Simple recurrent structure, susceptible to vanishing gradients	Complex gating structure
Key Equations	$ht = \tanh(Wxh + Whhht-1 + b_h)$	Includes **forget, input, and output gates**

This sophisticated mechanism, described through mathematical equations, depicts how LSTMs focus on relevant pieces of information one step at a time, and enables versatility in handling sequential data and avoiding vanishing gradients. In clinical diagnostics, this capability enables the identification of faint changes in patient data, such as warning signs of epileptic seizures in EEG *(Rajpurkar et al., 2017).*

4. The Possible Synergy of Multimodal Systems in Terms of EEG and ECG Data Analysis

The integration of artificial intelligence in analyzing EEG and ECG data through multimodal fusion offers clinicians a more comprehensive understanding of a patient's health. This approach not only enhances diagnostic accuracy but also elucidates the intricate connections between cardiac and neural functions. Multimodal systems may exemplify the transformative potential of AI-driven tools, as they are designed to integrate and analyze dynamic physiological signals, uncovering insights that would otherwise remain obscured [6].
Recurrent neural networks have opened new possibilities in clinical diagnostics by integrating diverse biomedical data sources into unified analytical frameworks. Their ability to model sequential dependencies allows for a deeper exploration of temporal patterns across modalities such as imaging, physiological signals, and clinical records. For instance, analyzing EEG and ECG data in tandem enables the identification of nuanced relationships between neural activity and cardiac rhythms, which might be overlooked when using single-modality approaches [21]. By bridging gaps between these data types, RNNs not only refine diagnostic precision but also contribute to a more comprehensive understanding of interconnected physiological systems [22]
In the field of neurodegenerative diseases, RNNs excel at detecting gradual and subtle changes in the brain that static diagnostic tools often miss. These networks process longitudinal data, such as sequential brain scans or neural activity records, to identify early signs of conditions like Alzheimer's disease. By recognizing trends in clinical and imaging data, RNNs provide valuable insights into the early onset of cognitive decline [7]. Expanding this approach to include EEG and ECG integration offers an exciting opportunity to explore how neural and cardiovascular health interact, potentially uncovering novel markers for disease progression and early intervention.

The versatility of RNNs also shines in cancer diagnostics, particularly in their ability to merge data from diverse sources like radiological imaging, histopathological analyses, and patient profiles.
Beyond diagnostics, RNNs extend their utility to predicting disease trajectories and monitoring treatment responses. By analyzing temporal data with innovative

methods like time-sensitive attention mechanisms, these networks can capture shifts in physiological states, offering a clearer picture of how conditions develop or resolve over time. Advanced multimodal fusion frameworks demonstrate the power of RNNs in integrating heterogeneous datasets. These systems align information from varied formats, such as time-series signals, tabular data, and images, to provide a unified perspective on patient health. The use of hierarchical structures within RNNs enhances their ability to identify cross-modal relationships, uncovering complex correlations that traditional methods might miss.

5. Conclusion

Much like the brain itself, RNNs retain memory, recognize long-term dependencies, and refine their understanding with every dataset they encounter. But intelligence is not built on algorithms alone. The true power of AI emerges when meticulous preprocessing meets sophisticated feature engineering, distilling raw data into meaningful representations. It is this synergy between data refinement and deep learning that allows AI to detect anomalies, predict health risks, and support clinical decision-making with unprecedented accuracy. As research pushes forward, multimodal AI systems—those capable of integrating EEG, ECG, imaging, and genetic data—stand at the frontier of precision medicine. The fusion of these technologies promises a future where diagnostics are faster, personalized, and seamlessly embedded into real-time clinical workflows. Nevertheless, he true impact of AI in medicine will not be determined by algorithms alone. It will be shaped by the scientists who build these systems, the clinicians who apply them, and the patients whose lives they transform. The journey is just beginning, and with every breakthrough, AI moves closer to fulfilling its ultimate promise—not to replace human expertise, but to amplify it, unlocking a new era of intelligent, data-driven healthcare.

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Machine Learning Modelling of CO_2 Emissions for Sustainable Development: A Comparative Study of Bosnia and Herzegovina, Croatia, and Slovenia

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Abstract: *The growing need for reducing CO_2emissions in the context of sustainable development has intensified the search for efficient analytical approaches to understand and manage emission drivers. In this paper, three machine learning models were developed using multiple linear regression for the countries of Bosnia and Herzegovina, Croatia and Slovenia. Renewable energy consumption, $PM_{2,5}$ air pollution, GDP per capita, foreign direct investment, urban population, forest area, and total population were used as inputs in the models, while CO_2 emissions for the period from 2000 to 2020 were used as outputs. The developed models for all three countries have good performance, with R^2values of 91,34%, 77,91%, and 77,20% respectively. For Bosnia and Herzegovina urban population increases CO_2emission, while renewable energy consumption and forest area decrease CO_2 emission. In Croatia $PM_{2,5}$ was the most influential factor that increases CO_2emission.In Slovenia population growth decreases CO_2 emissions, whileGDP per capita increases CO_2 emissions. Also, hypothesis testing for differences between means was performed for all variables between all three countries. The findings showed that for almost all variables there were statistically significant differences in mean differences between all countries. Regarding CO_2 emission there are not enough statistical evidence that Bosnia and Herzegovina have higher CO_2 emissions than Croatia, while both Bosnia and Herzegovina, and Croatia have significantly higher CO_2 emissions than Slovenia. This research shows the potential of machine learning models as tools for data-driven policymaking in the transition towards Industry 5.0 and a sustainable industrial future.*

Keywords: *CO_2 emission, sustainability, machine learning, multiple linear regression, hypothesis tests*

1. Introduction

The increase in greenhouse gas (GHG) emissions, primarily caused by human activities, is responsible for global warming and climate change, which is why the urgent action is needed to avoid potentially irreversible damage to the environment [1]. Climate change is a global problem whose consequences

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negatively affect humanity, biodiversity, terrestrial and marine ecosystems, but also peace and security [2]. The effects of climate change call for strengthening global responses with mitigation and adaptation actions to keep a global temperature rise below 2,0 degrees Celsius above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1,5 degrees Celsius, as set out in the Paris Agreement goals [2, 3]. The number of countries, cities, businesses and other institutions pledging to achieve net zero emissions grows constantly. However, the transition to a net-zero world is considered to be one of the greatest challenges as it requires the complete transformation of how the population produce, consume, and move about [4].

Under the EU Climate Law, the European Green Deal aims to make Europe the first climate-neutral continent by 2050, starting with the aim to reduce GHG emissions by at least 55% by 2030 compared to 1990 levels [5].EU aims to achieve climate goals and encourage transition in both EU and non-EU countries by introducing different measures through its legislation and mechanisms such as EU Emissions Trading System (ETS) and Carbon Border Adjustment Mechanism (CBAM). 'Fit for 55' package of legislation introduces reforms across all sectors of the EU's economy with measures for promoting zero-emission mobility, developing a net-zero industry, building a clean energy system based on renewable energy sources (RES), renovating buildings for energy efficiency, restoring nature and enabling biodiversity, all to accelerate the transition towards climate neutrality [5]. An important instrument for achieving EU climate goals in a cost-effective way is the EU ETS. As the world's first carbon market that currently operates in all EU countries, Iceland, Liechtenstein and Norway, and is linked to the Swiss ETS, EU ETS collects revenue that must be used to support the green transition by investing in renewable energy, energy efficiency, improvements and low-carbon technologies that help reduce emissions [6]. From 2026, EU will also apply the CBAM to prevent the risk of "carbon leakage" from countries with less stringent climate policies than in the EU. With CBAM, EU aims to put a fair price on the GHG emissions emitted during the production of carbon intensive goods and ensure that the carbon price of imports is equivalent to the carbon price of domestic production [7].

Total GHG emissions are the sum of emissions of various gases, but the most dominant one is carbon dioxide (CO_2). Total CO_2 emissions accounted for 74,89% of total GHG emissions in 2023 and amounted to 41,42 billion tons in the same year [8, 9].In advanced economiesCO_2emissions decrease, while in most emergingmarkets and developing economies CO2 emissions continue to grow, but more slowly due to a rise in clean energy deployment[10].

The divergence in emissions trends between different regions has led many organizations and researchers to explore the factors influencing $CO_2$and overall GHG emissions and their impact on sustainable development.Authors in [11] focused on analyzing the effects of GDP, renewable energy, household energy consumption and waste on the GHG emissions and found a positive relationship between real GDP, household energy consumption and waste generation and GHG emissions, while the share of renewable energy turned out to be slightly negative.The impact of artificial intelligence (AI), economic growth, FDI, energy consumption, and urbanization on CO_2emissions was investigated in [12]. The analysis showed that AI positively correlates with CO_2reduction, while GDP growth, energy consumption, FDI, and urbanization intensify CO_2emissions. Authors in [13] investigated the relationship between economic growth and CO_2 emissions worldwide using a multilevel model that accommodates interactions between fixed and random effects related to GDP and CO_2emissions. The results of the analysis showed a positive relationship between economic development and CO_2 emissions.

Because the precise forecasting plays an important role in regulating reductions in CO_2 emissions, the authors in [14] developed four machine learning algorithms to estimate CO_2 emissions based on the data on different energy sources that impact CO_2 emissions.In [15] authors did bibliographic analysis and content review to analyze the how using machine learning can be used in order to reduce CO_2emissions in construction. The research showed that different machine learning model were used such as artificial neural networks, genetic algorithms, regression models, support vector machines, and decision trees, were used to predict CO_2 emissions and to optimize sustainable construction.Study [16] used machine learning methods gradient boosting machine, support vector machines, random forest, extreme gradient boosting to predict city-level CO_2 emissions throughout China. The authors concluded that their findings can be used to create carbon footprint maps.The authors in [17] used AI and machine learning to predict CO_2 emissions in the near and far future, and different models were created to analyze CO_2 emission during and after COVID-19 pandemic.

In [18] the effects of economic growth, industrial structure, urbanization, investments in research and development, use of foreign capital, and energy consumption on CO_2emissions using machine learning algorithms was analyzed. The results showed the importance of region-specific industrialization and an optimal urbanization range as well as an increased research and development and foreign capital investment in green technologies to support the reductions in CO_2emissions, while sustaining economic growth. Magazzino et al. [19] did a study in which authors did a machine learning approach to analyze solar and wind energy production, coal consumption, GDP, and CO_2emissions. This research was done to analyzeCO_2 emissions for China, India, and USA and it was concluded that India has a potential for increased CO_2 emissions. USA and China demonstrate a stronger potential for achieving sustainability than India.Authors used machine learning methods such as adaptive boosted support vector machines (SVR) and Adaptive boosted Gaussian process (GPR) to predict loading of CO_2in the solvent phase. In this research temperature, solution concentration, CO_2 particle pressure, amino acid salt molecular weight, melting point of amino acid salt, molecular weight of cation were used as inputs, while loading of CO_2 in the solvent phase was used as output [20].Linear regression approach was used in [21] to explore the relationship between CO_2 emissions, energy use, GDP, and population. The findings of this case study showed a long-run equilibrium relationship from these factors to CO_2 emissions, and that an increase of 1% in energy use, GDP and population leads to an increase of 0,58%, 0,73%, and 1,30% in CO_2emissions, respectively. A comparison of conventional linear regression model and linear regression model with fuzzy numbers was done in [22] to predict CO_2 emissions, using data on CO_2emissions, fuel mix, transportation, GDP, and population. The results showed that multiple linear regression performed better in predicting CO_2emissions.

