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Industry 5.0 or industry 4.0S? Introduction to industry 4.0 and a peek into the prospective industry 5.0 technologies

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Abstract

The Industrial Revolution can be termed as the transformation of traditional industrial practices into new techniques dominated by the technologies available at that time. The first three industrial revolutions were driven respectively by mechanization, electrification, and automation which had gradually transformed the agrarian economy into a manufacturing-based economy. It helped in enhancing the lifestyle of the factory workers and the healthcare system, which improved the overall quality of living. The industries that adapted to the change witnessed a tremendous increase in the production of goods, competitive advantage, and cross-border business opportunities. While we are currently living to see the fourth industrial revolution (also known as Industry 4.0) unfolding around us, the world is poised for the next big leap, the fifth industrial revolution or Industry 5.0. Hence, the first half of the paper outlines the enabling technologies of Industry 4.0 and conceptualizes how they would act as the foundation for the fifth industrial revolution. The socio-economic challenges of the technologies and the need for Industry 5.0 technologies are also discussed. The second half of the paper outlines the prospective technologies of Industry 5.0, their potential applications from the perspective of industry leaders and scholars and conceptualizes how they can overcome the challenges of Industry 4.0. The definition of "sustainability trilemma" a new term coined by the authors, and the reasoning for calling the next industrial revolution "Industry 4.0S" (another new term) rather than Industry 5.0 are also presented.

Keywords Industrial revolution · Sustainability · Artificial Intelligence · Internet of things · Collaborative robots · Digital twins · Edge computing · Block chain · Cyber-Physical Systems

1 Introduction

In the early 1800s, the world witnessed the beginning of the industrial revolution through which the agrarian society shifted to industrialization and urbanization [1]. Coal, water, and steam were predominantly used to drive large steam engines that were used in the textile and manufacturing industries. During this time, people who worked on the farms and spun textiles by hand abandoned their villages and moved to neighboring cities to work in factories. It was believed to have started in Britain before spreading to the rest of Europe and America [2]. The late 1800s and the early 1900s witnessed the onset of the second industrial revolution which was characterized by the widespread science-based inventions such as mechanization of agriculture, textile industries, railroads, machinery, internal combustion engines, electric power, and the iron and steel production [229]. Vaclav Smil, a Czech Canadian scientist, professor, and policy analyst called the period between 1867 and 1914 the "age of synergy" during which the foundation for the 20th -century advancements was laid [3]. However, the drawback of both these industrial revolutions was associated with the poor and dangerous working conditions which resulted in the formation of labor unions and factory regulations to safeguard workers.

The third industrial revolution began in the 1950s with the inventions of transistors and microprocessors that paved the way for automated production, which was supported

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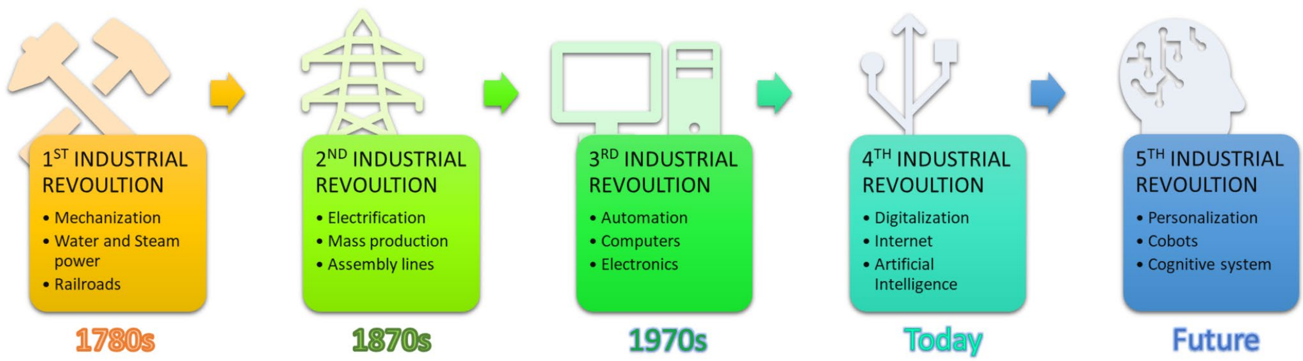


Fig. 1 The various stages of the Industrial Revolution

by various electronic devices. Digital sensors and computers became a part of the shop floor. Although the working conditions improved tremendously during this period, exploitation of labor continued, cities became overcrowded, and widespread pollution and environmental degradation became common across the world. The ongoing fourth industrial revolution which is commonly referred to as Industry 4.0 or 4IR is built upon the third industrial revolution which relied on transistors, sensors, and micro-electronics to generate data. The term Industry 4.0 was coined by German Professor Wolfgang Wahlster, in the year 2011 at the Hannover Fair. It is the digital transformation of manufacturing industries that focuses on automation, interconnectivity, and real-time process optimization using enabling digital technologies such as Internet of Things (IoT), Machine Learning (ML), Artificial Intelligence (AI), Cyber-Physical Systems (CPS), Cloud computing, Additive Manufacturing (AM), Digital twins, Cybersecurity and so on to communicate and control each other [4, 5]. In other words, it can be called the computerization of manufacturing in which advanced digital technologies are married to industrial machines and processes. The interconnection of these technologies into the manufacturing setup is to achieve operational efficiency, productivity, and automation to the highest possible extent [6]. This in turn creates a manufacturing ecosystem that is smart, connected, and driven by data.

The fundamental model of Industry 4.0 can be divided into digital or computing technologies that are married with the systems of the physical world. While AI, ML, Big Data, Cloud Computing, and cyber security form a part of the core computing technologies, other technologies such as Automation and Robotics, IoT, CPS, and AM form the physical part. These technologies together realize the benefits of Industry 4.0 systems to enable agile, flexible, and on-demand manufacturing which is an essential part of smart manufacturing or smart factories. While there are tremendous advantages for the industries in implementing these technologies to achieve competitive advantage and higher operational efficiency, there is widespread apprehension about the potential job loss for low-skilled laborers due to the high level of automation which can cause economic imbalance and greater inequality in the society [7]. The various stages of the Industrial Revolution with their timeline, driving force, and technologies are shown in Fig. 1.

While the world is still trying to adapt and realize the potential of Industry 4.0, some industrialists and scholars have started envisioning and discussing the next Industrial Revolution, Industry 5.0. If Industry 4.0 is about digitally connecting machines to enable a seamless flow of data and the highest possible optimization, Industry 5.0 is believed to bring humans back into the game for collaboration and introduce the human touch to manufactured products while simultaneously focusing on sustainable manufacturing [8, 9]. Elon Musk, a visionary entrepreneur and CEO of one of the most highly automated factories in the world, Tesla Inc., has acknowledged the downside of excessive automation through his tweet in April 2018, "Yes, excessive automation at Tesla was a mistake. To be precise, my mistake. Humans are underrated". He went on to admit that robots have slowed down production, and humans, not machines, were the solution. This is in line with the predictions that the next big thing would be the collaboration between humans, robots, and digital technologies.

1.1 Need for the study

Despite the ongoing adaptation of Industry 4.0 in various sectors and growing discussions on Industry 5.0, this paper aims to provide a brief background on the enabling technologies of Industry 4.0 and their application in various functions of manufacturing industries, the prospective Industry 5.0 technologies and their potential applications and attempts to answer the following five research questions (RQ),

RQ1. What are the enabling technologies of Industry 4.0 and their application in manufacturing industries?

RQ2. What are the socio-economic challenges of Industry 4.0 technologies? Why must the industries overlook these technologies and upgrade to the prospective Industry 5.0 technologies?

RQ3. What are the prospective technologies of Industry 5.0 and their application in manufacturing industries?

RQ4. What is "sustainability trilemma" and how does Industry 5.0 technologies help to overcome it?

RQ5. Why "Industry 5.0" must be called "Industry 4.0S"?

The above questions are answered through various sections of this article. The Sect. 2 introduces the various enabling technologies of Industry 4.0 and their application in manufacturing industries which aims to answer RQ1. The socio-economic challenges of Industry 4.0 technologies and the reason to overlook these technologies and upgrade to the prospective Industry 5.0 technologies are explained in Sect. 3 which answers RQ2. The Sect. 4 of the article discusses the predictions from industry leaders and provides the definitions of Industry 5.0 as quoted by industries and scholars. The scholarly articles related to the prospective Industry 5.0 technologies and their application in manufacturing industries are discussed in Sect. 5 which answers RQ3. The definition of "sustainability trilemma" a new term coined by the authors, the sustainability dimension of Industry 5.0 technologies, and how the industries can embrace sustainable development using the technologies are discussed in Sect. 6 which answers RQ4. The key difference between Industry 4.0 and Industry 5.0 technologies in terms of sustainable development (economic, social, and environmental sustainability) forms the core ideology of the paper. The article concludes with the justifications for calling the next industrial revolution "Industry 4.0S" rather than "Industry 5.0" which answers RQ5.

1.2 Methodology and structure

To understand the enabling technologies of Industry 4.0, prospective Industry 5.0 technologies, and their respective application in various functions of manufacturing industries, a comprehensive literature review was performed. The various search terms combinations such as "Industry 4.0", "Industry 5.0" and various technologies such as Artificial Intelligence, Machine Learning, Digital twins, and so on were used to find the relevant articles in Google Scholar, Scopus, and Web of Science. A preliminary screening of the articles to identify their relevance to the study was conducted by reading the title and abstract. The main findings and conclusions are summarized in a narrative or descriptive format. It should be noted that the study does not include all the articles published on the topic but is focused only to cover the latest and important progress in the area, to summarize and provide an overview to the readers on the status and future direction. The article follows a descriptive review approach, and the overall structure of the paper is shown in Fig. 2.

2 Enabling technologies of industry 4.0

2.1 Artificial intelligence (AI)

Artificial Intelligence (AI) is an algorithm-based intelligence fed to machines to impart problem-solving, decision-making skills, and perform human-like assignments [229]. In other words, AI make computers think and behave like humans. It is a combination of several digital and software technologies that acts as the driving force of Industry 4.0. The origin of AI can be traced back to the 1940s [10] and took the first big leap in the 1980s [11]. The subsequent inventions such as statistical learning [12], Greedy learning algorithm [13], Recurrent Neural Network [14], Graph Transformer Network [15], Deep Belief Network [16], and Convolutional Neural Network [17] paved the way for various new algorithms that are currently been used and are being developed on a regular interval.

The application of AI in Industry 4.0 has shown great potential in predictive maintenance, predictive analytics, inventory management, machine vision, industrial robotics, and supply chain management [231]. Liu et al. [18] have reviewed the application of various AI-driven algorithms such as k-NN, Naive Bayes, ANN, and Deep Learning in fault diagnostics of rotating machinery that helped in reducing the machine downtime, cost of maintenance, and eliminating safety threats. As each of the algorithms have their strengths and limitations such as accuracy, speed, and robustness, they propose to develop a hybrid intelligent system to address future challenges.

Zhao et al. [19] have used Recurrent Neural Networks (RNN) based algorithm as a predictive maintenance tool to monitor the health of the machine and successfully applied the technique to predict tool wear in a milling operation, and fault diagnosis in gearbox and bearings. Wang et al. [20] have applied Deep Belief Network (DBN), a data-driven technique to build an accurate relationship between various operational parameters used in a polishing operation and the amount of material removed. The same technique was also used by Deutsch [21] to predict the useful life of a hybrid ceramic bearing. As the various operations of manufacturing industries are nonlinear, stochastic, and have a lot of