Previously analysed research show that machine learning and artificial intelligence methods are effective tools for predicting CO_2 emissions, enabling a better understanding of the factors contributing to emissions and the identification of strategies to reduce them. Technologies such as automation, the Internet of Things (IoT), big data, AI and machine learning, associated with Industry 4,0, allowed industries to achieve higher levels of efficiency and productivity. However, even though the embracement of Industry 4,0 led to considerable improvements in performances, the industries globally are embracing the concepts of Industry 5.0 which emphasizes collaboration between humans and machines to achieve more flexible, adaptable, and sustainable systems. Industry 5.0 focuses more on sustainable practices to optimize resource use and lower environmental impacts, and on achieving more inclusive and responsible industrial practices [23]. This is in line with the global goals to reduce emissions and promote environmental sustainability.

In [24] authors identified 16 interdependent functions through which Industry 5.0 contributes to sustainability. Authors also emphasized that experts suggested that Industry 5.0 has been developed as a complement to Industry 4,0 to address social and environmental challenges brought by the digital transformation. Energy efficiency and renewable energy in Industry 5.0 and digital industrial revolution from the perspective of sustainability was analyzed in [25], while the need for mass personalization for sustainability and Industry 5.0 builds upon Industry 4,0 by introducing a human-centric approach that promotes greater

resilience and sustainability [26]. In [27] principal component regression machine learning model was used to predict levels of heavy metals like lead, zinc, nickel, arsenic, and cadmium, analyze the environmental data, and dealing with the variability in environmental data. Authors suggest that machine learning methods and decision analytics should be incorporated with resilient and human-centered approach in order to be aligned with goals of Industry 5.0. Research [28] aimed to address major challenges of the integration of human-centered AI methodology relevant to circular economy and Industry 5.0.
Various machine learning methods were used forprediction and analysis ofCO_2 emissions, and that in the context of Industry 5.0 where sustainability and the application of advanced technologies such as machine learning are key principles, the importance of this approach should be further emphasized. The aim of this research was to develop machine learning linear regression models for the countries of Bosnia and Herzegovina, Croatia, and Slovenia, as well as to analyze the impact of different statistically significant variables for each country individually. Also, hypothesis tests were performed to analyze the differences between means of all variables used in this research between each country. The structure of the paper is as follows: after the introduction, materials and methods are presented in Section 2. The results and discussion are given in Section 3. Finally, Section 4 presents the conclusion of the research with recommendations for future research.

2. Materials and Methods

In this research average yearly values from 2000 to 2020 were used for the countries of Bosnia and Herzegovina (BIH), Croatia (CRO) and Slovenia (SVN). Multiple linear regression models with backward analysis were developed for all three countries where:

- renewable energy consumption (% of total final energy consumption) – REC,
- $PM_{2,5}$ air pollution (mean annual exposure $\left[\frac{\mu g}{m^3}\right]$) –$PM_{2,5}$,
- GDP per capita (current US$) – $GDPpc$,
- foreign direct investment, net inflows (BoP, current US$) – FDI,
- urban population (% of total population) – UP,
- forest area [km^2]– FA, and
- total population – TP,

were used as independent variables, while CO_2 emissions (total) excluding LULUCF (Mt CO2e) –CO_2 emissionswas used as dependent variable.Also, hypothesis tests for the differences between two means for all variables between BIH, CRO and SVN were done.

2.1. Data

The data for this research were collected from World Bank [29]. Data for all variables were shown in Figure 1, Figure 2 and Figure3 for BiH, Croatia and Slovenia respectively.

From Figure 1 it can be seen that renewable energy consumption were increasing in years 2018, 2019 and 2020, while the values of $PM_{2,5}$were decreasing throughout the years. GDP per capita and urban population were increasing, while the total population was decreasing for Bosnia and Herzegovina.

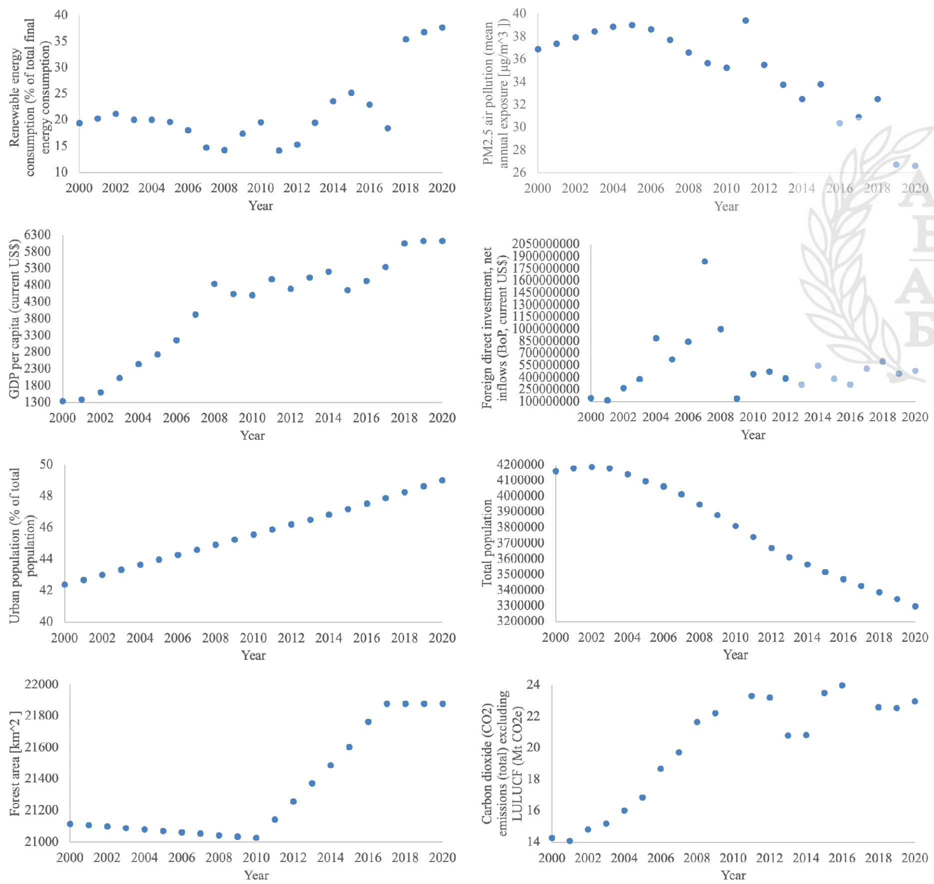

Figure 1. Scatter plots of all variables for Bosnia and Herzegovina for the period from 2000 to 2020

From Figure 2 it can be seen that the values of renewable energy consumption, GDP per capita, urban population and forest were increasing, while for Croatia the values of $PM_{2,5}$, total population, and CO_2 emissions were decreasing over the time period of 2000 – 2020.

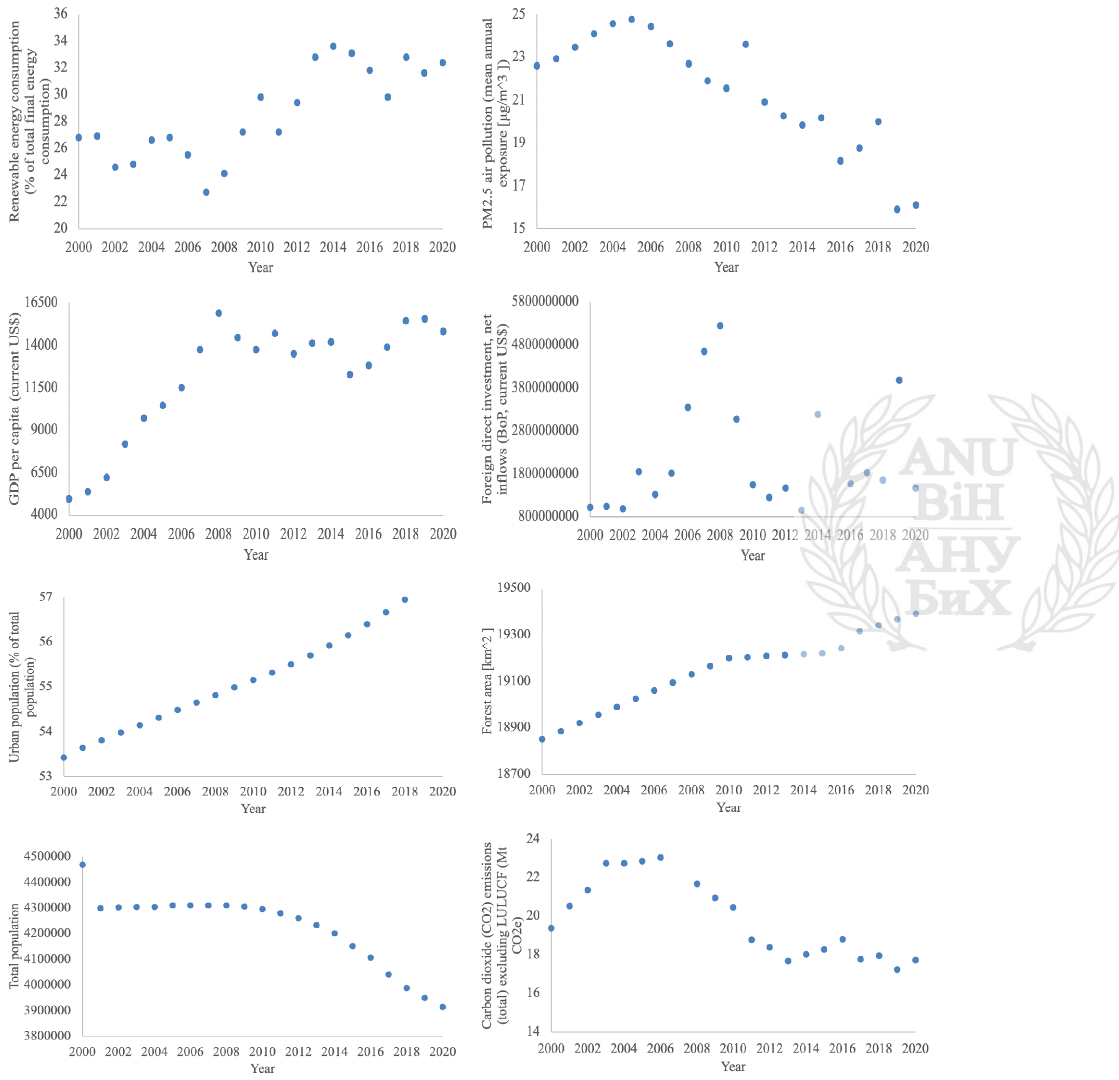

Figure 2. Scatter plots of all variables for Croatia for the period from 2000 to 2020

Figure 3 shows that for Slovenia renewable energy consumption, GDP per capita, urban population, and total population were increasing, while$PM_{2,5}$ and

CO_2emissions were decreasing through the years. Forest area was increasing until 2016 when it started decreasing until 2020.

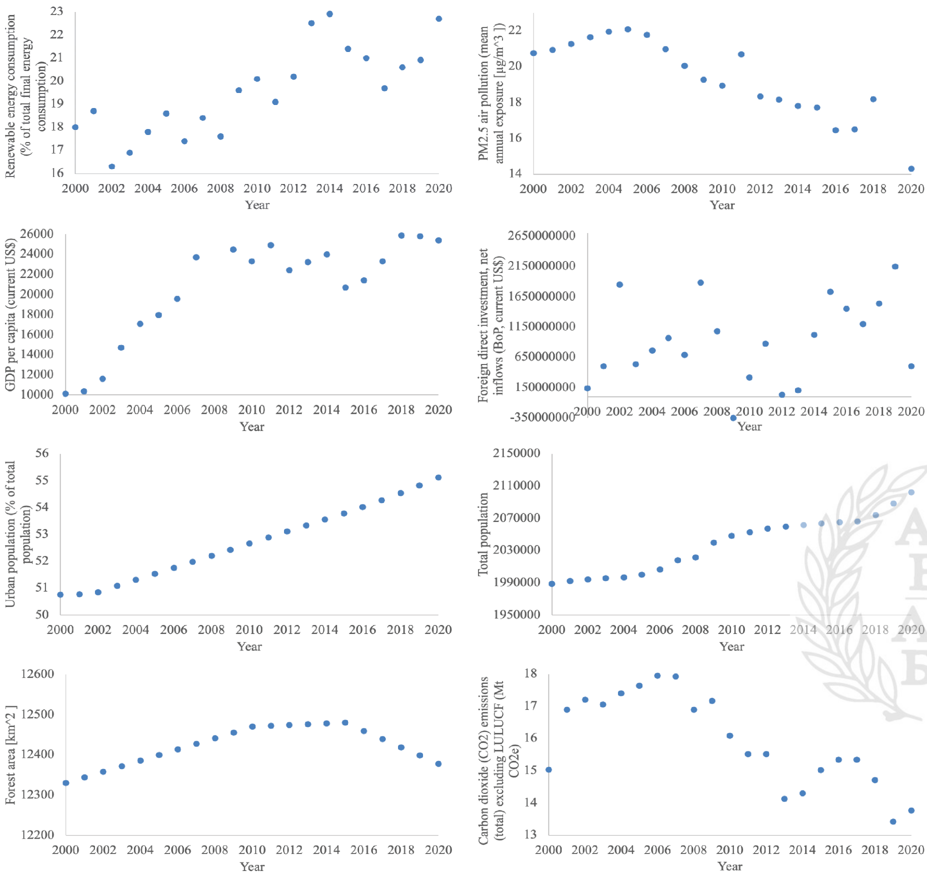

Figure 3. Scatter plots of all variables for Slovenia for the period from 2000 to 2020

Based on the Figure 1, Figure 2, and Figure 3 it is evident that the same variables show different trends for Bosnia and Herzegovina, Croatia and Slovenia, with some variables showing increasing while others showing a decreasing pattern over the years.

2.2.Multiple Linear Regression

In this research multiple linear regression with backward elimination was done. Due to the large differences in the order of magnitude among the variables, data were standardized to reduce potential numerical instability and to make the coefficients of linear regression easier to interpret. Data were analyzed using multiple linear regression modelsshown in equation (1) with the level of significance α= 0,05.

$$\hat{y}_j = b_0 + \sum_{i=1}^{k} b_i x_{ij} \qquad (1)$$

where:
$k -$ number of independent variables,
$\hat{y}_j -$ predicted value of dependent variable ($j = 1, \dots, n$),
$n -$ number of samples,
b_0 −intercept,
$b_i -$ regression coefficients ($i = 1, \dots, k$).

Significance tests were carried out for each stage of the backward regression analysis in order to provide statistical evidence regarding the independent variables that significantly contribute to the prediction of theCO_2 emissions. Variance Inflation Factor (VIF) was used to determine potential presence of multicollinearity between all significant independent variables. This calculation of VIF is shown in equation (2), where VIF value lower than 10 indicates that there is no multicollinearity between the significant independent variables[30].

$$VIF = \frac{1}{1 - R_i^2} \qquad (2)$$

where:
R_i^2 −coefficient of determination when the i^{th} independent variable is regressed against all other independent variables.
In order to identify the most impactful independent variable,standardized regression coefficients can be calculated as shown in equation (3).

$$b_{ist} = \frac{s_{x_i}}{s_{x_i}} \cdot b_i \qquad (3)$$

where:
$i - i^{th}$ independent variable (i = 1, …k),
$b_{ist} -$ standardized regression coefficient,
$s_{x_i} -$ standard deviation of i^{th} independent variable,
$s_y -$ standard deviations of dependent variable.

As standardized values of all variables were used in this study, calculated regression coefficients are standardized regression coefficients.

For each country, multiple linear regression model using backward elimination was evaluated using coefficient of determination(R^2)and mean squared error (MSE) as shown in equation (4) and equation (5) respectively.

$$R^2 = 1 - \frac{\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2}{\sum_{j=1}^{n}\left(y_j - \bar{y}_j\right)^2} \tag{4}$$

where:
$\hat{y}_j -$ predicted value of dependent variable ($j = 1, \dots, n$),
y_j – actual value of dependent variable,
$n -$ number of samples.

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2 \tag{5}$$

where:
$\hat{y}_j -$ predicted value of dependent variable ($j = 1, \dots, n$),
y_j – actual value of dependent variable,
$n -$ number of samples.

2.2.Hypothesis tests for the differences between two means for all variables between Bosnia and Herzegovina, Croatia and Slovenia

Hypothesis tests for the differences between two means for all variables were done in order to analyze whether there were differences between the means of the same variable for three countries, BIH, CRO, and SVN. Since in this research yearly average values have been used and the analyzed period is from 2000 to 2020, there are 20 samples per variable for each country. Since population standard deviations are unknown, the $t - test$was applied to test the difference between means. To determine whether to use $t\text{–} test$ that assumes equal variances (pooled variance $t - test$) or the one that does not, $F - test$was performed to assess whether the variances between two samples are different. The F statistic (F_{stat}) is calculated as shown in equation (6):

$$F_{stat} = \frac{s_1^2}{s_2^2} \tag{6}$$

where s_1^2 and s_2^2 are the sample variances of the two groups (with $s_1^2 > s_2^2$).

If the $F - test$shows that the variances are not significantly different, the pooled variance $t - test$ is applied. The t-statistic (t_{stat}) for the pooled variance version is calculated by equation (7):

$$t_{stat} = \frac{\overline{x}_1 - \overline{x}_2}{s_p \cdot \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{7}$$

where s_p is pooled variance calculated by equation (8):

$$s_p = \sqrt{\frac{(n_1 - 1) \cdot s_1^2 + (n_2 - 1) \cdot s_2^2}{n_1 + n_2 - 2}} \tag{8}$$

If the $F - test$showed unequal variances, then the $t_{stat}$was calculated as shown in equation (9):

$$t_{stat} = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^1}{n_1} + \frac{s_2^2}{n_2}}} \tag{9}$$

3. Results and Discussion

In this research multiple linear regression models with backward elimination were created for all three countries, Bosnia and Herzegovina, Croatia, and Slovenia. Renewable energy consumption (% of total final energy consumption) (REC), $PM_{2,5}$ air pollution (mean annual exposure $\left[\frac{\mu g}{m^3}\right]$) ($PM_{2,5}$), GDP per capita (current US$) ($GDPpc$), foreign direct investment, net inflows (BoP, current US$) ($FDI$),urban population (% of total population) (UP), forest area $[\mathrm{km}^2]$ (FA), and total population (TP), were used as independent variables, whileCO_2 emissions (total) excluding LULUCF ($\mathrm{Mt\,CO2e}$)(CO_2) was used as dependent variable. The aim of creating these models was to analyse which independent variables are statistically significant in the models and to analyse the impact of statistically significant variables on models' output CO_2 emissions for each country individually.

Also, hypothesis tests for the differences between two means for all variables between BIH, CRO and SVN were done. Since in this research there were 20 samples for each variable, first $F - test$ was performed to analyze the difference between variances for each variable, and after that $t - test$ was done.

3.1.Analysis of developed linear regression models with backward elimination for each country

Developed linear regression models for Bosnia and Herzegovina, Croatia, and Slovenia are shown in equations (10 – 12) respectively. Since the variables were of different orders of magnitude, their values were standardized prior to developing the linear regression model and thus standardized regression coefficients were obtained. Standardized coefficients indicate how many standard deviations the dependent variable changes when an independent variable changes by one standard deviation. Independent variables with the largest standardized coefficients in absolute terms have the greatest influence on the dependent variable.

1.1 $$CO_{2\,BIH} = -0{,}317 \cdot REC_{BIH} + 1{,}514 \cdot UP_{BIH} - 0{,}551 \cdot FA_{BIH} \quad (10)$$

$$CO_{2\,CRO} = 0{,}813 \cdot PM_{2,5\,CRO} + 0{,}355 \cdot FDI_{CRO} \quad (11)$$

$$CO_{2\,,5\,SVN} = 0{,}573 \cdot GDPpc_{SVN} - 1{,}240 \cdot PT_{SLO} \quad (12)$$

From equations (10 – 12) it can be seen that for all three countries different independent variables are statistically significant. These models demonstrate that the analysis of carbon emissions in the context of transitioning from Industry 4,0 to Industry 5.0 must be considered individually for each country, as the context is highly complex. Equation (10) for BIH shows that UP has the greatest influence on CO_2 emissions, indicating that as UP increases, CO_2 emissions also increase. Increase in values of REC and FA lead to decrease in CO_2 emissions, showing that BIH should focus more on renewable energy consumption and increase of forest area in order to achieve decarbonization and CO_2emission reduction.In CRO, equation (11), $PM_{2,5}$ is the most influential variable with highest value of standardized coefficient, where higher levels of this pollutant are associated with increased CO_2 emissions. Equation (12) in the case of SVN, shows that $PT$is the most important variable and that higher PT values are associated with lower CO_2 emissions. Additionally, $GDPpc$ is positively associated with CO_2emissions. It is interesting to notice that for SVN with the increase of population CO_2emissions decrease.

Table 1 shows that the models have high performances, withhighR^2 values and low MSE. Among all statistically significant variables across the models, the VIF is low, indicating that there is no multicollinearity among the input variables.

Table 1.Summary of linear regression models for BIH, CRO and SVN

Variable	Country	St. Coef	$t - value$	$p - value$	VIF	R^2	MSE
REC	BIH	-0,317	-2,85	0,011	2,43	91,34%	0,319
UP		1,514	10,20	0,000	4,32		
FA		-0,551	-3,06	0,007	6,37		
$PM_{2,5}$	CRO	0,813	7,34	0,000	1	77,91%	0,495
FDI		0,335	3,03	0,007	1		
$GDPpc$	SVN	0,573	3,25	0,004	2,46	77,20%	0,503
PT		-1,240	-7,03	0,000	2,46		

3.2.Hypothesis tests for the differences between two means between each country

Hypothesis tests for the differences between the means of all variables between Bosnia and Herzegovina, Croatia, and Slovenia were conducted. Given that each variable consisted of 20 samples, $F - test$ was first performed to examine whether variances were different. Depending on the outcome of the $F - test$, either $t - test$ assuming equal variances or $t - test$ assuming unequal variances were applied to assess the differences in means. The proposed hypotheses for $F - test$ are shown in equations (13 – 15).

$$\begin{gathered} H_0: s_{BIH}^2 = s_{CRO}^2 \\ 1.2 \quad H_1: s_{BIH}^2 \neq s_{CRO}^2 \end{gathered} \tag{13}$$

$$\begin{gathered} H_0: s_{BIH}^2 = s_{SVN}^2 \\ H_1: s_{BIH}^2 \neq s_{SVN}^2 \end{gathered} \tag{14}$$

$$\begin{gathered} H_0: s_{CRO}^2 = s_{SVN}^2 \\ H_1: s_{CRO}^2 \neq s_{SVN}^2 \end{gathered} \tag{15}$$

Tables 2 – 4 show results of $F - test$ for differences of variances between all countries, BIH – CRO, BIH – SVN, and CRO – SVN respectively, where Table 2, Table 3, and Table 4 show decisions for proposed hypotheses in equation (13), equation (14), and equation (15) respectively.