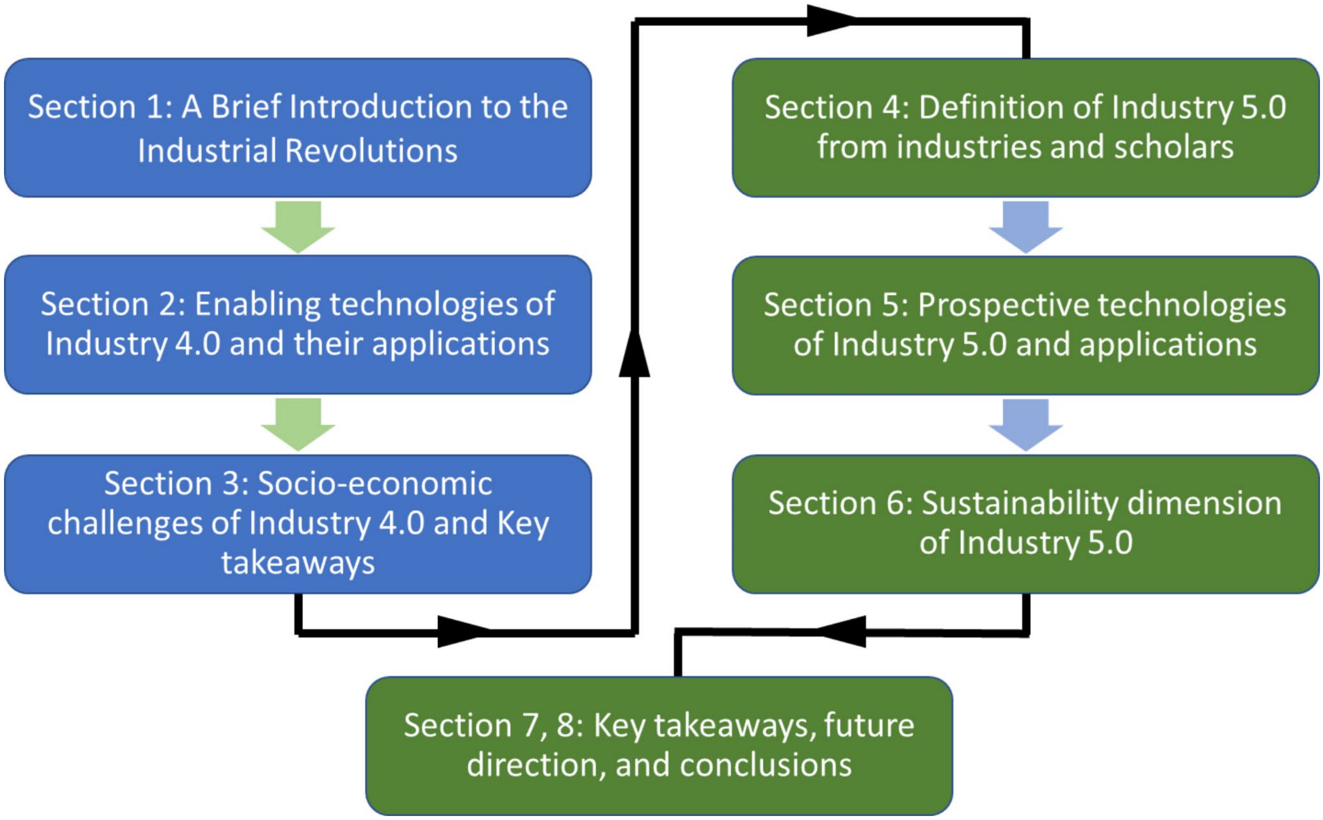


Fig. 2 The structure of the article

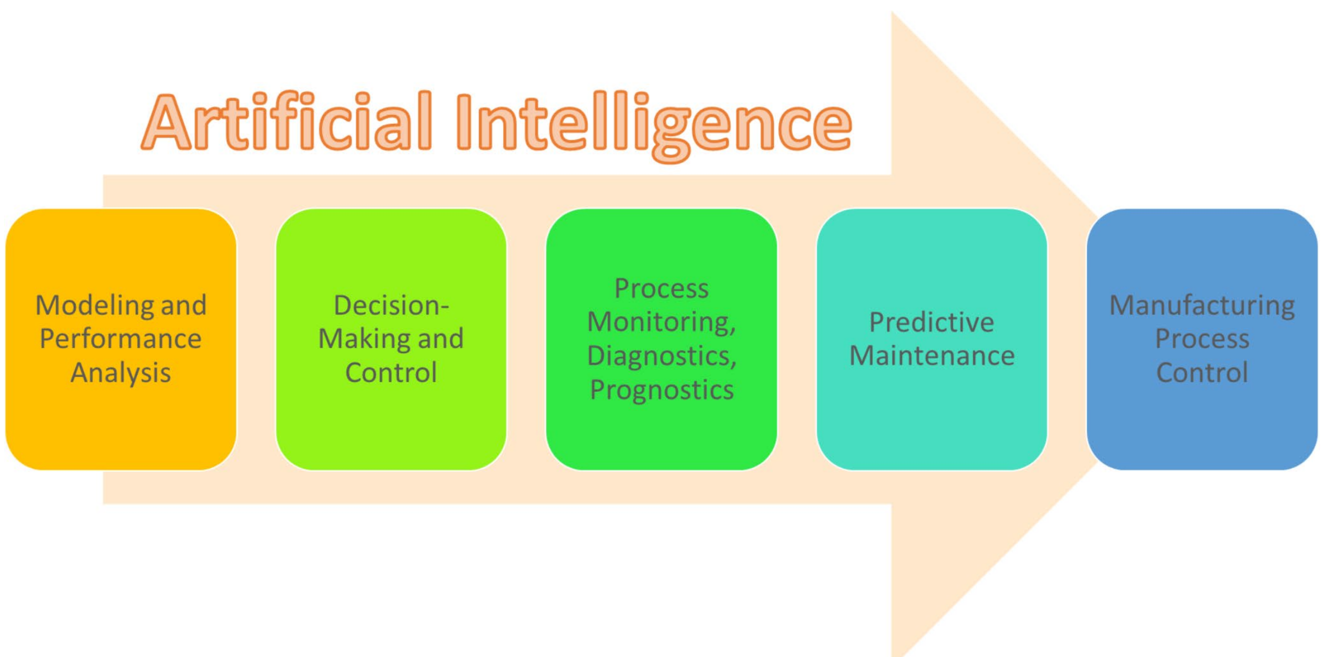


Fig. 3 Opportunities of AI in a manufacturing system

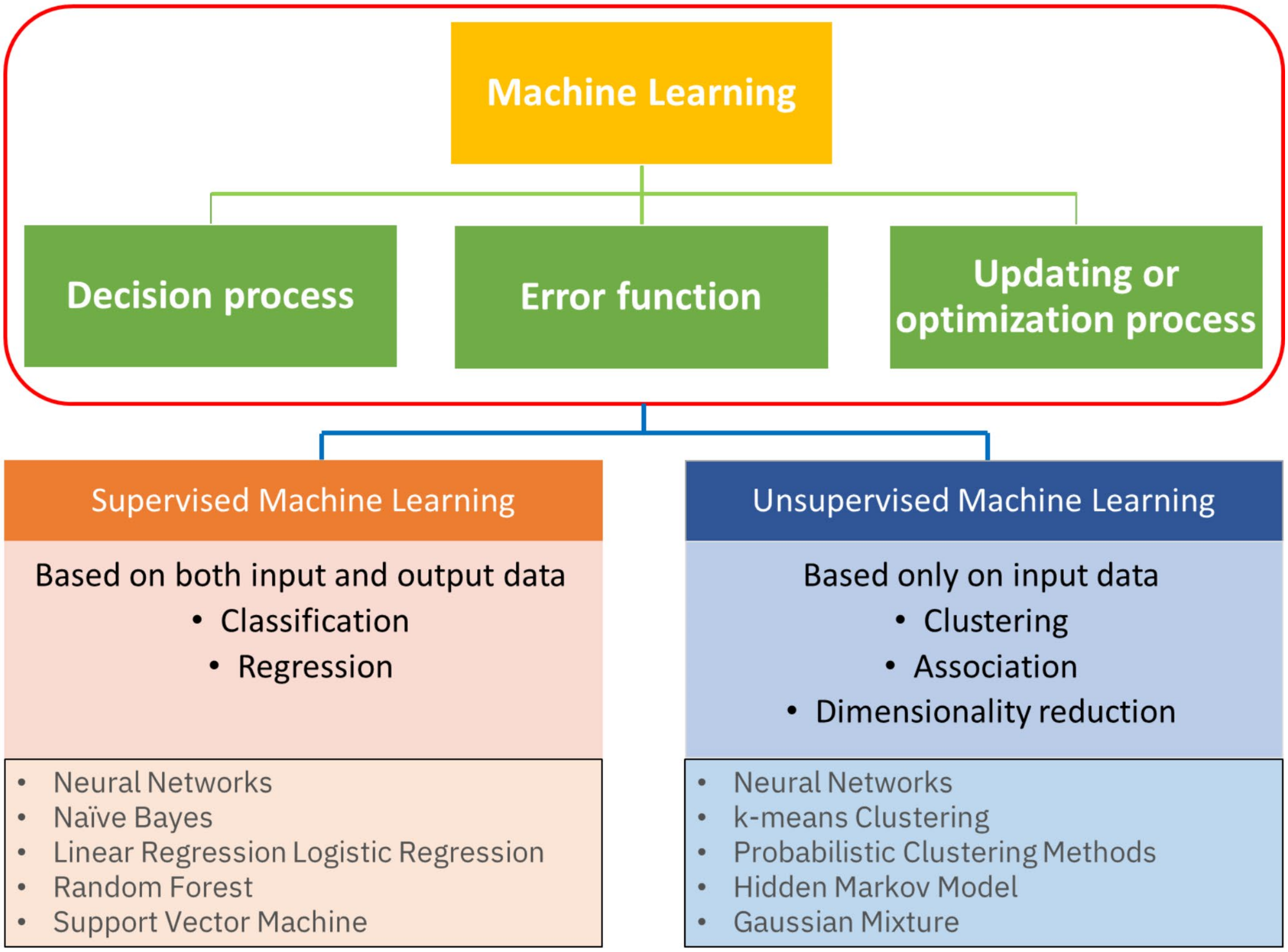


Fig. 4 Supervised and unsupervised machine learning algorithm

uncertainties many researchers have tried different AI-based techniques to enable the optimal material flow. The potential opportunities of artificial intelligence in the manufacturing industry are shown in Fig. 3.

2.2 Machine learning (ML)

Machine learning is a subset of artificial intelligence that uses data, algorithms, and software to predict the outcome accurately through statistical learning. The historical data is used to train the system to make predictions and improve gradually to increase the prediction accuracy. Although machine learning, deep learning (DL), and neural network or artificial neural network (ANN) are all a subset of artificial intelligence, IBM classifies DL as a branch of ML, and ANN as a branch of DL. While traditional machine learning is dependent on human teaching to learn, deep learning can do it automatically. ANN has an input node layer, output node layer, and numerous intermediate hidden layers. Each node that is connected to the other acts as an artificial neuron to mimic the human brain. Machine learning methods can be broadly classified into supervised and unsupervised learning, although few literatures show two more categories, semi-supervised and reinforcement learning. The classifications of ML and a few common algorithms are shown in Fig. 4.

ML allows the connected systems to transfer data between them and improve the process on its own based on algorithms. The repeated learning and optimization loop lead to unprecedented performance that converts a traditional automated factory into a smart factory. Condition monitoring of machinery, health monitoring of structures, predictive maintenance, predictive quality control, and supply chain management are some of the applications of ML in the manufacturing industry [231]. The data collected through various sensors are processed using machine learning algorithms to recognize the pattern of failure and even predict future failures which can eliminate the routine manual inspections. By combining machine vision with ML algorithms, real-time monitoring and identification of defective

Table 1 Successful applications of machine learning based algorithm

S#	Authors	Application
1	Cao et al. [22]	Predict rolling force in hot rolling of electrical steel
2	Reddy et al. [23]	Predict temperature distributions in electron beam–welded plates
3	Shahani et al. [24]	Predict slab behavior in the hot rolling process
4	Hu et al. [25]	Predicting failure pressure of composite cylinders for hydrogen storage
5	Kazan et al. [26]	Prediction model for spring back in wipe-bending process
6	Umbrello et al. [27]	Predict optimal cutting conditions and residual stresses in machining
7	Jun et al. [28]	Stress prediction in SLA additive manufacturing process
8	Patil et al. [29]	Deep learning algorithms for condition monitoring of milling tools
9	Fahle et al. [30]	Machine learning algorithms for various manufacturing processes

parts can be performed automatically without human intervention. Predicting consumer behavior and managing the supply chain is another area of the business that has a higher impact on profitability due to unsold inventory or lack of inventory, both of which affect the manufacturer. Machine learning algorithms have been successfully used in demand forecasting and inventory management. A few successful applications of machine learning-based algorithms in a manufacturing environment are shown in Table 1.

Other real-world common-man applications include speech recognition (Alexa, Siri), customer service (bot-controlled chat messenger), computer vision (self-driving cars), recommendation engines (internet search engines, and product search tools in e-commerce websites), and automated stock trading.

2.3 Big data & analytics

The wide Variety and Volume of data that comes at a high Velocity (also known as 3Vs) is Big Data. In simple words, big data is an enormous amount of data that is usually measured in petabytes or zettabytes. The advanced analytic technique that is used systematically to identify the unknown patterns behind the data and correlate them with certain behavior that helps to make decisions is Big Data Analytics. Researchers have added additional "V"s to the original 3Vs to define the characteristics of Big Data. For instance, Liao et al. [31] defined it as 4Vs (3V + Variability), while Gandomi and Haider [32] emphasized on 6Vs (4V + Veracity and Value). Perhaps, with the emergence of artificial intelligence, sensor-based connected systems, social networking, and digital communication devices, a massive amount of data is generated every second that requires real-time processing to predict the outcome and make faster decisions.