Table 2.F-test results – BIH vs. CRO

Variable	s^2_{BIH}	s^2_{CRO}	F_{stat}	$p-value$	F_{crit}	Decision
REC	47,81	11,51	4,155	0,001	2,124	Reject H_0
$PM_{2,5}$	14,84	7,02	2,114	0,051	2,124	Do not reject H_0
$GDPpc$	2,48·10^6	1,16·10^7	4,676	0,001	2,124	Reject H_0
FDE	1,45·10^{17}	1,71·10^{18}	11,779	0,000	2,124	Reject H_0
UP	4,12	1,5	2,755	0,014	2,124	Reject H_0
PT	9,89·10^{10}	2,05·10^{10}	4,825	0,000	2,124	Reject H_0
FA	114117,23	25102,21	4,546	0,001	2,124	Reject H_0
CO_2	13,37	4,94	2,709	0,015	2,124	Reject H_0

Table 3.F-test results – BIH vs. SVN

Variable	s^2_{BIH}	s^2_{SVN}	F_{stat}	$p-value$	F_{crit}	Decision
REC	47,81	3,68	12,980	0.000	2,124	Reject H_0
$PM_{2,5}$	14,84	5.92	2,507	0.023	2,124	Reject H_0
$GDPpc$	2,48·10^6	2,77·10^7	11,175	0.000	2,124	Reject H_0
FDE	1,45·10^{17}	4,67·10^{17}	3,215	0.006	2,124	Reject H_0
UP	4,12	1,95	2,115	0.051	2,124	Do not reject H_0
PT	9,89·10^{10}	1,24·10^9	79.563	0.000	2,124	Reject H_0
FA	114117,23	2284,15	49.961	0.000	2,124	Reject H_0
CO_2	13,37	2,02	6.620	0.000	2,124	Reject H_0

Table 4.F-test results – CRO vs. SVN

Variable	s^2_{CRO}	s^2_{SVN}	F_{stat}	$p-value$	F_{crit}	Decision
REC	11,51	3,68	3,124	0.007	2,124	Reject H_0
$PM_{2,5}$	7,02	5.92	1,186	0.353	2,124	Do not reject H_0
$GDPpc$	$1{,}16 \cdot 10^7$	$2{,}77 \cdot 10^7$	2,390	0.029	2,124	Reject H_0
FDE	$1{,}71 \cdot 10^{18}$	$4{,}67 \cdot 10^{17}$	3,664	0.003	2,124	Reject H_0
UP	1,5	1,95	1,302	0.280	2,124	Do not reject H_0
PT	$2{,}05 \cdot 10^{10}$	$1{,}24 \cdot 10^9$	16.490	0.000	2,124	Reject H_0
FA	25102,21	2284,15	10.990	0.000	2,124	Reject H_0
CO_2	4,94	2,02	2,444	0.026	2,124	Reject H_0

In Tables 2 – 4 where the decision was to 'Do not reject H_0', $t-test$ assuming equal variances was done, otherwise $t-test$ assuming non-equal variances was performed. From Tables 5 – 7 the results from performed $t-test$ between all countries can be seen.

From Table 5 it can be seen that there is enough statistical evidence to conclude that CRO has higher REC, $GDPpc$, FDI, UP, and PT, while BIH has higher $PM_{2,5}$ and FA. Also, there is not enough statistical evidence to conclude that BIH has higher CO_2emissions than CRO. Although the null hypothesis for CO_2 emissions was not rejected, as it was seen in equations (9) and (10) different independent variables are statistically significant in the final linear regression forCO_2 emissions predictions showing the complexity of this problem for each country individually.

Table 6 shows results of $t-test$ of differences between means of all variables for BIH and SVN. There is enough statistical evidence to conclude that BIH has higher $PM_{2,5}$, PT, FA and CO_2 emissions than SVN, while SVN has higher $GDPpc$, FDI, and UP than BIH. Also, there is not enough statistical evidence to conclude that BIH has higher REC than SVN.

Table 5.t-test results – BIH vs. CRO

Variable	μ_{BIH}	μ_{CRO}	Hypothesis	$t-stat$	$p-value$	$t-crit$	Decision
REC	21,63	28,59	$H_0: \mu_{CRO} - \mu_{BIH} \leq 0$ $H_1: \mu_{CRO} - \mu_{BIH} > 0$	4,139	0,000	1,699	Reject H_0
$PM_{2,5}$	34,97	21,45	$H_0: \mu_{BIH} - \mu_{CRO} \leq 0$ $H_1: \mu_{BIH} - \mu_{CRO} > 0$	13,256	0,000	1,684	RejectH_0
$GDPpc$	4080,87	12172,27	$H_0: \mu_{CRO} - \mu_{BIH} \leq 0$ $H_1: \mu_{CRO} - \mu_{BIH} > 0$	9,881	0,000	1,701	Reject H_0
FDI	$5,32 \cdot 10^8$	$2,08 \cdot 10^9$	$H_0: \mu_{CRO} - \mu_{BIH} \leq 0$ $H_1: \mu_{CRO} - \mu_{BIH} > 0$	5,211	0,000	1,714	Reject H_0
UP	45,60	55,28	$H_0: \mu_{CRO} - \mu_{BIH} \leq 0$ $H_1: \mu_{CRO} - \mu_{BIH} > 0$	18,720	0,000	1,692	Reject H_0
PT	$3,80 \cdot 10^6$	$4,22 \cdot 10^6$	$H_0: \mu_{CRO} - \mu_{BIH} \leq 0$ $H_1: \mu_{CRO} - \mu_{BIH} > 0$	5,654	0,000	1,701	Reject H_0
FA	21330,32	19142,41	$H_0: \mu_{BIH} - \mu_{CRO} \leq 0$ $H_1: \mu_{BIH} - \mu_{CRO} > 0$	26,871	0,000	1,701	Reject H_0
CO_2	20,31	20,04	$H_0: \mu_{BIH} - \mu_{CRO} \leq 0$ $H_1: \mu_{BIH} - \mu_{CRO} > 0$	0,295	0,385	1,692	Do not reject H_0

Table 6. t-test results – BIH vs. SVN

Variable	μ_{BIH}	μ_{SVN}	Hypothesis	$t-stat$	$p-value$	$t-crit$	Decision
REC	21,63	19,543	$H_0: \mu_{BIH} - \mu_{SVN} \leq 0$ $H_1: \mu_{BIH} - \mu_{SVN} > 0$	1,332	0,098	1,714	Do not reject H_0
$PM_{2,5}$	34,97	19,130	$H_0: \mu_{BIH} - \mu_{SVN} \leq 0$ $H_1: \mu_{BIH} - \mu_{SVN} > 0$	15,933	0,000	1,691	RejectH_0
$GDPpc$	4080,87	20842,51	$H_0: \mu_{SVN} - \mu_{BIH} \leq 0$ $H_1: \mu_{SVN} - \mu_{BIH} > 0$	13,976	0,000	1,711	Reject H_0
FDI	$5,32 \cdot 10^8$	$9,04 \cdot 10^8$	$H_0: \mu_{SVN} - \mu_{BIH} \leq 0$ $H_1: \mu_{SVN} - \mu_{BIH} > 0$	2,182	0,018	1,696	Reject H_0
UP	45,60	52,70	$H_0: \mu_{SVN} - \mu_{BIH} \leq 0$ $H_1: \mu_{SVN} - \mu_{BIH} > 0$	13,221	0,000	1,684	Reject H_0
PT	$3,80 \cdot 10^6$	$2,04 \cdot 10^6$	$H_0: \mu_{BIH} - \mu_{SVN} \leq 0$ $H_1: \mu_{BIH} - \mu_{SVN} > 0$	25,453	0,000	1,721	Reject H_0
FA	21330,32	12422,61	$H_0: \mu_{BIH} - \mu_{SVN} \leq 0$ $H_1: \mu_{BIH} - \mu_{SVN} > 0$	119,646	0,000	1,721	Reject H_0
CO_2	20,31	15,91	$H_0: \mu_{BIH} - \mu_{SVN} \leq 0$ $H_1: \mu_{BIH} - \mu_{SVN} > 0$	5,133	0,000	1,706	Reject H_0

Table 7. t-test results – CRO vs. SVN

Variable	μ_{CRO}	μ_{SVN}	Hypothesis	$t-stat$	$p-value$	$t-crit$	Decision
REC	28.59	19,543	$H_0: \mu_{CRO} - \mu_{SVN} \leq 0$ $H_1: \mu_{CRO} - \mu_{SVN} > 0$	10,633	0,000	1,694	Reject H_0
$PM_{2,5}$	21,45	19,130	$H_0: \mu_{CRO} - \mu_{SVN} \leq 0$ $H_1: \mu_{CRO} - \mu_{SVN} > 0$	2,952	0,003	1,684	Reject H_0
$GDPpc$	12172,27	20842,51	$H_0: \mu_{SVN} - \mu_{CRO} \leq 0$ $H_1: \mu_{SVN} - \mu_{CRO} > 0$	6,336	0,000	1,691	Reject H_0
FDE	$2,08 \cdot 10^9$	$9,04 \cdot 10^8$	$H_0: \mu_{CRO} - \mu_{SVN} \leq 0$ $H_1: \mu_{CRO} - \mu_{SVN} > 0$	3,654	0,000	1,697	Reject H_0
UP	55,28	52,70	$H_0: \mu_{CRO} - \mu_{SVN} \leq 0$ $H_1: \mu_{CRO} - \mu_{SVN} > 0$	6,356	0,000	1,684	Reject H_0
PT	$4,22 \cdot 10^6$	$2,04 \cdot 10^6$	$H_0: \mu_{CRO} - \mu_{SVN} \leq 0$ $H_1: \mu_{CRO} - \mu_{SVN} > 0$	67,876	0,000	1,717	Reject H_0
FA	19142,41	12422,61	$H_0: \mu_{CRO} - \mu_{SVN} \leq 0$ $H_1: \mu_{CRO} - \mu_{SVN} > 0$	186,079	0,000	1,711	Reject H_0
CO_2	20,04	15,91	$H_0: \mu_{CRO} - \mu_{SVN} \leq 0$ $H_1: \mu_{CRO} - \mu_{SVN} > 0$	7,158	0,000	1,691	Reject H_0

Results of $t - test$ for differences between means for all variables for CRO and SVN are shown in Table 7, where there is enough statistical evidence to conclude that CRO has higher values of REC, $PM_{2,5}$, FDI, UP, PT, FA and CO_2 than SVN, while SVN has higher value of $GDPpc$ than CRO.

From these results it can be seen that SVN has significantly lower values of CO_2 emissions than both BIH and CRO showing that they are much further in the decarbonization process than BIH and CRO, while other variables vary differently between countries.

4. Conclusion

This research shows that CO_2emissions and other variables analyzed in this research vary significantly between Bosnia and Herzegovina, Croatia and Slovenia, which indicates the need for an individualized approach in creating decarbonization strategies for each country. Using machine learning method multiple linear regression with backward elimination, models were developed that allow the identification of variables with a statistically significant impact on CO_2 emissions.

For Bosnia and Herzegovina, developed linear regression model showed that increase of urban population increasesCO_2 emissions, while the increase of values of renewable energy consumption and forest area reducesCO_2 emissions. This clearly indicates the areas where Bosnia and Heregovina needs to focus its attention in order to achieve its decarbonization goals. The developed model for Croatia shows that $PM_{2,5}$air pollution was the most influential variable, where the increase of $PM_{2,5}$ increases values of CO_2 emissions, suggesting a need to focus on measures to improve air quality. In the case of Slovenia, the developed model shows that with the increase of total population the value of CO_2 emissions decreases, which may indicate a higher level of environmental awareness, while the increase of GDP per capitaincreases CO_2 emissions.

In addition to the models, conducted hypothesis tests show that there are significant differences in the means of the most variables between the countries, which further confirms the complexity of this problem and the necessity of locally adapted measures. However, it is important to emphasize results show that there is enough statistical evidence to conclude that Slovenia has significantly lower mean values of CO_2 emissions compared to Bosnia and Herzegovina and Croatia, while there is not enough statistical evidence to conclude that CO_2 emissionsare higher in BiH than in Croatia. These results show that Slovenia was more successful in reducing CO_2 for the analyzed period. This research shows the potential of using machine learning in data analysis and decision-making support in the field of sustainable development and CO_2 emission. Future research recommends using other machine learning algorithms and to include other variables that may influence CO_2 emissions in order to support the transition to sustainable industrial practices which are highly important in transitioning to Industry 5.0.

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Women and Industry 5.0: Expanse for Inclusion and Diversity in the Context of Developing Country

Munira Šestić*[1], Mirha Bičo Ćar, Elvir Šahić[1]

Abstract: *The era of the fifth industrial revolution (5IR) undoubtedly brings new perspectives and thus new challenges for women. Bearing in mind that generally, in context of developing country, women face different and more difficult professional challenges, this paper will seek to direct future academic interests to research questions that are of particular importance for greater inclusion of women, given the business streams of 5IR. By posing these focused questions now on the example of Bosnia and Herzegovina, guidelines and recommendations for future support mechanisms for greater inclusion of women in the context of 5IR, from the perspective of developing economy, would be offered. This paper will attempt to make an additional contribution to the full inclusion of women in business ventures of developing country in the era of 5IR, pointing out the possibilities for national economies not to be "deprived" of women's business potentials.*

Keywords: *Industry 5.0,women, Bosnia and Herzegovina, developing country*

1. Introduction

The "new era" of the fifth industrial revolution (Industry 5.0)[1, 2] will change business horizons in the coming decades, improving robotics and automation through a people-centered approach. Thus, the Industry 5.0 context multiplies the challenges for women – if women, who make up half of the national workforce and talent pool, do not realize their full economic opportunities, the country's economy will grow less than its potentials.

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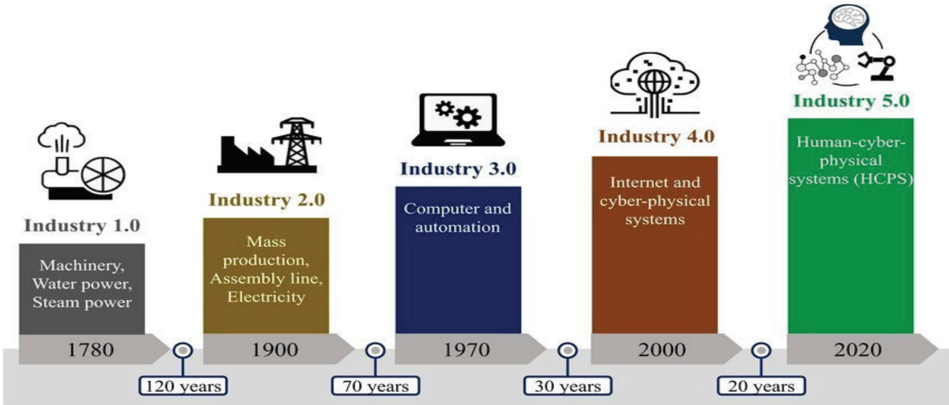

Figure 1. Industry and Society [3]

Women bring benefits crucial for the challenges of Industry 5.0 [4]trailblazing recognition that [5, 6]:

- Gender diversity enhances innovation and profitability through fostering creative and inclusive businesses for Industry 5.0;
- Women have unique strengths (collaboration, communication, empathy, and organizational skills) as leaders roles crucial for Industry 5.0;
- Women face significant barriers, including lack of flexibility, childcare support, and female role models, which can hinder their career advancement within Industry 5.0;
- Encouraging women in Industry 5.0 requires inclusive corporate cultures, flexible work arrangements, suitable facilities, and targeted recruitment initiatives to improve gender diversity.
- Empowering women is essential for economic growth in the Industry 5.0 era, demanding a shift towards gender equality and valuing diversity for a more sustainable industry.

The goals of future academic researches, especially from the perspective of developing countries, should be detailed analysis of the factors that influence the overall future social position of women, with special emphasis on inclusion in the labor market - in relation to the opportunities brought by the contemporary economic and technological context of the Fifth industrial revolution.

2. Women in Era of Industry 5.0

As Industry 5.0 is firmly linked to STEM (science, technology, engineering, mathematics), there is a space to explore direct and dependent gender relationships in order to achieve the development goals of the economy in the context of Industry 5.0 [7, 8].

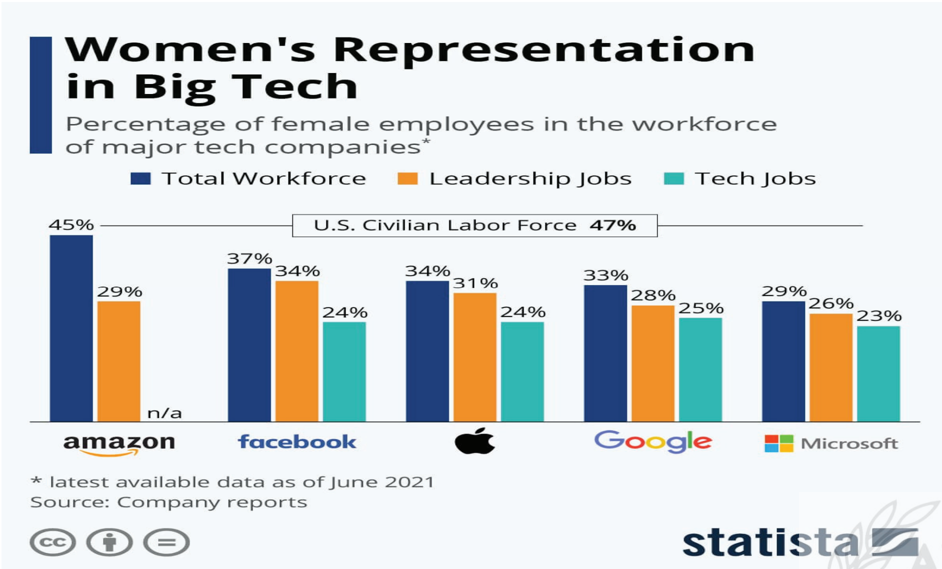

Figure 2. Women in Tech [9]

Researches on gender differences in STEM fields in Bosnia and Herzegovina[10]show that the choice of women and girls to enter these fields is influenced by stereotypes about social roles and perceptions of self-efficacy in STEM fields. It is estimated that in Bosnia and Herzegovina, around 25 percent of employees in the IT sector are women, while 33% of young women believe that their families would not support and encourage them to study in STEM fields[10]. Unfortunately, data shows that less than 10% of start-ups in the ICT sector have women as founders (Idem), so supporting the development of women's business competencies is an important issue in Bosnia and Herzegovina[11] and should be focused on specific areas[12].

Chuang and Eversole [13]state that women often possess key characteristics for success as leaders in modern business, such as adaptability, creativity, and teamwork skills. These traits enable them to effectively adapt to market challenges and collaborate with their teams to achieve a common goal.
According to Offerman and Foley [14], women as leaders are characterized by high adaptability and creativity, which helps them overcome business obstacles. Research also highlights that women leaders often demonstrate a high degree of emotional intelligence and the ability to build close relationships with their teams, which contributes to better business results.

Gorska and Burlakova[15]point out that, women in managerial positions use their creative abilities and adaptability to successfully respond to the challenges of the business market. Also, the research emphasizes the importance of teamwork and the ability to build long-term, productive relationships with employees and business partners, which contributes to their business success.
Additionally, balancing work and private life is always a significant challenge for women. Traditional societal expectations often place women in a position where they are expected to take care of the household and family, which can negatively affect their ability to fully commit to professional challenges[16]. This challenge is particularly pronounced in developing countries, where the traditional roles of women are still dominant[17]. Traditional gender roles often impose on women the responsibility of taking care of the household and family, which creates additional obstacles in the organization of time and resources.

3. WOMEN AND INDUSTRY 5.0: RESEARCH DIRECTIONS FOR DIVERSITY AND INCLUSION WITHININ DEVELOPING ECONOMIES

Given the above, a specific academic focus within the "Industry of the Future" – an industry that benefits businesses, workers and society[18], should be – research interests on inclusion and diversity in Industry 5.0. This is particularly relevant for contexts that currently face reduced development opportunities, such as developing countries.
In this sense, future researches could focus on the following objectives:
1. To explore the level of women's empowerment in the context of the Fifth Industrial Revolution, taking into account technological and social changes in focus in Bosnia and Herzegovina,
2. To explore the impact of education in STEM fields on the capabilities of women in Bosnia and Herzegovina, with an emphasis on technological sectors,
3. To examine the impact of gender stereotypes within Bosnia and Herzegovina on women's access to educational and professional opportunities, with a special focus on STEM fields.
4. To examine the key motivational factors that encourage women to enter the labor market, focusing on economic, social and personal reasons.

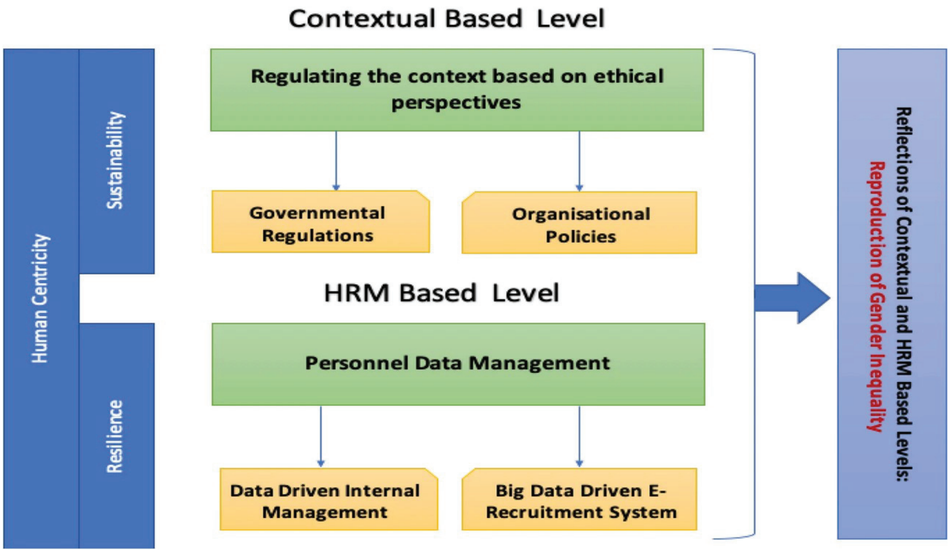

Figure3. Elements of Supply Chain for Providing Human Capitals in Industry 5.0[7]

5. To analyze the challenges of balancing work and private life faced by women in Bosnia and Herzegovina, including the impact of social expectations and support from the environment.
6. To detect and analyze the main obstacles that "hinder" women's economic empowerment in Bosnia and Herzegovina, such as limited access to finance, lack of support and regulatory barriers.

RRI Keys	Dimension of RRI-processes
• Ethics; • Gender Equality and Diversity; • Open Access and Open Science; • Science Education, and • Societal/Public Engagement.	• Anticipation and Reflexivity; • Diversity and Inclusiveness; • Openness and Transparency, and; • Responsiveness and Adaptation.

Figure 4. Five Keys and four process dimensions of RRI [19]

Therefore research questions, to be asked, for social and economic (re)positioning of women in Bosnia and Herzegovina within era of Industry 5.0 could be:
1. Within new era context, what are the most common motivational factors that encourage women in Bosnia and Herzegovina to enter the labor market?