The concept of Big Data can be traced back to the early 1960s when the first database management system and data centers were created to collect and store data. Over the years with the widespread availability of high-speed internet, more and more physical objects got connected to the internet (IoT) which started collecting an enormous amount

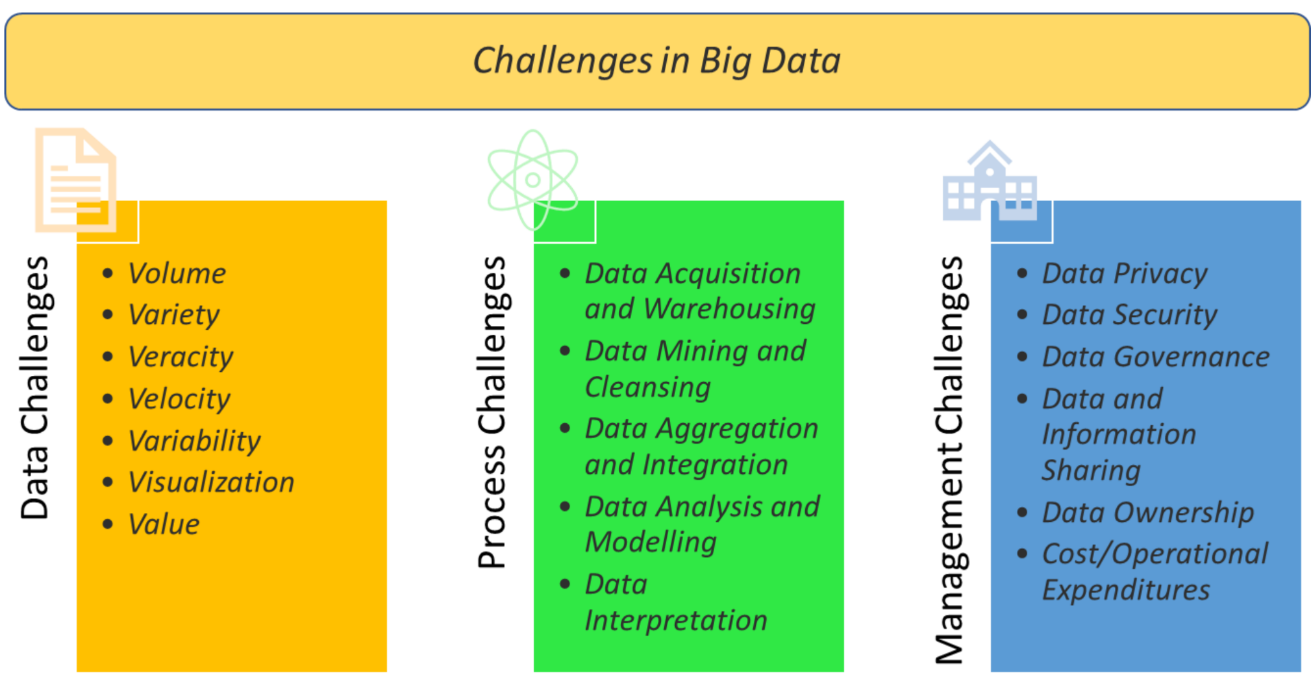
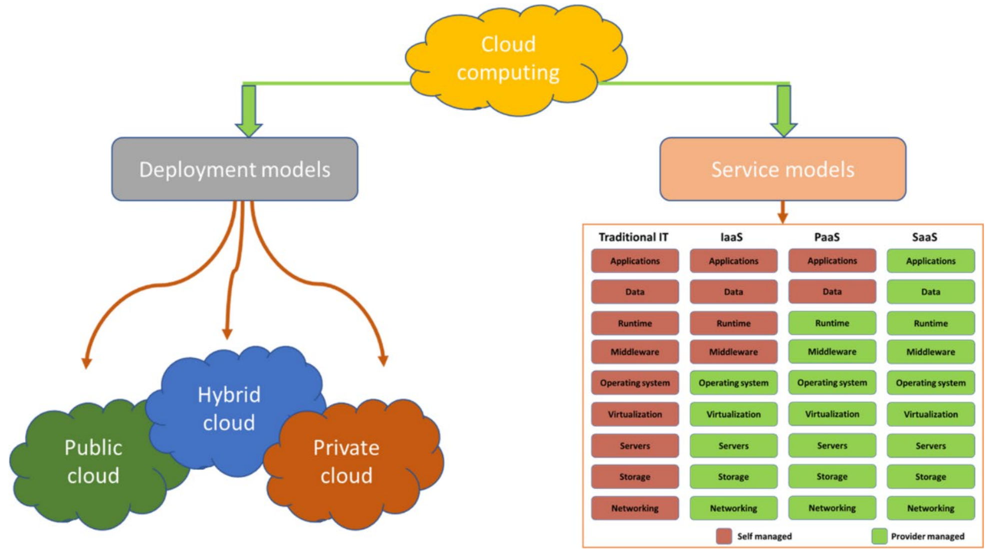


Fig. 5 Various challenges associated with Big Data

Fig. 6 Deployment and service models of cloud computing



of user and machine data. The development of ML and AI further accelerated the growth of data creation which skyrocketed the volume of data that is handled and processed. So basically, artificial intelligence, machine learning, and big data are all interconnected, and one cannot exist independently without the other. As the raw data doesn't provide any value, to unlock its potential, industries perform different analyses which are fundamentally classified as descriptive, inquisitive, predictive, prescriptive, and preemptive [33]. Such analysis helps large organizations to acquire and retain customers, targeted advertisements, develop new products, optimize product prices based on customer behavior, supply chain management, risk management, and faster decision making [229].

However, storing and handling a large volume of data comes with its challenges. A report by Oracle shows that organizations are struggling to handle the data as the volume of data that is getting generated is doubling every year. It is not just the storing of data, but the real challenge lies in data curation. To be precise, cleaning up unwanted data, processing, analyzing, and securing the data to give granular level access to get more insight and make a meaningful decision out of it. The various other challenges associated with Big Data as classified by Akerkar [34] and Zicari [35] are summarized in Fig. 5.

Table 2 The major categories of research in cloud manufacturing

Category of research	Description	Research studies
Architecture and platform design	Details the fundamental structure of the cloud manufacturing system and its behavior.	Qu et al. [39], Wu et al. [40], Liu et al. [41], Yang et al. [42], Wang et al. [43]
Resource description and capabilities	Transformation of abstract capabilities to formalized cloud manufacturing services.	Zhang et al. [44], Tao et al. [45], Xu et al. [46], Xu et al. [47], Lu et al. [48]
Service selection and composition	Integration of distributed services into a group that can work together.	Lu et al. [49], Zhou et al. [50], Zheng et al. [51], Zhang et al. [52], Zhou et al. [53]
Resource allocation and service scheduling	Allocation of resources and scheduling to enable multi-tasking.	Liu et al. [54], Wang et al. [55], Cao et al. [56], Thekinen et al. [57], Akbaripour et al. [58]
Service searching and matching	Search and match the service based on customer demand and fulfill the requirement.	Yuan et al. [59], Tai et al. [60], Cheng et al. [61], Sheng et al. [62], Guo et al. [63]

2.4 Cloud computing and cloud manufacturing

The delivery of networking and computing services over the internet is called cloud computing. As the services like server, storage, database, networking, analytics, and intelligence are delivered through the internet (the "cloud") it is cost-effective and highly flexible. Reliability, scalability, and centralized management of data and software are some of the benefits of adopting cloud computing. While the entire infrastructure is managed by professional IT service providers, the business organizations and individuals can get on-demand access through heterogeneous internet services. As shown in Fig. 6 the three major service models of cloud computing are, Software as a Service (SasS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS), and the three major deployment models are public, private, and hybrid clouds.

The manufacturing sectors adopted cloud computing in two different ways-one is the direct adaptation of digital technologies to enable "cloud computing in manufacturing" and the other is "cloud manufacturing". The integration of distributed and distribution of integrated manufacturing resources such as software applications, machines, and

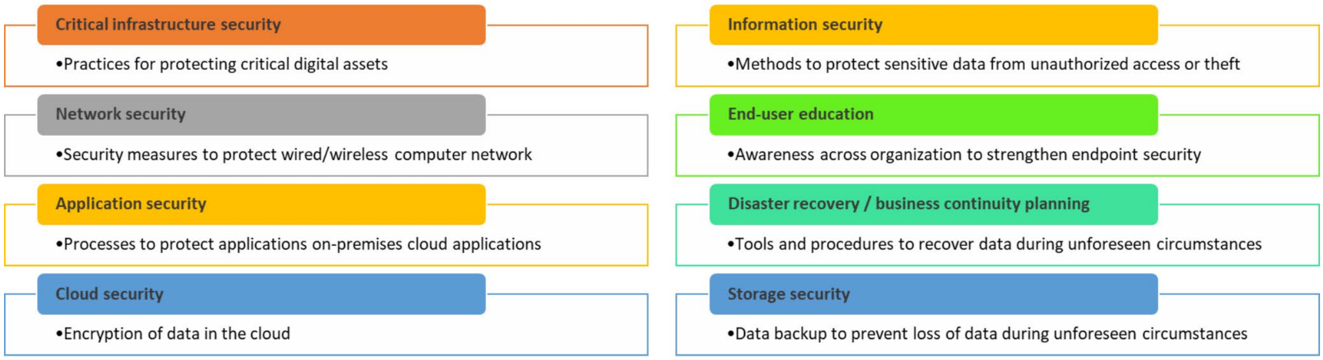


Fig. 7 Various cybersecurity domains

capabilities used for design, manufacturing, and fulfillment to manage a product's manufacturing lifecycle is cloud manufacturing. The concept of "design anywhere and manufacture anywhere" that was conceptualized in the early 2000s can be accomplished by cloud manufacturing [36]. It provides manufacturers the benefit of high efficiency, cost-effectiveness, and flexibility in managing their processes. The modern digital and computing technologies such as IoT, Radio-Frequency Identification (RFID), sensors, GPS, cyber-physical systems, and cloud computing come together as enablers of cloud manufacturing service [37]. Design engineers get access to various design resources whenever and wherever they get access to the internet which leads to faster lead time while the manufacturing engineers can access their resources anytime and anywhere to enable uninterrupted manufacturing even from outside the factory premises. The efficiency of the supply chain can be increased, and the costs lowered by storing parts digitally and manufacturing them only when required [38].

The detailed literature review has shown that the numerous studies performed by various researchers on cloud manufacturing can be grouped into five broad categories. They are studies on architecture and platform design, resource description and capabilities, service selection and composition, resource allocation and service schedule, and service searching and matching [37]. A brief overview of the studies is shown in Table 2.

2.5 Cyber security

As many industries have started embracing or preparing to embrace Industry 4.0, more and more isolated systems are getting connected to the internet which increases the vulnerability of them getting exposed to potential security risks such as, data theft, malware, denial of service, and device hacking. Cyber security is the technique to defend the connected systems from such malicious digital attacks. As manufacturing is one of the sectors with less regulated compliance standards the vulnerability to threats is much higher when compared to other sectors. Besides, the complexity in understanding the security system, disparate technologies, and lack of in-house expertise further intensify the threats to manufacturing industries.

According to Honeywell's "Industrial USB Threat Report 2021" which details the consolidated findings from various industries across more than 60 countries, threats that are designed to take advantage of removable storage devices such as USB drives have increased from 19% to 2019 to 37% in 2020. Besides, 79% of the threats were capable of completely disrupting the operational technology. The report also outlines that the usage of removable USB drives has gone up by 30% which shows the level of security exposure that these industries are facing [64]. Another report from IBM shows that the average cost of a data breach has gone up from USD 3.86 M to USD 4.16 M globally which is an all-time high in the past 17 years of the report's history [65]. Ransomware, insider attacks, server access, theft of credentials, remote access trojans, business email compromise, spam, web script, and misconfiguration are some of the types of threats that are commonly targeted at industries. The eight major widely accepted cybersecurity domains to protect against theft of information as outlined by IBM are shown in Fig. 7.

Over the past few years, numerous agencies have come up with guidelines containing documents to assist industries with procedures to address cybersecurity-related issues. Some of those guidelines for the businesses that are in the process of moving towards Industry 4.0 practices can be seen in Table 3.

Researchers have applied various frameworks and methodologies to deal with cybersecurity-related threats in an Industry 4.0 environment. Some of them are SDN-based

Table 3 Cybersecurity guidelines

Document	Industrial asset	Reference
ISA/IEC 62,443	Industrial Automation and Control Systems (IACS)	Ref [66]
IACS Cybersecurity Certification Framework (ICCF)	Industrial Automation and Control Systems (IACS)	Ref [67]
ANSSI Cybersecurity for Industrial Control Systems	Industrial Control Systems (ICS)	Ref [68–70]
API Standard 1164	Supervisory Control and Data Acquisition (SCADA)	Ref [71]
ICS Security Compendium	Industrial Control Systems (ICS)	Ref [72]
Catalog of Control Systems Security	Control Systems of critical infrastructures and key resources	Ref [73]
ICS-CERT Assessments	Industrial Control Systems (ICS)	Ref [74]
NIST 800 – 82	Industrial Control Systems (ICS)	Ref [75]

Table 4 Impact of cyberattacks

Risk	Security requirements	Business impact
Availability	Availability of data when required	Denial of service, poor product quality, and loss of production time
Integrity	Protection of data from alterations	Damage to critical physical infrastructure, unsafe work conditions for workers, and poor product quality
Confidentiality	Protection of confidential data from leaks	Loss of trade secrets and competitive advantage, damage to reputation, breach of data protection contracts with partners

(software-defined networks) [76], DevOps-based approach [77], attack tree approach [78], hierarchical model [79], impact assessment model [80], and vulnerability assessment based on SCADA [81].

A recent study shows that businesses that are affected by cyber-attacks have resulted either in the closure of production lines, loss in man-hours, enormous financial damage, or all the above. Apart from financial losses, it could also lead to loss of reputation, losing customer confidence, and even judicial actions. According to a study by IBM, manufacturing industries moved to the 2nd position in 2020 (the financial sector is at the 1st position) from its 8th position in 2019 in the list of most targeted industries [82]. This is primarily due to the increase in adaptation to digital technologies and connected devices. Some typical examples of cyber-attacks on big manufacturing industries include website breaches in OXO International and Hanesbrands Inc., a whaling attack targeting the accounting department of FACC AG, ransomware attacks on Norsk Hydro, Visser Precision, and Renault-Nissan, and an internet worm infection on Daimler Chryslers' manufacturing units. Besides, a cyber-attack on Ukraine's power grid infrastructure in 2015 through a malware-infected email was the first known attack on the power infrastructure which shows the vulnerability of physical industrial assets [83]. The various risks, security requirements, and the impact of threats to the businesses as outlined by Corallo et al. [84] are summarized in Table 4.

The studies show that although implementing digital technologies on a factory shopfloor has a huge potential, businesses must be cautious of the increasing cyber threats, and they must develop and invest in suitable data security programs to get the real benefits of Industry 4.0 transformation.

2.6 Automation and robotics

Both automation and robotics go hand in hand as their purpose is to work independently and efficiently in the industries to improve productivity. By connecting robots to a centralized computer system, their activities can be controlled which would help them to complete the task without the intervention of humans [85]. With the advancements in machine vision techniques, they take the advantage of high-resolution cameras attached to the robotic arms to track the movement of objects in real-time and perform visual assignments such as identifying and removing defective parts from the production line. Although automation and robotics are used in industries for many decades, the robots that would be used in Industry 4.0 environment would have advanced sensors, control algorithms, data communication channels, navigation and guidance systems, and data processing abilities [86]. The major differentiating factors between the earlier generation and current generation robots are their capabilities to self-learn, flexibility to perform a wide variety of operations, and agility which are supported by the various complex algorithm-based neural networks.

The significant applications of automation and robotics in Industry 4.0 includes performing complex and dangerous jobs [87], enabling uninterrupted production [88], improving productivity and reliability [89], extracting data [90], working in unpleasant environments [91], perform monotonous and difficult tasks [92], deliver higher efficiency [93], working for long hours [94], material handling [95], customer service [96], surveillance [97], manage assembly lines and fabrication [98, 99] which all are supported by various digital technologies.

Robotic Process Automation (RPA) is another technology that has enormous benefits and use-cases in automating various processes of an organization, especially in ERP-related (Enterprise Resource Planning) activities. Various technologies such as AI algorithms, text recognition, and language processing techniques come together to achieve this goal. RPA which is also referred to as a "digital worker" is a software program that is used in the automation of high volume, routine, and repeatable production tasks to boost the overall productivity of an organization. Automatic singing-in into software applications, data editing and migration, autoreply to emails, filling online forms, report generation, and automatic invoicing are a few applications of RPA [100]. The major disadvantage of RPA is that it works based on a set of simple rules and is incapable of using data or analytical models to work in complex, data-intensive decision-making systems. However, combining RPA with ML can overcome this to some extent [101].

2.7 Internet of things (IoT) and industrial internet of things (IIoT)

The network of various physical objects ("things") integrated with sensors, software, and digital technologies that allow them to connect and communicate with each other using the internet is termed as Internet of Things (IoT). The key difference between IoT and IIoT lies in the "things" that are connected to the internet. IoT refers to the connected devices or systems that are used in general consumer applications such as consumer electronics, smart home appliances, personal health tracking devices, etc., while IIoT refers to the connected industrial devices or systems used to support industrial operations like manufacturing, quality control, and supply chain and logistics.

The entire concept of the fourth industrial revolution is built around establishing a communication channel through the internet that allows a seamless two-way flow of data between human-machine and machine-machine [102]. The small size and cost-efficient IoT sensors would allow the connection of more physical objects that make the system work efficiently, smartly, and safely [103]. In a manufacturing system, the data from these sensors such as heat, temperature, pressure, moisture level, humidity, vibration, friction, and movement are collected real-time to build a statistical relationship with the product performance. From reducing the manufacturing cost to assisting in preventive maintenance and providing a safer work environment the potential of IoT is enormous in future smart factories. Stopping a production line to fix repairs would result in loss of production time and affect the dependent assembly lines. Hence, identifying the malfunction in advance using appropriate sensors would support manufacturing by eliminating failures which in turn results in saving.

Zhang et al. [104] developed models based on Long Short-Term Memory (LSTM) network and used 21 sensors placed at different locations to collect and monitor the health of an aero propulsion engine system and monitor its performance and predict its degradation. Using appropriate sensors and AI-based algorithms Lee et al. [105] presented a model to predict the wear of a cutting tool and failure of spindle motor bearing. Researchers have shown that IoT systems can be used in predictive maintenance of machine tools [106], anomaly detection [107], and error prediction in machine centers [108]. The IoT system can also be used in hazardous work environments such as nuclear power plants, chemical factories, wastewater treatment, and manufacturing industries to collect critical machine data through appropriate sensors that can be used to monitor and control production and operation. However, as more and more "things" are connected, the complexity of protecting sensitive information increases manyfold that needs novel safety algorithms [109].

2.8 Cyber-physical systems (CPS)

A cyber-physical system is an intelligent computer system that integrates sensing, computation, control, and networking capabilities into physical objects, and connects them to the Internet and to each other. While IoT and CPS look much similar, there is one major difference between them. IoT refers to a physical object embedded with critical sensors (sensing) that can gather data and transmit (networking) it through the internet. On the other hand, apart from the sensors and internet, a CPS contains components that are required for computation and control that make the system highly efficient. The diverse application area of CPS includes aviation, self-driving cars, energy, disaster and emergency management, healthcare, smart manufacturing, and smart city.

In the case of smart manufacturing, CPS can be implemented in a factory for monitoring production and assembly lines, monitoring of assets, predictive analysis, and supply chain management. A typical CPS framework has a physical layer that contains the physical sensory, communication, and data processing modules. Various physical components such as sensors, GPS, RFID, machine vision camera, and IoT modules recognize and generates an enormous amount of real-time data about their surroundings and send it to the communication layer. The middle layer or the communication layer is responsible for the real-time transfer of data from the physical layer to the cyber computation layer. The layer has various communication channels such as local area network (LAN), wide area network (WAN), Bluetooth, Wi-Fi, switches, and routers. It creates a channel between external applications, the physical layer, and the cyber layer. The computation layer acts as the third layer that is responsible for the intelligent processing of data received from the physical layer. It also performs supervisory control, makes decisions based on the data, and sends commands back to the physical layer [110]. The guidelines of a cyber-physical

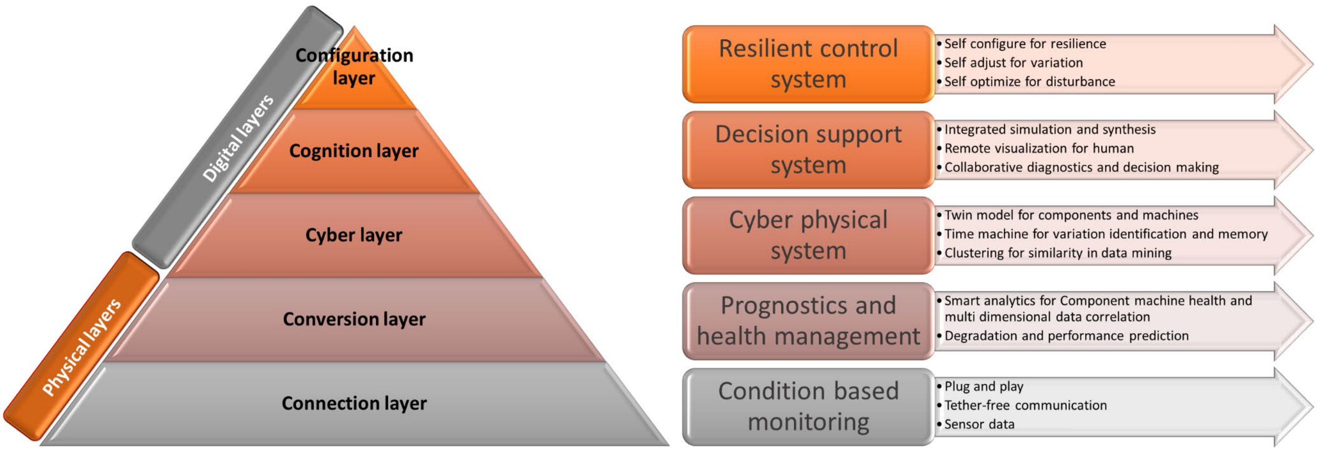


Fig. 8 5C architecture of a CPS

system based on 5C architecture as proposed by researchers [111, 112] are shown in Fig. 8.

Some of the successful applications of CPS in a manufacturing environment includes CPS modules for a machining cell, plug and work applications, automatic process plan generation in a dynamic manufacturing unit, CPS based automatic process planning and maintenance system, adaptive scheduling and alternative routing, inter-company data transfer, and set up pilot systems for research and development activities [113]. Despite their tremendous benefits, industries and researchers are also wary about the associated challenges and risks. Especially the challenges such as the complexities in design, testing, and validating the holistic functionality of the system, and implementation challenges. Besides the safety and security issues that are typical to any system connected over the internet like the threat to data privacy and confidentiality, data corruption, and malware are valid for a CPS as well [114].

2.9 Additive manufacturing (3D printing, 4Dprinting, and 5D printing)

Additive Manufacturing (AM) is a technique of printing 3-dimensional solid objects by building a layer of materials one over the other using CAD models [230]. Although the technology was developed in the early 1980s it started gaining traction in the last decade with the adoption of supporting digital and intelligent technologies in the industries [115]. As mass customization is one of the core contexts of Industry 4.0 [116], it is critical in developing unconventional manufacturing processes like AM which is expected to become a key technology driver to fabricate highly sophisticated customized products with advanced features that are otherwise not possible to produce with conventional manufacturing processes [117]. Over the past few decades, the AM technology has matured which currently allows the manufacturing industry to print highly complex functional parts in any required material with very tight precision and good aesthetics which are critical in industries such as aerospace, biomedical, automotive, manufacturing, and consumer goods [115]. While conventional additive manufacturing is already used by many manufacturing industries, the current interest is on the system's flexibility in adapting to different challenging applications such as printing of smart materials, printable electronics, printable assemblies, and hydraulic components.

Soft robotics is one of the emerging fields in robotics that is used to manufacture robots from highly compatible flexible materials such as thermoset elastomers that can mimic human motion, and additive manufacturing plays a vital role as the key technology enabler [118]. Some of the applications of soft robots in a manufacturing setup include soft actuators [119], stiffness-controllable robot links [120], inflatable robotic arms [121], continuum robots [122], and adaptive graspers [123]. The smart materials (shape memory alloys and polymers) printed by additive manufacturing technique develop the ability to be flexible and react to their surroundings by changing their shapes or properties which gives rise to a new technique called "4D printing" [124]. MacCurdy et al. [125] have designed and 3D printed a novel functional hydraulic force transmitting mechanism pre-filled with hydraulic liquid that eliminates the need for assembly. In the studies conducted by Ota et al. [126] and Macdonald et al. [127] they have demonstrated the possibilities of 3D printing electronics components such as LEDs, circuits, temperature sensors, and related control electronics. The other latest addition to the AM portfolio is 5D printing in which the printing head gets additional degrees of freedom to print objects from 5 different axis (similar to 5-axis machining centers), and hybrid manufacturing that combines the possibilities of performing both additive and subtractive manufacturing in a single setup to gain the benefits of both the technologies [128].