2. What are the key obstacles that hinder women in Bosnia and Herzegovina from entering the labor market within new era context?
3. Within new era context, what challenges do women in Bosnia and Herzegovina face in balancing work and private life?
4. To what extent do gender stereotypes affect women's access to educational and professional opportunities in STEM fields in Bosnia and Herzegovina, within new era context?
5. Within new era context, how does education in STEM fields affect the abilities and success of women in Bosnia and Herzegovina?
The answers on above questions would clarify the developing country dimensions in terms of whether women in Bosnia and Herzegovina are sufficiently empowered for social and economic inclusion in the context of the Fifth Industrial Revolution, and what recommendations are in terms of improving the ecosystem that would enable greater diversity and inclusion.

3. Conclusion

Industry 5.0 is portrayed as a holistic approach for implementation of mission-oriented policies to achieve developmental goals[19]. In increasingly tough macro-economic and business environment, gender parity is recognized as competitive advantage[20]and development directions enveloping diversity, equity, and inclusion leads to increased productivity, adaptability to change and stronger innovation outcomes[20].
Therefore gender equality and diversity, is an important issue for responsible research and innovation (RRI) as they have the potential to strongly influence society towards inclusion [21].The gender equality and diversity framework is contextually oriented, engaging research and innovation to influence societal visions through norms, priorities and goals that shape future programs for progress and development[21].
The answers to the above questions have their own research significance, considering the fact that the human resources readiness of developing countries faces special challenges in promoting and implementing development goals[22].Therefore, especially important for less developed contexts is to redact academic contributions by setting a framework for realizing diversity, equality, and inclusion, as pillars of Industry 5.0.

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Accelerating Innovation in Healthcare through High-Performance Computing: Applications, Challenges and Future Perspectives

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Abstract: *Accurate estimation of wheat yield is essential for ensuring food security, especially given wheat's role in providing around 20 % of global calories and protein. Traditional yield estimation often relies on manual counting of wheat ears, a method that is labour-intensive, time-consuming, and impractical for large-scale production. To address these limitations, modern agriculture is increasingly turning to advanced technologies such as remote sensing, drones, and machine learning, which enable more efficient and precise monitoring of crop growth and yield potential.In this context, the present study introduces an automated ear-counting approach that applies machine learning to high-resolution images captured by unmanned aerial vehicles (UAVs). Drone imagery was collected during the late growth stage from 15 wheat fields in Bosnia and Herzegovina and processed at a resolution of 1024 × 1024 pixels. Images were manually annotated to mark regions containing wheat ears, resulting in a curated dataset of 556 high-resolution images. For detection, state-of-the-art models including Faster R-CNN, YOLOv8, and RT-DETR were used. While lower-quality images slightly reduced detection accuracy, overall model performance remained strong. This research demonstrates the value of combining UAV-based imaging with machine learning to modernise agricultural practices, offering an efficient, scalable solution for yield prediction and supporting greater sustainability and competitiveness in wheat production.*

Keywords: *precision agriculture; wheat ear counting; artificial intelligence; computer vision; real-time processing; detection*

1. Introduction

Wheat provides about 20 % of global calories and protein, making it essential for food security, particularly in developing regions. The Food and Agriculture Organization of the United Nations's 2030 agenda prioritises ending hunger and achieving food security, which requires investments in advanced agricultural technologies [1]. Accurate wheat yield forecasting supports better farm management and resource use but is complex due to factors like climate, soil,

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water availability, and farming practices. Traditional methods for counting wheat ears (e.g. using 1 m² frames) are labour-intensive and impractical on large fields. Automating this process can improve efficiency and accuracy. Recent advances include drones, sensors, and machine learning. Unmanned aerial vehicles (UAVs) equipped with multispectral cameras and sensors enable real-time crop monitoring, classification, and yield estimation, reducing costs and environmental impact [2-5] They also support tasks such as precision spraying, weed control, and water stress monitoring [6-11].

Bosnia and Herzegovina has underused agricultural land and suitable climate, but wheat yields are below national and European averages. Challenges include outdated techniques and limited technology adoption. Modernising production requires integrating advanced technologies. The shift to Agriculture 4.0 focuses on sustainability and automating tasks to boost efficiency [12-14]. Research has demonstrated machine learning algorithms with high precision in analysing crop images, such as TWSVM and deep learning models like PyTorch-based frameworks [15-16].

This study develops an automated wheat ear detection system using UAV imagery and computer vision models (Faster R-CNN, YOLOv8, RT-DETR) to improve accuracy over manual counting. The work aims to modernise farming practices in Bosnia and Herzegovina, supporting sustainable development and food security.

2. Materials and Methods

2.1. Locations

This study covers three locations in Bosnia and Herzegovina – Derventa, Odžak, and Goražde – where data were collected from 15 carefully selected fields of varying sizes (0.3–45.5 ha) and different wheat varieties. The locations were chosen to capture the geographic and climatic diversity of the country, from the lowland areas in the north to the hilly southeast. Although not all microclimatic and soil types are represented, the selected fields reflect key agricultural zones, making the results relevant for yield prediction and agricultural planning.

2.2. Data Collection

For the purposes of this study, data were collected using a digital camera and a drone. A PVC frame measuring 1 × 1 m was used with the drone, while a 0.5 × 0.5 m frame was used with the camera. This resulted in two separate datasets—one consisting of drone images and the other of images captured with the camera.

Figure 1. Example image taken by drone at height of 5m

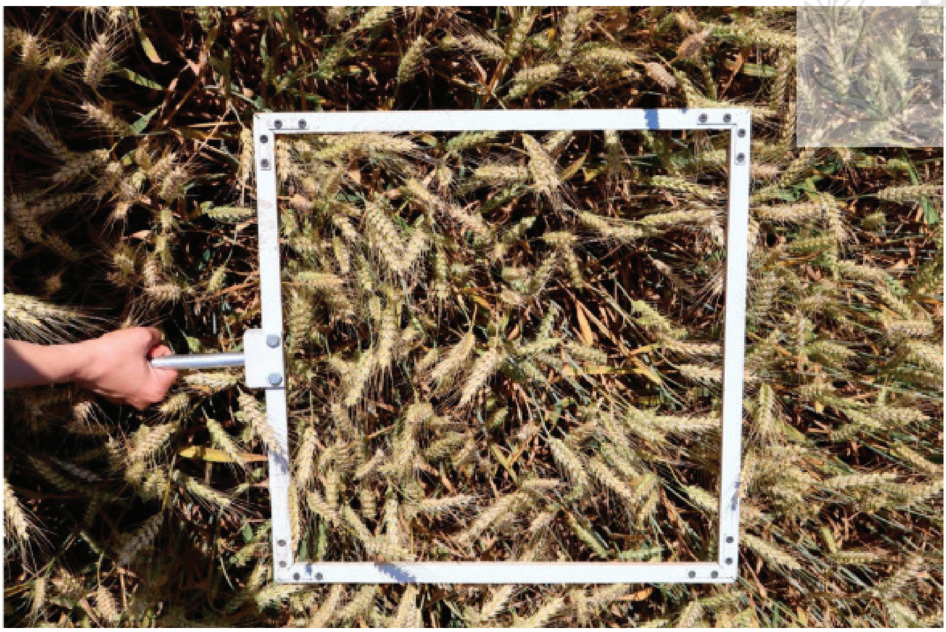

Figure 2. Example image taken by handheld digital camera

A DJI Mavic 3 Pro Cine drone equipped with a 20 MP RGB camera and HDR capability was used for aerial imaging, while a Canon EOS R10 camera was used for handheld imaging. For each location, 4 to 6 sample points were selected to reflect variations in wheat density, weed presence, and other factors. The drone captured images from heights of 5 m, 10 m, and 20 m (Figure 1.), while the handheld camera introduced variations in height and angle due to manual operation (Figure 2.).

2.1. Data Preprocessing

After collection, the images were transferred from the drone's internal memory (which is volatile and prone to data loss) to more secure locations—an external SSD as a physical backup and a cloud repository as the main storage for long-term use. This ensured the long-term availability and safety of the data required for training the AI model.

The original drone images were captured in high resolution (5280 × 2970 pixels), 96 dpi, and 24-bit color depth, enabling a high level of detail necessary for accurate object recognition. However, further processing was required to prepare them for use in model training. The first step in the processing was the extraction of the PVC frame from each image. Since the frame position varied from image to image and was not fixed, this step could not be automated and was instead performed manually.

During this process, the parts of the images containing the PVC frame—which defined the sample area in the field—were selectively cropped. Figure 3.a) shows the original image with a clearly marked blue frame (indicating the region of interest), while Figure 3.b) shows the cropped image used for further processing.

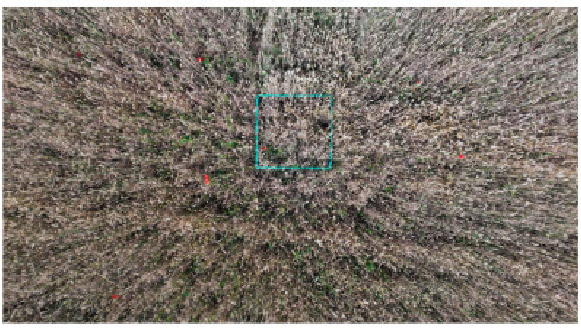

Figure 3.a) Original image take by arial drone; b) scaled image with extracted frame

After frame extraction, the images were resized to dimensions of 2048 × 2048 pixels to standardize the input size. These images were then divided into four quadrants, each 1024 × 1024 pixels in size. This division facilitated the annotation process, as smaller image segments allowed for more precise detection and labeling of wheat ears.
The complete image processing workflow—from image capture to annotation—is presented in the diagram below.

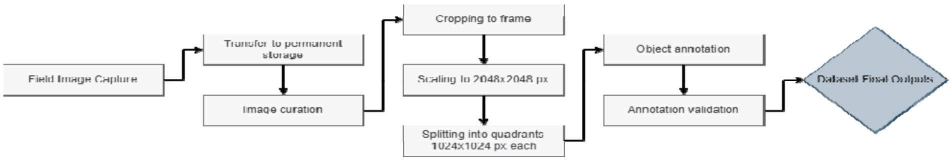

Figure 4. (a) Flowchart diagram depicting steps for image processing

Image annotation involved marking regions of interest (ROI) that contained the object to be detected—in this case, a wheat ear. Typically, each ROI contained only one wheat ear, and each was labeled with the tag "wheat ear." No other objects (e.g., weeds, flowers, soil) were annotated in the dataset, to keep the model focused solely on wheat ear detection.
The annotation process was carried out entirely manually by human annotators. To ensure the accuracy and consistency of the dataset, a two-person review protocol was implemented. One person performed the initial annotation, while another independently reviewed each image, checked the accuracy of the labeled wheat ears, and made corrections as needed. This two-step quality control system significantly reduced the possibility of errors and improved the reliability of the dataset used for training the AI model.