3 Socio-economic challenges of industry 4.0

Before the Industrial Revolution, communities and societies were diversified with varieties of occupations, some of them are physically demanding while others depend on the creativity and intellectuality of the human mind. Although the focus of the industrial revolutions was to improve productivity and product quality, it has also eliminated humans from the hazardous and unpleasant working environment. The introduction of automation and robots into the industries helped humans to channel their focus on jobs that demands decision-making, problem-solving, intuition, persuasion, or cognitive skills, while the heavy lifting was done by the machines. Especially, various artistic occupations that are based on expressing human creativity such as poetry, story, painting, sculpture, architecture and so on which are exclusive to humans are considered a prohibited zone for machines. However, studies show that recent technology such as AI has the potential even to challenge and even surpass humans in the cognitive space. Hence, apart from the technical challenges such as handling exponential data growth, interoperability, data sensitivity, data security, cost, high processing power and energy consumption the other critical challenges like human and social factors that can be disrupted by Industry 4.0 technologies are discussed on this section.

3.1 Challenges of industry 4.0

3.1.1 Unemployment

Studies have shown that unemployment is predominantly influenced by major social events such as the industrial revolution, the great depression, and world wars. Although the earlier industrial revolutions have increased the demand for labor which led to urbanization and population concentration, it also resulted in inequality in the rural and urban employment market [129]. The machines and robots of the earlier industrial revolution assisted humans by providing their muscle power to help industries improve productivity while leaving brainpower to humans. But the real threat of Industry 4.0 technologies is the challenge of AI's capability to autonomously solve complex problems and attempting to substitute even human intelligence. A study by the UN Department of Economic and Social Affairs (DESA) shows that the risk of job loss due to automation can be over 80% in the low- and medium-income group. While the high-skilled labor stands to gain from the implementation of AI, the huge pressure on the low and medium-skilled laborers could intensify wage disparity. The study also warns that soon AI-enabled robots can replace even high-skilled professions such as software programmers, doctors, and architects [130]. While AI and robots continuously encroaching the fields that were previously thought exclusive to humans, and UN data estimates a 6 billion working-age population by 2050, the increase in threat to human employment is highly likely.

3.1.2 Loss of craftsmanship

Since the 1980s the chess competition between human chess masters versus computers is a battle that was keenly watched by more technocrats rather than sports enthusiasts which is believed as a demonstration and successful use case of AI algorithms. Besides, there are numerous successful examples of AI beating humans in visual recognition, reading comprehension, complex strategy games, and autonomous cars. Some recent demonstrations show that AI can even write original melodies, and even beat experienced lawyers in accurately identifying issues with legal contracts [131]. In 2016, an attempt was made through an AI project named "The Next Rembrandt" to replicate the artwork of one of the greatest painters, printmakers, and draughtsman of the 17th century, Rembrandt. By analyzing and studying the paintings pixel by pixel, AI learned Rembrandt's style and reproduced a highly convincing masterpiece [132]. Recently, the AI went further and restored the missing pieces of one of Rembrandt's paintings [133]. The above few examples of AI's capabilities show that AI technologies can compete with humans not only in labor-intensive and monotonous jobs but also in creative, artistic, niche, human-only jobs.

3.1.3 Wage disparity

The rapid adoption of new technologies over the past few decades has significantly affected the wage difference between different labor categories. A recent study [134] by the World Bank highlights the polarization of the labor market with increasing wage disparity and a steady decline in the income of medium-skilled occupations since the 1990s. This was partly attributed to the rise of information technologies and the cognitive job market which has increased the wages of high-skilled labor. Acemoglu and Restrepo [135] studied the impact of automation on the US labor market and reported that the employment and wages of low-skilled labor are highly affected, but the high-skilled labor is unaffected. The threat of automation and AI has once again brought the old idea of universal basic income which ensures a regular and guaranteed sum of money to every adult irrespective of income or financial condition [136].

3.2 Key takeaways

From the various sections discussed till now, it can be interpreted that the entire concept of Industry 4.0 revolves around collecting, processing, monitoring, storing, and analyzing data from various sources in digital form to improve the process efficiency, make decisions, learn, and improve on the go. The data collected from various sensors that are connected to a physical system are processed in a centralized location using AI and ML algorithms to understand the manufacturing processes which helps the industries to optimize their operation and even teach the learnings back to the system. The in-depth analysis of data collected from various processes gives a new level of understanding of the process which helps industries to operate at the highest possible efficiency.

If Industry 3.0 is about generating data, then Industry 4.0 is about processing and analyzing it to achieve the highest possible optimization which improves the quality of the manufactured parts to an unprecedented extent. Although industries can realize the benefits of adopting these digital and computing technologies, the higher implementation cost and requirements on the highly skilled workforce are a few deterrents to their rapid adaptation. Besides, many organizations are still skeptical about how these new-age disruptive technologies would benefit their business considering their size of the business and the cost of restructuring and reskilling requirements. However, rather than the cost and technical challenges, the impact of these technologies on the socio-economic factor is the serious concern. If left unchecked, the disruption it can have on society would be enormous and irreversible. Hence, business leaders and policymakers must urgently investigate the technologies and identify methods to adopt them without affecting people and communities. Hence the current need is to find ways to include humans in the game rather than alienating them again which may altogether require a different set of technologies or a new Industrial Revolution (Industry 5.0) which are discussed in the following sections.

4 Industry 5.0: definitions from industries and scholars

Many industries that are closely associated with digital technologies have come up with different definitions for the impending fifth industrial revolution. While Industry 4.0 concept itself is yet to get a head start in many developed and emerging economies, these definitions could be considered as a wish list or predictions for the upcoming revolution.

The European Commission has termed Industry 5.0 as the vision of industries to think beyond increasing productivity and efficiency and contribute to society by placing the workers at the center of the production process. The emphasis was on research and innovation that is sustainable, human-centric, and resilient [137].

Esben H. Østergaard, CTO of Universal Robots has termed Industry 5.0 as the transformation of mass customization enabled by Industry 4.0 technologies to mass personalization and hence labeled it as the "human touch" revolution. He also forecasts a return of the pre-industrial way of manufacturing that is supported by technologies in which humans play a critical role rather than being alienated. The importance of bringing humans back to the manufacturing loop to provide personalization and human touch was reiterated through collaborative robots or cobots [138].

Nexus Integra, a service provider in Big Data and Industrial IoT platforms defines Industry 5.0 as *"the next step, which involves leveraging the collaboration between increasingly powerful and accurate machinery and the unique creative potential of the human being"* [139].

The Global Electronic Services repairs and services define Industry 5.0 as *"the revolution in which man and machine reconcile and find ways to work together to improve the means and efficiency of production"* [140].

Levity, a service provider in Artificial Intelligence terms Industry 5.0 as something that *"adds a personal human touch to the two main pillars of Industry 4.0, automation and efficiency. It refers to people working alongside robots, smart machines, and technologies."* They have also pointed out that the core element of Industry 5.0 would be the personal touch which cannot be provided by technologies [141].

Frost & Sullivan calls Industry 5.0 as *"a model of the next level of industrialization characterized by the return of manpower to factories, distributed production, intelligent supply chains, and hyper customization, all aimed to deliver a tailored customer experience time after time"* [142].

Association for Advancing Automation has predicted that the need for greater customization and personalization would drive the fifth industrial revolution that would revolve around a larger collaboration between machines and humans to realize the dual benefits of cognitive computing and human intelligence [143].

Andreas Eschbach, founder, and CEO of a software solutions provider says that Industry 5.0 would be an evolution in the manufacturing process in which humans are assisted by machines to realize the dual benefits of accuracy and cognitive skills [144].

Neil Sharp of JJS manufacturing, a manufacturing solution provider has stated that human-centric development, sustainability, and resilience would be the three pillars of the

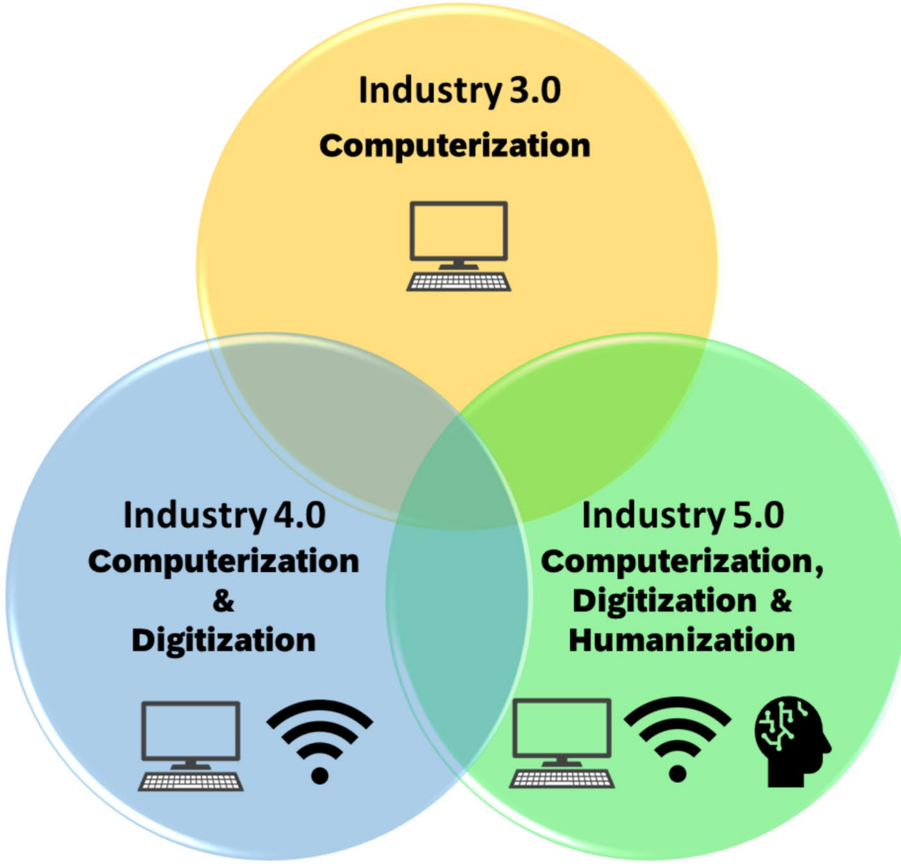


Fig. 9 The key differential factors of Industry 3.0 Vs 4.0 Vs 5.0

fifth industrial revolution which aims to empower humans and not replace them [145].

Eric Howard of Simio LLC, a simulation software provider has also indicated that combining human capabilities and automation to meet the demand for personalization would be the driver of the next industrial revolution [146].

Ozdemir and Hekim [147] proposed Industry 5.0 to be a much-required evolutionary and incremental development that is built on the concept and practices of Industry 4.0.

So far, every industrial revolution had attempted either to eliminate or alienate humans who stand to lose against the superior productivity and efficiency of automation and digital technologies. However, for the first time, most of the definitions have confirmed the inclusion of humans and sustainability as the additional key pillars of the fifth industrial revolution. Even at the heart of Japan's "Society 5.0" model, they strive to create a human-centered revolution to attain economic development by integrating physical and cyberspace [148, 149].

5 Prospective technologies and applications of industry 5.0

From the previous sections, it can be implied that Industry 4.0 has solely focused on improving profits by concentrating only on product quality and process efficiency using different digital technologies. However, it has widely ignored the need for human intelligence and failed to acknowledge the impact of digital technologies on the environment and society. Hence Industry 5.0 is predicted to include the two key missing elements, the inclusion of humans and sustainable development. In addition, it is also expected to provide flexibility and agility that industries require to quickly respond to the changing market conditions and customer preferences. However, although most industrial leaders and many scholars have predicted leveraging human creativity as the key difference of Industry 5.0, few other scholars argue that Industry 5.0 would just be an evolution or an incremental advancement of Industry 4.0 technologies and practices [150, 151]. The key differentiating factors between the industrial revolutions are shown in Fig. 9.

Despite being conceptualized as an incremental advancement, discussions on various enabling technologies and the

Fig. 10 The prospective technologies of Industry 5.0

applications of the fifth industrial revolution have already gathered pace. The union between the accuracy and efficiency of digital technologies and the creative thinking ability of humans would create a synergy between humans and machines. The increasing customer requirements for highly personalized products is believed to be another benefit of Industry 5.0 which can leverage various software tools, artificial intelligence, machine learning, and additive manufacturing. If the earlier industrial revolution was about mass production, the future is predicted to be driven by mass personalization as "there is no one size that fits all".

In his autobiography "My Life and Work", Henry Ford has mentioned that he once said, "any customer can have a car painted any color that he wants, so long as it is black". The statement was around the launch of "Model T" in the year 1909 when mass production was the buzzword of industries. It was an era during which any minor changes on the product like even a variation in paint color would need a break in the production line which increases the complexities and compromises its efficiency, quality, and results in higher cost. In fact, his black-only strategy has helped Ford to reduce the overall cost of the model by more than half in a few years. This mass production strategy significantly changed the American economy and society and even helped Ford's own factory workers to afford a car which was until then possible only for rich and elites. Nearly after a century, the concept of mass production has already started fading in favor of mass personalization in the name of the fifth industrial revolution with the support of digital technologies which would be discussed in the following sections. The diagrammatic representation of prospective Industry 5.0 technologies is shown in Fig. 10.