2.1. Models for Object Detection

In this study, we utilized three state-of-the-art object detection models—Faster R-CNN [17], YOLOv8 [18] and RT-DETR [19] to detect wheat ears in RGB drone images. These models were chosen for their complementary strengths in terms of accuracy, speed, and ability to handle varying conditions.
Faster R-CNN is a two-stage detector that combines region proposal generation and object classification. It uses a Region Proposal Network (RPN) to generate candidate object regions and a CNN backbone (in our case, ResNet-50 with FPN) for feature extraction. Though highly accurate, especially in complex scenes, it is computationally demanding and not suitable for real-time applications.
YOLOv8, part of the "You Only Look Once" family, is a single-stage detector optimized for real-time performance. It uses a CSP-based backbone and

combines FPN and PANet structures to extract multi-scale features. YOLOv8 is efficient and versatile, supporting object detection, classification, and segmentation. We used the lightweight "nano" version (~3 million parameters) suitable for fast inference, although its performance may decrease in cluttered or low-contrast scenes.
RT-DETR (Real-Time Detection Transformer) is a transformer-based detector capable of modeling global context and detecting small objects effectively. It employs self-attention mechanisms and learnable object queries to predict bounding boxes and classes. While powerful, its reliance on large datasets and a higher parameter count (~43 million) may limit its use in resource-constrained settings.
All models were trained for 100 epochs on a stratified dataset split (56% training, 14% validation, 30% test). During initial tests, we also examined model performance on a smaller high-quality subset to evaluate the impact of image clarity on detection results. This multi-model approach allowed us to assess detection performance under different conditions and requirements.

3. Results

The main outcome of this study is the development of a comprehensive dataset for wheat ear detection that can be used to train artificial intelligence models for agricultural applications. A total of 556 high-resolution images were collected under varied field conditions using drones and handheld cameras. Each image was carefully annotated and organized by location (lot), capture height, and sensor type, ensuring a transparent structure and reproducibility in data processing. This dataset provides a foundation for building effective systems for crop monitoring and yield prediction.
After preprocessing, deep learning models (Faster R-CNN, RT-DETR, and YOLOv8) were trained for 100 epochs, with their accuracy assessed using standard metrics: precision, recall, and F1-score. Initial experiments were conducted on a smaller set of high-quality images (4 for training and 5 each for validation and testing) to evaluate the effect of image quality on model performance. Including lower-quality images led to a slight drop in metrics, particularly in recall, but did not significantly affect overall test results.

Figure 5. Image fragment with labels

Figure 6. Detection examples for low-quality images: (a) Faster R-CNN (F1:0.87), (b) RT-DETR (F1:0.77), (c) YOLOv8 (F1: 0.77)

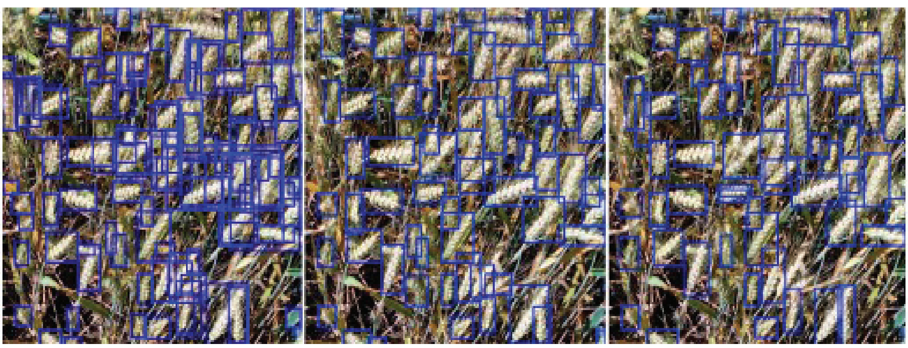

Figure 7. Detection examples for high-quality images: (a) Faster R-CNN (F1: 0.81), (b) RT-DETR (F1:0.74), (c) YOLOv8 (F1: 0.69)

For example, in early tests, RT-DETR achieved 0.77 precision and 0.72 recall, showing the best balance between accuracy and detection capability. By contrast, YOLOv8 tended to miss more true positive instances, while Faster R-CNN often produced multiple overlapping boxes in dense image regions, highlighting challenges in localizing individual wheat ears in complex conditions.

Full-dataset testing confirmed these trends. YOLOv8 achieved the highest precision (0.87), indicating few false positives, but had significantly lower recall (0.46), suggesting it often failed to detect all wheat ears present in an image. RT-DETR achieved the highest F1-score (0.69), thanks to its attention mechanism and two-stage detection process, which enable better detection of objects of varying sizes, including small and partially occluded wheat ears.

While YOLOv8 is well-suited for applications requiring high speed and precision, RT-DETR proved to be the most reliable model for wheat ear detection across diverse field data conditions, making it suitable for integration into smart agriculture systems.

Table 1. Evaluation metrics for initial experiments with high-quality training images

Num.of High/Low-Quality Images	Model	Precision	Recall	F1 Score
4/0	Faster R-CNN	0.69251	0.69299	0.6932
	RT-DETR	0.77081	0.71687	0.743
	YOLOv8	0.66957	0.67749	0.6736
4/2	Faster R-CNN	0.67938	0.6988	0.6885
	RT-DETR	0.74461	0.7259	0.7336
	YOLOv8	0.66901	0.6575	0.6613
4/4	Faster R-CNN	0.6844	0.6534	0.6691
	RT-DETR	0.762	0.63392	0.6926
	YOLOv8	0.64574	0.6015	0.6232

Table 2. Evaluation metrics for final models

	Precision	**Recall**	**F1 Score**
Faster R-CNN	0.60209	0.57907	0.59036
RT-DETR	0.68422	**0.70811**	**0.69596**
YOLOv8	**0.87257**	0.46132	0.60355

4. Discussion

Wheat yield prediction systems leverage various data sources and machine learning techniques to forecast crop yields accurately and in a timely manner. This synthesisAgriEngineering 2024, 6 4717 examines the effectiveness of different wheat yield prediction systems based on recent research findings. Through the development of automated systems for tasks like wheat ear detection, this study has shown how UAVs, high-resolution cameras, and deep learning models can drastically improve efficiency, accuracy, and scalability compared to traditional manual methods. By utilising large datasets collected from diverse geographical locations and processing them using state-of-the-art AI models, such as Faster R-CNN, YOLOv8, and RT-DETR, significant strides were made in object detection and precision agriculture. It can be observed from Table 2 that the YOLOv8 model achieves the highest precision, indicating that this model is the most effective for minimising false positives. However, its recall is considerably lower, suggesting the model misses more than a half of labelled wheat ears. The RT-DETR model has the highest recall, meaning it is more effective at identifying true positives but with slightly lower precision than YOLOv8. The results show that there are strengths and weaknesses among the models used in the study. Another factor that is worth considering is that the dataset used included images from fields of various sizes, altitudes, and wheat species sown. This enables these models to be able to detect wheat ears in varied conditions. However, this approach emphasises the importance of a high-quality dataset as well as the size of the dataset. The results achieved in this study demonstrate an improvement compared to those from two previously discussed studies [15,20], where the highest precision for wheat ear detection reached 82%. Unlike these prior works, which focused on datasets with limited variability in terms of wheat species, field conditions, and image quality, this study utilised a more diverse dataset that included images captured under varied conditions such as different field sizes, altitudes, and wheat species. This diversity enhanced the generalisability of the models, enabling them to perform well across a broader range of scenarios. Future improvements should address the limitations observed in the current results, particularly the low recall of YOLOv8, which indicates missed detections due to dense or overgrown wheat ears. Given that the collected data span various climatic conditions and include wheat of different varieties and soil types, our future work will focus on examining how these factors influence the models. In this study, we concentrated on the general task of detecting wheat ears; however, we are particularly interested in investigating whether the models exhibit any bias towards specific wheat varieties or climatic conditions in which the wheat grows. This research highlights that high-quality datasets combined with robust deep learning algorithms enable reliable models for crop monitoring. The integration of artificial intelligence automates labour-intensive tasks, facilitates timely decision-making, and improves yield forecasting.

5. Conclusion

The application of digital technologies, such as computer vision and artificial intelligence, represents a powerful tool in precision agriculture, particularly for crop detection and yield estimation. The performance of algorithms, with a precision of 0.87257 achieved with YOLOv8, a recall of 0.70811 with RT-DETR, and an F1 score of 0.69596, highlight theAgriEngineering 2024, 6 4718 potential deep learning has when it comes to wheat ear detection. This study lays the groundwork for future research, not only for wheat production but also for other crops and agricultural products. These technologies can be used for precise fruit counting, plant species identification, crop growth and development monitoring, and pest and disease detection at early stages, reducing the need for chemical treatments and enhancing resource efficiency. Additionally, they have potential applications in assessing the quality of fruits and vegetables, optimising irrigation through soil moisture analysis, and estimating yields for various types of grains, fruits, vegetables, and industrial crops. In the future, such systems could be integrated into broader farm management platforms, providing farmers with personalised recommendations based on data collected from drones, satellites, and other IoT devices. This would enable not only resource optimisation and yield improvement but also represent a significant contribution to global food security through sustainable and competitive agricultural practices.

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Accelerating Innovation in Healthcare Through High-Performance Computing: Applications and Future Perspectives

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Abstract: *The healthcare sector is undergoing a profound transformation driven by the convergence of data-intensive biomedical research and advanced computational technologies. High-Performance Computing (HPC) has become a cornerstone infrastructure for addressing the growing complexity, volume and heterogeneity of health data. This paper explores the multifaceted role of HPC in modern healthcare, focusing on its integration with artificial intelligence, medical imaging, genomics and simulation-based modeling. HPC accelerates tasks ranging from genomic sequencing and drug discovery to organ-level simulations and real-time diagnostics, enabling more precise and personalized interventions. Through case studies, we illustrate how HPC supports large-scale cancer genomics, simulates hemodynamic responses in cardiovascular therapies, enhances image-based diagnostic pipelines and facilitates the development of AI models for clinical decision support. In each of these domains, HPC boosts computational throughput and enhances reproducibility, scalability and predictive power. Despite its transformative potential, several challenges hinder widespread adoption, including limited access to infrastructure, lack of parallelized software and the need for secure and interoperable systems. The paper discusses future directions, including cloud-based HPC democratization, exascale computing and federated learning models that ensure data privacy while promoting collaboration. By positioning HPC as a strategic enabler of innovation, this paper underscores its central role in transitioning from reactive to predictive, precision-driven healthcare. The integration of HPC with AI and biomedical data sciences will continue to shape the future of medicine, bringing scalable and explainable solutions to clinical practice worldwide.*

Keywords: *HPC, AI, biomedical data, healthcare*

1. Introduction

The healthcare sector is undergoing a profound digital transformation driven by rapid advances in data acquisition technologies, biomedical research and

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artificial intelligence (AI). As a result, healthcare professionals and researchers face an unprecedented deluge of data generated from diverse sources such as electronic health records, imaging modalities, wearable devices and omics platforms. Managing, processing and analyzing this complex, high-volume data requires computational capabilities far beyond those of conventional systems. High-Performance Computing (HPC) has emerged as a cornerstone technology that enables timely, accurate and scalable analysis, thereby reshaping the landscape of modern medicine [1-3].

High-Performance Computing refers to the aggregation of computing power, through parallel processing, distributed systems, or specialized architectures, to perform complex computations at high speed and precision. Traditionally used in fields such as physics and climate modeling, HPC has become increasingly integral to biomedical research and clinical practice [4]. Its applications span genomic sequencing, drug discovery, image analysis, predictive modeling and real-time decision support systems, with the common goal of improving patient outcomes through speed, accuracy and personalization. One of the most transformative impacts of HPC in healthcare is seen in genomic medicine [5]. The sequencing of the first human genome, which took over a decade and billions of dollars, can now be accomplished in less than a day thanks to integrated HPC platforms [6]. Similarly, during the COVID-19 pandemic, HPC-enabled simulations of the virus's spike protein binding mechanisms contributed significantly to vaccine development [7]. Beyond genomics, HPC is revolutionizing diagnostics and treatment planning. In cancer research, petabyte-scale data analysis is employed to link tumor composition with genetic profiles, leading to individualized treatment plans. Moreover, AI models powered by HPC systems are used to predict cardiovascular disease risks using retinal image analysis, while supercomputers simulate blood flow dynamics to optimize prosthetic heart valve designs [8,9].