5.1 Collaborative robots (cobots)

Although robots are used in industries for many decades the highly connected fourth industrial revolution robots are designed to work autonomously without human supervision, and they already play an active role in many factories currently. However, instead of working independently, the fifth industrial generation robots are expected to collaborate with humans and work under his guidance. Thanks to the advancement in digital technologies such as artificial intelligence, machine learning, and conventional robotics that gave rise to the next-gen collaborative robots or “cobots”. Such cobots can sense their surroundings, adapt to them, and learn on the go. This makes them highly flexible and adapts to the changes instantaneously to support the manufacturing of small batch sizes and fulfill highly personalized products which would be one of the major requirements of future manufacturing. While the current generation robots work inside fenced surroundings to perform a predefined set of operations, the cobots are released from their confinement to enable 3Cs (Coexist, Cooperate and Collaborate) with their human counterparts. These lightweight, sensitive, precise, and highly flexible cobots are easily programmable to work aside humans to relieve them from physically demanding, hazardous, or monotonous activities.

KUKA, a leading manufacturer of industrial robots and automation systems has already introduced their first-generation lightweight collaborative robot named “LBR iiwa” which is currently being used in assembly and production lines of Ford, Daimler, BMW, Skoda, and many other automotive companies. As the cobots are small and mobile, they are capable of working in almost all the areas of an industrial setup such as laboratories, handling of raw material, production and assembly lines, material handling, transportation, packaging, quality control, and shipping of finished products to the customers. Their flexibility to adapt to different job requirements can reduce the dependency on conventional industrial robots that significantly reduce the cost of ownership in the manufacturing industries. The recent advancements in technologies such as distributed artificial intelligence, edge computing, parallel processing, and linked data enable cobots to make real-time decisions effectively [152]. As the cobots are highly affordable, versatile, and easy to deploy, it gives the advantage of a level playing field for the small-scale industries to compete with large conglomerates and multinational corporations.

For instance, a cobot installed in Craft and Technik Industries in India which is an automotive part manufacturing company has shown a 20% improvement in the product quality by handling the monotonous job of loading and unloading components from a CNC machine while simultaneously performing inspection [153]. Stela Laxhuber, a mid-sized German manufacturer of drying machinery products has reported a tremendous improvement in its productivity and quality of parts after employing a cobot in their welding cell. The welding operation which typically takes a day was completed by a 6-axis KUKA KR Cybertech cobot with the required precision and top-notch craftmanship in a mere 50 min [154]. Few other industries that are realizing the benefits of employing cobots in their operations include biomedical, agriculture, food processing, electronics manufacturing, warehousing, automotive, metal processing, packaging, and logistics. Although cobots prove to be highly efficient in an industrial environment, the other aspects such as safety, trust, loss of shared emotions between workers, and possible job loss for humans still looms large which must be addressed [155].

5.2 Smart sensors

A sensor is an electronic device that can sense any changes in physical properties and convey them through an appropriate change in electrical output. For instance, a thermocouple sensor responds to the change in temperature by producing a suitable output voltage. While a conventional sensor has only the base sensing elements, a smart sensor system can independently perform data collection, data conversion, data processing, and establish communication to an external system such as a cloud server which are some of the critical requirements of future smart factories. Such extended capabilities are achieved through a suitable base sensing element, microprocessor, communication, and memory modules all embedded in one system. Basically, smart sensors and actuators are an integral element of IoT, CPS, automation, robotics, and all intelligent systems which are the driving force behind Industry 4.0 and Industry 5.0 technologies. Hence the importance and functionality of a smart sensor can be understood from the various sections of this article.

5.3 Digital twins

The accurate digital replication of a physical system that acts as its virtual counterpart is the digital twins. In general, using the data gathered from the original model and mirroring it on its replicate model to simulate and understand the real-time behavior is the core concept of twinning [231]. The concept of using “twins” was believed to be in practice since the late 1960s when NASA was working on the Apollo space mission. NASA scientists have made two identical spaceships to allow precise mirroring of the conditions that the spaceship in orbit experiences with its twin on the earth [156]. However, with the advancements in digital technologies, currently, it is possible to mirror the

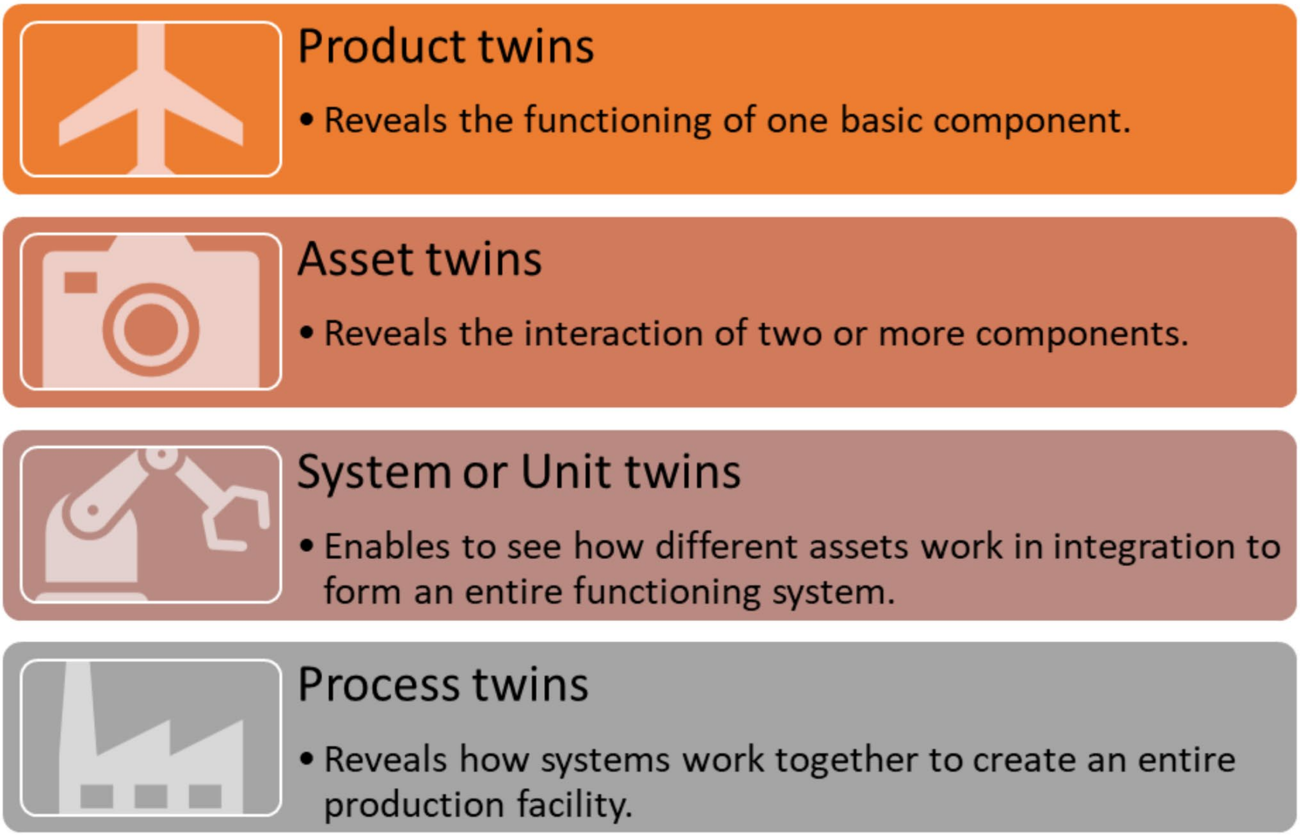


Fig. 11 Types of digital twins

condition on a digital model rather than on a physical model and hence derived its name, "digital twins". Even the term "digital twins" was first coined by NASA in its 2010 report to denote its Simulation-Based Systems Engineering [157].

NASA has defined a digital twin as a system that is designed to integrate multi-physics, multi-scale, probabilistic simulation to mirror its twin using sensors and appropriate data derived from the source. The system on the digital twin can prevent the failure of a physical system and extend its life by suggesting suitable changes and optimizations. Although both simulations and digital twins use the digital versions of a physical system the main differential factor of digital twins is that they can be used to simultaneously run and study multiple processes. The different types of digital twins as outlined by IBM are shown in Fig. 11.

The three main capabilities of digital twins are mirroring, shadowing, and threading [158]. The capability to accurately mirror the physical system to meet the purpose of twinning is mirroring. The synchronization between the physical and virtual models is shadowing. The data from the physical model is transmitted to its digital counterpart at a regular interval through appropriate communication channels to enable synchronization. The data received from the physical system are stored in the form of a record in the digital model to track the history and evaluation of data and this process is called threading. Cloud computing technology is used to store these data [159]. As digital twin is an ultra-realistic representation of a physical system, it can be combined with other digital technologies such as IoT, Big data, Artificial intelligence, and Machine Learning to collect real-time data and monitor the health of the system, predict remaining useful life and in preventive maintenance. The various applications of digital twins in the manufacturing industries include product design and new product development, product manufacturing, asset management, process monitoring and optimization, quality control, predictive maintenance, supply chain management, and assist in decision making by supporting cross-functional (engineering, manufacturing, marketing, and sales) collaboration [231,160]. The other industries that benefit from the technology are aerospace, space research, bio-medical, energy storage, automotive, electricity production and distribution, and autonomous vehicles. As the scope of the article is to briefly introduce the different digital technologies of Industry 5.0, the scholars interested to know further details and few real-life successful implementations of digital twins can refer to these articles [161–171].

Fig. 12 Ideology of IoE

5.4 Internet of everything (IoE) and artificial intelligence of things (AIoT)

The term "Internet of Everything" was coined by Cisco to describe the all-around connectivity between, people, things, data, and processes. The hybrid connection enables to gain of more valuable information which can be converted into new capabilities, rich experiences, and exceptional opportunities. If IoT refers to the connection of physical objects with the internet which is a single technology transition, IoE contains many technology transitions in which IoT is one of the parts. The philosophy of IoE revolves around connecting the billions of devices, objects, and common things around the world with sensors that give them wide networking capability and make them smarter. The idea of IoE and its data flow is shown in Fig. 12.

The ideology of IoE is a closed loop in which the real-time data flows through its four key pillars. The user preferences and insights ("people") collected from devices such as wearables, smartphones, social media, smart appliances, and smart digital systems ("things") are processed and analyzed by artificial intelligence algorithms ("process") to provide a personalized experience back to the "people". Cisco has estimated that the real benefits of IoE can be realized once the 99.4% of the currently unconnected physical objects become a part of IoE one day in the future. Improving productivity and reduction in costs, increase in employee productivity, highly efficient supply chain and logistics, innovation in new product development and research, and superior customer experience are some of the benefits that companies stand to gain from IoE [172].

The lethal union of Artificial Intelligence and Internet of Things gives birth to Artificial Intelligence of Things (AIoT) which is becoming a new technology topic in industrial automation. A conventional IoT system consists of sensors that have the potential to generate an enormous amount of unstructured data. In an industrial set up as many IoT devices are connected to form a network, the volume of real-time data that needs to be handled and analyzed gets too huge. With AIoT, a connected physical device gains the power to solve problems and make decisions that were impossible for conventional IoT-enabled devices. It is achieved by embedding AI algorithms in the components of a physical system such as programs and chipsets which all are connected to an IoT network. An appropriate application programming interface is deployed to provide interoperability between the components at device, software, and platform levels. They operate in unison to optimize the system and extract the required useful data from it for the data analytics functionality, make decisions, optimize the system functionality, and learn from it, all without the intervention of humans. As the technology is relatively new the further capabilities of the system must be explored. However, few of the many possible applications of the technology include consumer goods, industrial, enterprise, smart health tracking devices, smart home appliances, autonomous vehicles, and service sectors.

5.5 Blockchain

Blockchain is a digitally managed, distributed, and decentralized ledger used to store both tangible and intangible assets in a business network in the form of transactions in an immutable format. The characteristics of the technology in providing trust, transparency, and traceability make it attractive for applications where transactions are involved [5]. Each block is a file where the transactions are permanently recorded and when a new transaction is performed it gets added to the block similar to adding a new page to a ledger. In simple terms, the technology can be defined as a chain that contains data blocks in the chronological sequence that are permanently stored in encrypted form as a distributed ledger that is tamper-proof or fake proof. As all businesses rely on data and information flow across various stakeholders it is critical to ensure that the flow is accurate and faster, and Blockchain is the ideal technology that can deliver information from a permanent ledger only to the approved members. Originally created as a hack-proof system for banking and financial institutions, the Blockchain technology with its decentralized, distributed, and immutable features is proclaimed to be a game-changer for all the sectors that require secure data sharing within and outside their organizations [5].

The combination of new-generation information technologies such as Internet of Things, cloud computing, and Bigdata along with Blockchain technology has the potential to transform the way data is currently handled in almost all the industrial sectors. As the current IoT architecture is centralized, it is susceptible to security threats. So, adopting blockchain architecture would ensure data security by providing secure, private, and encrypted data transfer [173]. The technology helps in solving trust-related problems and enables the automated allocation of resources on a global scale. The possibility of distributed data storing, decentralized P2P transactions, automatic approval process, programmable smart contracts, eliminating counterfeit products, and dynamic encryption algorithms makes Blockchain an attractive option for industries to adopt [174, 175]. As this technology is a new entrant in manufacturing industries, the literature review shows that most of the current research on the topics is around the concept of the technology and its architecture [176–181]. However, studies have recommended that reducing the size of the blockchain, block size optimization, and a lightweight blockchain to reduce transaction latency and computing power are the potential area of future research to make the technology sustainable [5].

5.6 Edge and fog computing

The current efficiency of cloud-computing technology is insufficient in analyzing a large volume of data generated in a shorter time which affects the service quality and the overall performance of the network and the IoT system [182]. Hence, the disadvantages of cloud computing technology can be overcome by using edge computing. Edge computing is a distributed computing and storage framework deployed near the source where the data is created which keeps data on the local parts of the network or the edge devices, instead of using a centralized data server. It allows data from IoT devices to be processed at the edge (in the local system itself) before sending it to the cloud which improves the response time and saves network bandwidth. A schematic showing the typical functioning of edge computing is shown in Fig. 13.

Edge computing and Fog computing are essentially the same in terms of leveraging the computing capabilities that are available within a local network. The key difference between cloud, edge, and fog computing lies in the place at which data processing is done. In cloud computing the data processing occurs at the centralized cloud servers that are managed by a few service providers at geographically dispersed data centers, while in edge computing it occurs at the physical device in which the IoT sensors are embedded or at a gateway device that is close to the sensors. However, in Fog computing, the activities are performed on the processors that are a part of the LAN hardware which are far apart from the sensors. The main advantage of cloud computing is in its capability to provide in-depth and advanced processing, while edge and fog are suitable for quick and real-time

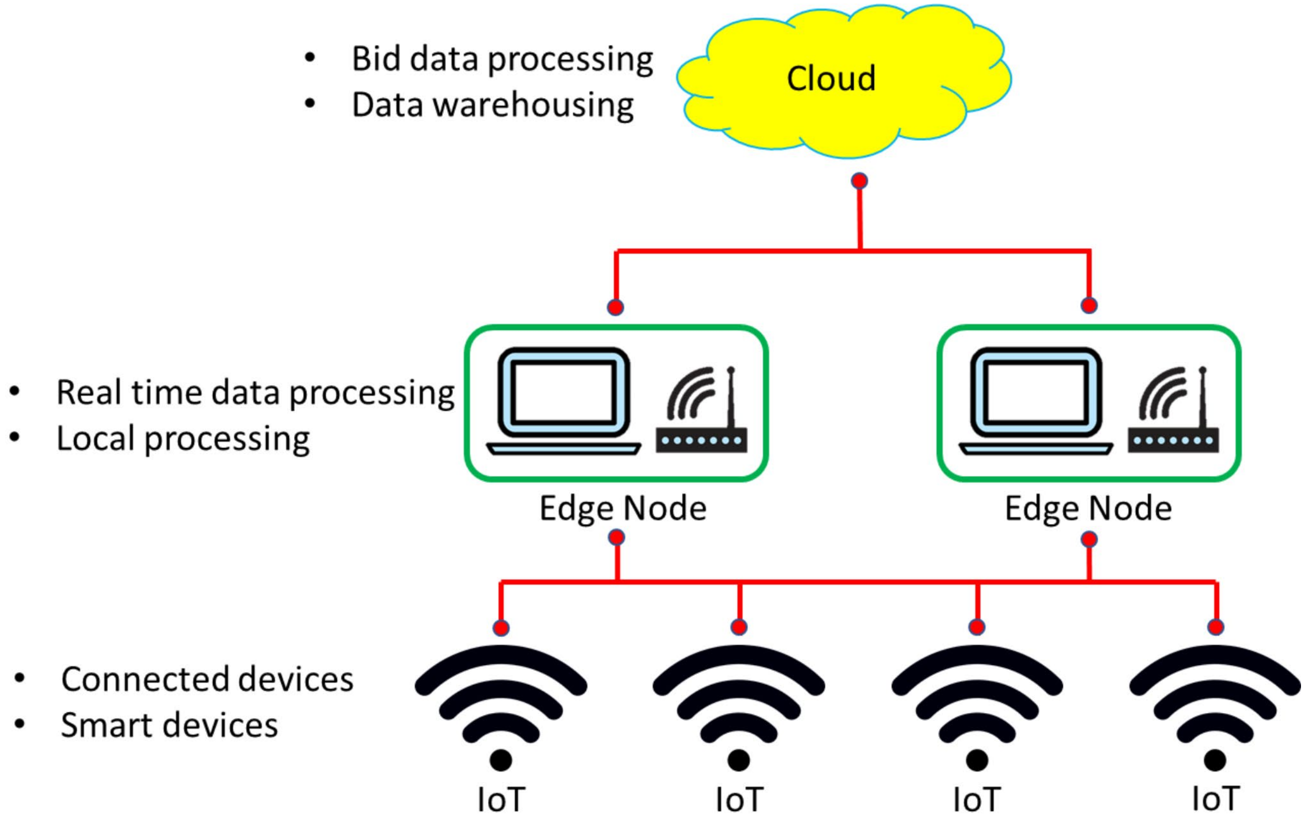


Fig. 13 Data processing in Edge computing

response. The difference between edge, fog, and cloud computing is shown in Fig. 14.

Although cloud computing is considered a critical infrastructure to support IoT applications, it is prone to latency-related issues in applications that involve high volume and high velocity of data. Hence, the downside of cloud computing can be solved by edge or fog computing architectures that provide the service near the IoT device instead of centralized cloud infrastructure which is important in critical applications such as real-time manufacturing, autonomous vehicles, cognitive assistance, and healthcare [183]. In general, cloud computing is high latency, high power consuming infrastructure with high processing capabilities, whereas edge and fog computing are low latency, low power consuming infrastructure with low to moderate processing capabilities [184]. Despite their advantages, scalability, service availability, mobility support, energy management, and security are a few challenges that must be addressed for a successful implementation of edge or fog computing infrastructure for IoT applications.

5.7 Cognitive computing

Cognitive computing refers to the set of technology platforms that uses computerized models to mimic human thought processes to solve complex problems [185]. Although some scholars classify cognitive computing as a subset of artificial intelligence, basically they are two entirely different disciplines but with overlapping methodologies. While the focus of artificial intelligence is to reflect reality and produce accurate results based on a set of theories and algorithms, cognitive computing is built on participation from two distinct interdisciplinary fields such as computing (artificial intelligence, machine learning, pattern recognition, data mining) and cognitive science (visual recognition, language processing, psychological, philosophy, and anthropology) to augment human thinking and reasoning abilities similar to the human brain [186].

Machine vision, machine learning, deep learning, and robotics are some technologies that are a critical part of AI that supports learning from the vast set of data, reasoning to make sense of the data, and self-correction to take decisions. With repeated learning, an AI system is capable of surpassing humans in terms of accuracy and finding new ways to solve a problem. However, the focus of cognitive computing

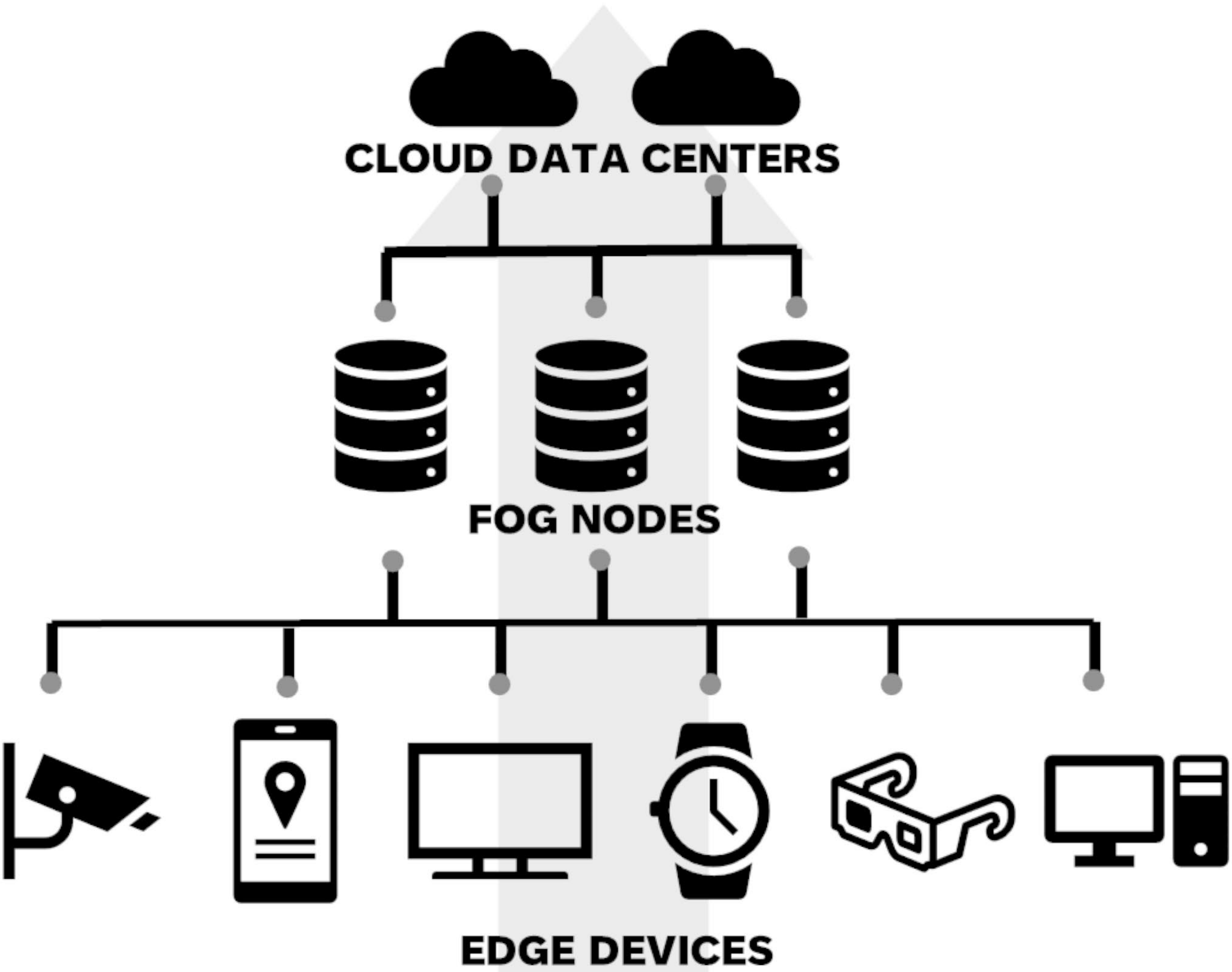


Fig. 14 Edge, fog, and cloud computing

is to replicate human reasoning using technologies such as data mining, image recognition, and language processing to solve problems and optimize human processes. Hence, the goal of cognitive computing is not to replace humans but to supplement humans in making a decision by processing a large volume of data [187]. In fact, a system with cognitive computing capabilities can interact with humans, interpret contextual language, analyze the data based on experience and make assumptions based on the interaction [188].

A smart IoT-enabled physical system that has cognitive computing capabilities embedded in it can assist humans by providing critical suggestions and help in making decisions by analyzing the collected data. Such a system that combines IoT with cognitive computing results in Cognitive Things [189]. According to an article in the World Economic Forum, it has been estimated that around 463 exabytes (1 exabyte $= 1\times10^{6}$ terabyte) of data would be created every day by 2025 which is equivalent to the volume of data that requires approximately 213 million DVDs every day [190]. With the number of connected devices increasing every day, analyzing the data (Big data) generated would be a daunting task for the industries which can be intercepted using cognitive computing to convert the raw data into meaningful information and invaluable knowledge [191]. The real potential of cognitive computing can be obtained by combining it with big data analytics and unique human elements such as ethics, common sense, and self-directed goals. The major difference between cognitive computing and ML techniques in terms of data processing is that the former works on vectors having objective data while the latter learns by performing different mathematical calculations on the data. Hence, the unstructured data (the data that are derived from texts, pictures, videos, etc.) must be converted to a quantitative value which is derived as vectors to integrate cognitive

Table 5 KPIs of 5G and 6G technologies

S#	KPI	5G	6G
1	Peak data rate (Gb/s)	20	10,000
2	Experienced data rate (Gb/s)	0.1	1
3	Peak spectral efficiency (b/s/Hz)	30	60
4	Experienced spectral efficiency (b/s/Hz)	0.3	3
5	Maximum channel bandwidth (GHz)	1	100
6	Area traffic capacity (Mbps/m^2)	10	1000
7	Connection density (devices/km^2)	10^6	10^7
8	Latency (ms)	1	0.1
9	Reliability (packet error rate)	10^{-5}	10^{-9}
10	Mobility (km/h)	500	1000
11	Energy efficiency (Tb/J)	Not specified	1
12	Delay jitter (ms)	Not specified	10^{-3}

computing and ML. To gain the real benefits from cognitive computing, the system must be taught using numerous such vectors which it can interpret and learn the underlying patterns from the data [188].