The integration of HPC in clinical workflows is further supported by national and regional HPC competence centers across Europe, including initiatives under the EuroHPC Joint Undertaking and projects such as EuroCC. These centers assist academic and industrial users in leveraging HPC resources for healthcare innovation, demonstrating that democratized access to HPC infrastructure is crucial for translating scientific advances into medical applications. This paper explores the multifaceted applications of HPC in healthcare by presenting examples that illustrate its transformative role. It also discusses the benefits and future directions, emphasizing the need for secure, accessible and interoperable HPC solutions that align with the goals of personalized and precision medicine.

2. The Role of High Performance Computing in Modern Genomics

The field of genomics has witnessed a data explosion, driven by next-generation sequencing (NGS) technologies capable of producing terabytes of data in a single run. Analyzing such complex and voluminous datasets requires computational power far beyond what conventional systems can provide. HPC has emerged as a fundamental enabler of genomic discovery, offering the scalability, speed, and efficiency needed to process, analyze, and interpret massive genomic datasets. Its applications have become particularly prominent in pan-genomics, single-cell transcriptomics and large-scale population sequencing studies. Despite its growing relevance, the integration of HPC into genomics still faces significant challenges, including high data complexity, substantial memory requirements and suboptimal scalability of certain algorithms [10].

The analysis of genomic data demands computationally intensive methods for efficient storage, transmission, and processing which makes HPC an essential tool. Since conventional tools often fall short in handling such complex data, modern HPC infrastructure, including GPUs, TPUs, and multi-core systems, enables the use of machine learning (ML) and deep learning (DL) algorithms in tasks such as gene classification, prediction of functional DNA regions, enhancer-promoter interaction mapping and alternative splicing analysis. This synergy between HPC and ML/DL significantly contributes to the development of precision medicine by allowing therapeutic approaches to be tailored to a patients genetic profile. Beyond enabling the processing of large-scale data, HPC in genomics allows for the application of sophisticated deep learning models that are transforming how genetic information is analyzed and interpreted. For instance, convolutional neural networks (CNNs) are used to classify DNA sequences, while recurrent neural networks (RNNs and LSTMs) model genetic sequences as biological languages. These methods pave the way for novel approaches to predict genomic functional elements, protein localization, and gene expression regulation. They significantly outperform traditional statistical methods and support automated analysis of heterogeneous and high-dimensional omics data [11].

According to Patil et al. (2024), leveraging HPC for AI-driven genomics research, significantly outperforms conventional methods, achieving up to 216× faster data processing, 10% higher accuracy in variant calling and notable improvements in scalability, data security and computational efficiency, highlighting its potential for real-time clinical applications in genomics [12].

The exponential growth of genomic data has created significant computational challenges, particularly in detecting complex genetic interactions such as epistasis. Traditional computing systems are often inadequate for handling the vast number of possible SNP-SNP interactions, which can reach into the billions

even in moderately sized datasets. HPC provides a viable and necessary solution to this challenge, enabling the parallelization of computationally intensive tasks and dramatically reducing analysis time. For instance, an epistatic analysis that would take over a year on a single processor can be completed in a matter of days using hundreds of CPU cores or GPU-based architectures. By leveraging HPC infrastructures through distributed memory models like MPI, shared memory models like OpenMP, or cloud-based solutions, researchers can now conduct exhaustive genomic interaction analyses at scales that were previously impractical, thus accelerating discoveries in genomics [13].
Applications of HPC are particularly critical in population genomics, cancer genomics and single-cell sequencing, where datasets are not only large but also highly multidimensional. Despite the clear advantages, the integration of HPC into genomics research poses challenges such as software optimization for parallel architectures, high memory demands and the need for robust data storage and transfer solutions [12].

3. Simulation and Modeling of Biological Systems Using HPC

HPC has become a tool for simulating and modeling complex biological systems, offering unprecedented capabilities for understanding the dynamic behavior of biological processes across multiple scales. From molecular interactions and protein folding to organ-level physiology and whole-body systems biology, HPC enables researchers to perform highly detailed simulations that would be computationally prohibitive on standard computing platforms. By leveraging parallel processing, large memory capacities and specialized architectures such as GPUs, HPC facilitates the use of advanced methods like molecular dynamics (MD), agent-based modeling and finite element analysis (FEA) to replicate biological phenomena with high temporal and spatial resolution. These simulations are not only critical for hypothesis testing and systems-level understanding but also for predictive modeling in personalized medicine, such as simulating drug interactions with target proteins or modeling tumor growth under different therapeutic strategies. As biological data becomes increasingly complex and voluminous, the integration of HPC with biophysical modeling stands at the forefront of computational biomedicine, enabling virtual experiments that complement and often guide laboratory and clinical research. Simulating complex biological systems (cellular networks or molecular interactions) requires both high precision and substantial computational resources. HPC frameworks like CODES, built upon the ROSS parallel discrete-event simulation engine, enable realistic and scalable modeling of systems involving tens or even hundreds of thousands of nodes. These tools support design space exploration and allow researchers to preserve causal relationships between biological events. By replaying traces from real scientific applications, such simulations can uncover communication bottlenecks and performance patterns in biological systems, much like evaluating interconnect efficiency in supercomputers. This approach brings new depth to biomedical modeling, where theoretical constructs can be validated through high-fidelity virtual experiments. Ultimately, HPC-based simulations are instrumental in advancing personalized medicine and improving our understanding of disease mechanisms at the systems level [14].

Alam et al. (2016) provide an early evaluation of IBM Blue Gene/Q, emphasizing its efficiency in large-scale parallel computing tasks. These capabilities are crucial in the simulation of biological systems, which often involve highly complex, multi-scale models, from molecular dynamics to whole-organ modeling. The study demonstrates how advanced interconnects, high memory bandwidth, and energy efficiency contribute to scalable performance, which directly supports large-volume simulations, such as protein folding, cardiac electrophysiology, or even population-wide epidemiological modeling [15].

Recent advances in computational immunology emphasize the growing need for HPC to model such complexity accurately. Mechanistic models of immune responses now span multiple scales, molecular pathways, cellular interactions, tissue dynamics, and require the integration of vast, heterogeneous data from genomics, proteomics, and imaging. HPC infrastructures are essential for running agent-based simulations, solving large systems of differential equations, and calibrating models through data assimilation and parameter sweeps. These computational tools allow for in silico exploration of immune responses to infection, vaccination, or cancer, enabling personalized simulations that could eventually inform clinical decisions [16].

4. Medical Imaging and AI-Assisted Diagnosis

Medical imaging plays an important role in modern diagnostics, enabling non-invasive assessment of anatomical and pathological conditions. With the rise of high-resolution modalities such as MRI, CT and PET, the volume and complexity of imaging data have grown exponentially. HPC has become indispensable in this domain, providing the computational infrastructure required to process, analyze and interpret vast amounts of imaging data in real time or near-real time.

One prominent example comes from the National Competence Centre of the Czech Republic, where a remote tissue segmentation tool was developed to support radiologists in clinical environments. The tool is based on a hybrid architecture in which a frontend interface at the hospital enables clinicians to interact with imaging data via open-source 3D Slicer, while the backend executes deep learning-based segmentation models on an HPC cluster using

NVIDIA's Clara Train SDK. Only anonymized data in NIfTI format is transmitted and all communication is encrypted, ensuring compliance with privacy regulations. This setup enables rapid and precise AI-assisted segmentation of organs and lesions, significantly reducing the time and subjectivity associated with manual image analysis [17]. Similarly, the Swiss National Supercomputing Centre has demonstrated how HPC can enhance diagnostics and treatment planning by improving the simulation of blood flow in aortic valve replacement procedures. Through massively parallel simulations involving more than 300 million grid points, researchers were able to model turbulent flow patterns around prosthetic valves with unprecedented accuracy. These insights not only improve the design of implants but also facilitate the development of diagnostic tools, such as the HPC-PREDICT pipeline, which integrates 4D Flow MRI with Kalman filters and deep learning to provide automatically annotated, high-resolution imaging suitable for clinical use [18,19]. These cases highlight a broader trend in diagnostic medicine: the convergence of imaging, AI and HPC to enhance speed, accuracy and personalization. In cardiology, ophthalmology, neurology, genotoxicology and oncology, AI models trained on large imaging datasets are being used for risk stratification, disease detection and prognosis prediction. However, their clinical deployment often depends on the availability of sufficient computing power. Training deep learning models for image segmentation or classification, for instance, typically requires powerful GPUs or cloud-based HPC environments [20-24].

Despite this progress, challenges remain. AI models trained on imaging data can exhibit biases due to non-diverse training sets and performance may degrade in real-world conditions. Furthermore, many healthcare institutions, especially in low- and middle-income regions, lack access to HPC infrastructure or secure data transfer systems needed for integration of these tools. There is a growing need for federated HPC platforms and national competence centers to support hospitals and SMEs in adopting AI-assisted diagnostic solutions.

5. Future Perspectives on the Role of HPC in Healthcare

As biomedical research becomes increasingly data-intensive and model-driven, the role of HPC in healthcare will only grow in importance. Future advances are expected in several key directions. Tighter integration of HPC with artificial intelligence and machine learning will enhance predictive accuracy in diagnostics, drug discovery and treatment personalization. These AI-HPC synergies will enable real-time decision support systems trained on multiscale biomedical data, from omics to imaging and clinical records. Second, the expansion of exascale computing and quantum-inspired architectures will allow researchers to simulate biological processes at unprecedented levels of detail, enabling breakthroughs in areas such as whole-organ modeling, virtual drug screening, and individualized immune system simulations. Democratizing access to HPC resources through cloud-based platforms will help smaller institutions and developing regions participate in cutting-edge medical innovation. Federated models of computation may further support secure, collaborative research across institutions while preserving data privacy. The ethical and regulatory landscape must evolve alongside these technical advances. As patient-specific modeling and simulation enter clinical workflows, transparency, explainability and reproducibility will become critical to ensure trust and clinical adoption.

6. Conclusion

High-Performance Computing has emerged as an important pillar in the digital transformation of healthcare, enabling the biomedical community to meet the computational demands of modern diagnostics, therapeutics and biomedical research. Across domains, from genomic sequencing and molecular simulations to AI-powered imaging diagnostics and clinical decision support, HPC enables high-resolution, scalable and timely processing of increasingly complex biomedical data. This paper has illustrated how HPC is not merely accelerating data analysis but fundamentally reshaping how healthcare problems are approached and solved. In genomics, HPC has made population-scale sequencing and real-time variant interpretation feasible. In simulation biology, it has transformed our capacity to model multiscale biological systems and test hypotheses in silico. In medical imaging and diagnostics, HPC-powered AI models are bringing precision and speed to disease detection that rivals, and in some cases augments, expert-level decision-making. However, realizing the full potential of HPC in healthcare is contingent on several critical factors. These include addressing disparities in infrastructure access, optimizing software for parallel computing, safeguarding data privacy and ensuring model fairness and clinical interpretability. Equally important is the development of human capital, clinicians, researchers and engineers capable of co-creating next-generation tools using HPC. Looking ahead, the convergence of HPC with AI, cloud platforms and emerging exascale and quantum systems will unlock new paradigms in precision medicine. These technologies will enable not just faster analysis but smarter systems: capable of learning, adapting and predicting across diverse patient populations and data modalities. Cloud-accessible HPC frameworks and federated platforms will be essential for bridging the global equity gap, empowering researchers and clinicians in resource-limited settings to harness the same tools as world-class centers.

7. References

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