IBM Watson is one of the most popular cognitive computing-based systems that is revolutionizing the healthcare sector by helping doctors to make superior decisions [192]. Besides, the image recognition algorithm can identify faults and provide solutions just by reading photographs of the machine, thus providing cognitive maintenance. The speech recognition can be used by the machine operator to control the machine which otherwise requires specialized programming skills. The system can recognize texts and pictures, hear speeches, and interpret the questions to provide solutions. In-process visual inspection, adaptive robotic maintenance, predictive maintenance, improve operational efficiency, and develop personalized products and services are a few other applications of a cognitive system in manufacturing industries [193]. Although cognitive computing is still in its nascent stage of development there are numerous studies that highlight the benefits of the technology in analytics-oriented industries such as banking finance [194], education [195], health care [196], marketing [197], behavioral analysis [198], and customer support [199].

5.8 6G and beyond

To fulfill the requirements of a fully connected digital world, innovations in digital and computing technologies alone are insufficient, but a substantial advancement in communication technologies is also critical. However, with the next gen 5G technologies just around the corners, the telecom giants have already kickstarted their research activities towards the next technological breakthrough that is required to achieve the 6G goals which are expected for a commercial launch by 2030. 6G and beyond can help address the wireless connectivity requirements of the rapidly growing intelligent devices and services. As a 6G network will be able to use higher frequencies when compared to 5G, it can provide higher capacity and lower latency. However, as the expected commercial launch of 6G technology is almost a decade away it is premature to predict the enabling technologies over which it would be built. But the envisioned key performance indicators are, very high data rates of up to 1Tbps, improved spectral efficiency and coverage, wide bandwidths of up to 100 GHz, improved energy saving, ultra-low latency, and exceptionally high reliability. A brief comparison of the key performance indicators (KPI) of 5G and 6G technologies as reported by Rajatheva et al. [200] and Strinati et al. [201] is shown in Table 5.

The usage of 6G and beyond is expected to deliver the required latency, provide an excellent service quality, network infrastructure for connected devices, and support integrated artificial intelligence capabilities [202]. AI-based autonomous supply chain, e-health, collaborative robots, massive twinning (digital twins created from humans, physical objects, processes, and large infrastructures), telepresence using holographic techniques are some of the use cases of 6G technologies predicted by Ericsson [203]. In addition, with the expected increase in the number of connected devices and the enormous amount of data collected to support Industry 5.0 applications, energy management is another critical environmental aspect that needs to be considered and 6G and beyond is expected to provide a highly optimized energy consumption strategy.

5.9 Augmented reality (AR), mixed reality (MR), and holography

Augmented reality (AR) is a technology used to superimpose digital information into real-world applications to provide a composite view to the users. It is an interactive 3D environment that combines real and virtual world together [204]. In virtual reality (VR) a head-mounted display unit is used to disconnect users from the real world and to give them the experience of a computer-generated virtual world, whereas AR keeps the real-world details. Although augmented reality is one of the technologies that is often discussed along with the digital technologies of the latest industrial revolution, its history can be traced back to the 1960s [205, 206]. Mixed reality as the name implies is a mixture of real and virtual worlds where the users can also interact and manipulate the virtual environment with support from high-end sensing and imaging technologies. Holography is another visualization tool that is also called 3-dimensional photography. The technique records the feature of a 3D object using lasers which are digitally reconstructed to reproduce the original objects accurately [207].

These technologies are built around advancements in the auxiliary technologies such as digital cameras, optical sensors, display, accelerometers, GPS, gyroscopes, solid state compasses, motion tracking, radio-frequency identification, wireless network, and battery. Hence, although AR, MR, and Holography (which can be collectively called "Extended reality technologies") [208] are not considered the technology enablers of Industry 4.0 or Industry 5.0, it is one of the technologies that is expected to benefit from the digital adoption and play a key role in the future smart factories. For instance, Metaverse, one of the buzzwords of the ongoing decade is a fully immersive, interactive environment that takes elements of VR, AR, and MR to create a virtual world. The technologies together would play a critical role in reducing the overall lead time in product design, prototyping, and process development. It also has the potential to conduct conferences, product launches, live events, and webinars virtually on a real stage without the physical participation of the presenters which can be a cost effective and eco-friendly alternative to business meetings and in-person collaborations. Interactive manuals and catalogs [209], remote expert guidance [210], quality assurance [211], assembly and maintenance instructions [212], product demonstrations [213], collaborative engineering [214], error diagnosis [215], and employee training [216] are few other applications of the extended reality technologies.

6 Sustainability dimension of industry 5.0

From the various sections of this article, it can be inferred that the entire concept of Industry 4.0 and Industry 5.0 technologies revolves around collecting, processing, monitoring, storing, and analyzing data from numerous connected sources to improve the process efficiency, make decisions, and learn on the go. The computing, information, and digital technologies come together to achieve this common goal. Apart from manufacturing industries, these technologies are used independently or along with other supporting technologies in banking, financial, biomedical, health care, social media, automotive, aerospace, autonomous vehicles, and numerous other sectors.

The world leaders and industrial behemoths have agreed that data is the new gold. If Industry 3.0 is about generating data, then Industry 4.0 is about processing and analyzing it, while industry 5.0 must be all about intelligently using it with a focus on sustainability. However, sustainability is not merely about reducing wastes that go into the manufacturing of products, but it's also about achieving sustainability throughout the product life cycle (from procuring raw material till the product reaches the customer and later bringing it back for recycling) and identifying ways to achieve it with a minimal amount of data and in less time. In addition, the impact of these technologies must go beyond production and industrial units to focus on protecting the environment and society as well. Hence, sustainability can be categorized as economic sustainability, social sustainability, and environmental sustainability which are collectively referred to as the three pillars of sustainability. However, in addition to the three pillars, few authors have added additional pillars such as institutional, cultural, and technical [217]. In fact, the United Nations' blueprint to achieve a better and more sustainable future which is called the "2030 Agenda" or "Agenda 2030" has listed 17 interlinked objectives as future Sustainable Development Goals.

Although the various Industry 4.0 technologies have assisted industries in achieving economic sustainability by reducing and eliminating product waste, improving product quality and process performance, streamlining the manufacturing processes to reduce power consumption, optimizing process time, reducing the number of manufacturing steps, inventory management, and improving the useful life of machinery, it has failed in checking the waste generated in the form of data. Processing such a huge volume of data requires enormous computing power, energy, and time to analyze and make a meaningful decision that affects environmental sustainability. Environmental sustainability refers to the reduction of waste generated in manufacturing, reduction in resources utilized, promotion of a circular economy, reduction in energy consumption, and using renewable energy sources [218]. This is in line with the report by the World Economic Forum, which details that about 75% of IoT projects are small and medium-sized, and they focus only on profitable applications such as energy efficiency, productivity, competitiveness, and cost reduction, but sustainability was mostly neglected [219]. The technologies can also cause social disruption by replacing low and medium-skilled human labor on the shop floor with automation and industrial robots which affects social sustainability.

"Sustainability trilemma" refers to the current challenges that industries face in achieving all the three sustainability pillars such as economic, social, and environmental sustainability simultaneously. For instance, businesses focusing to achieve higher profits (economic sustainability) through excessive automation can result in job losses which disrupt social sustainability. Of the three sustainability pillars, the environmental pillar is the largest and the most critical to focus on as it encompasses both the social and economic systems inside it. In addition, according to a 2022 report by World Health Organization, 99% of the global population breathes air that is beyond the recommended air-quality limits [220]. Under such circumstances, enforcing stringent pollution control norms and instantly moving away from fossil fuels to achieve environmental sustainability can take a huge toll on economic sustainability. Similar would be the case if the usage of plastics is banned altogether. Any such drastic efforts can increase inflation, create inequality, and trigger disruptions in society. Social sustainability is another important but often ignored factor. Studies have also shown that the work environment has a significant impact on the personal welfare of the workers which in turn has an influence on social wellness. Focusing on the human aspects such as ensuring the well-being of workers, work-life balance, healthy workplace, and providing suitable employee assistance can boost productivity, product quality, and efficiency [221]. Hence, a balance between economic growth, environmental degradation, and social wellbeing is required.

However, this problem can be addressed to some extent by using next-gen Industry 5.0 technologies such as AIoT, edge computing, and smart sensors which can filter the unwanted data at the machine level itself and send only the minimum required data to the subsequent stage for processing and making decisions which can provide significant benefits in terms of processing power and energy requirements. For instance, while the aim of automation and industrial robots is to eliminate humans from the shop floor, the intention of cobots is to work in collaboration with humans. In addition to their agility and adaptability to the changing shop floor requirements, the processing power and energy required to operate them are comparatively minimal due to their size which makes them environment friendly. Similarly, while digital sensors are capable of only collecting the process data from machines, the smart sensors can independently perform data collection, data conversion, data processing, and establish communication to an external system such as a cloud server which can save an enormous amount of processing time, money, and energy consumption which supports environmental sustainability. AI and its associated technologies can help develop alternative eco-friendly materials to plastics. Nevertheless, once these technologies evolve and mature over the years, achieving all the three key sustainability pillars simultaneously is possible in the future. Few authors also argue that following lean manufacturing practices such as Just-in-Time (JIT), Total Quality Management (TQM), Total Preventive Maintenance (TPM), and Human Resource Management (HRM) can help industries to address a wide range of sustainability issues [222].

Although some of these next-gen technologies are already used by a few industries, the real benefits can be obtained only when all the technologies are used together. For instance, big data without AI or ML is just a digital waste. Hence, the businesses that want to improve economic sustainability must have a strategy to address the job loss to low- and medium-skilled labor. Employee training such as reskilling and upskilling programs, university collaborations to facilitate new learning, development of interdisciplinary competencies, and novel training strategies (like virtual and flexible learning modules) must be considered by the industries before embracing these new technologies. Correspondingly, industries trying to achieve environmental sustainability goals through renewable energy sources might take a blow on economic targets as the current cost of green energy is much higher than the energy from non-renewable resources. Hence the industries need to incorporate a sustainability awareness culture that focuses on all three sustainability elements and future research must be in the direction to achieve it. In short, to maintain sustainable practices and a circular economy, the focus of the businesses must be on "how the business is made" rather than on "how much is made" [5].

7 Key takeaways and future directions

Based on the detailed literature review it can be implied that Industry 4.0 and 5.0 technologies can be categorized into three: core technologies, supporting technologies, and beneficial technologies. The technologies such as IoT, IoE, AIoT, AI, cognitive computing, automation, and robotics can be classified as the core technologies or the foundation technologies around which the next industrial revolution was built. The technologies such as cloud computing, edge computing, big data, blockchain, 6G, and cyber security can be classified as the supporting technologies which provide critical infrastructure for the functioning of core technologies. Cyber-physical systems, additive manufacturing, cobots, digital twins, smart sensors, and extended reality are a few of the beneficial technologies that rely on the core and supporting technologies for their functionality and gain benefits from them.

The technologies discussed under Industry 5.0 enablers may look like a minor improvement or an upgraded version of Industry 4.0 technologies. Although it is partially true, a closer look at each of the technologies would reveal their strong focus on the inclusion of humans, environmental, and social conscientiousness. ESG (Environmental, Social, and Governance) and Sustainability are the two other buzzwords of the decade that industries are trying to adapt [223]. Going by the dictionary definition although they are different, ESG is an evolution of sustainability. In simple terms both can be together called "doing good to the environment and society", and in terms of doing good to the society, it doesn't get bigger than the inclusion of humans. From a survey conducted at various manufacturing industries, Brozzi et al. [224] have concluded that the focus of industries is more on economic sustainability while social and environmental sustainability are often ignored which reemphasizes the need to adopt Industry 5.0 technologies. Literature also shows that there are no studies that have

Table 6 A brief comparison of Industry 4.0 and Industry 5.0 technologies

S#	Industry 4.0 technologies	Industry 5.0 technologies
1	Mass customization	Mass personalization
2	Highly automated autonomous systems	Individualized human-machine interactions
3	Automation and Industrial robots	Intelligent automation, Collaborative robots
4	Artificial intelligence, Machine learning	Cognitive computing
5	Internet of Things (IoT), Industrial Internet of Things (IIoT)	Internet of Everything (IoE), Artificial Intelligence of Things (AIoT)
6	Cloud computing	Edge computing, Fog computing
7	Simulations	Digital twins
8	Centralized traditional databases	Decentralized blockchain
9	LAN, Internet	Ultra-low latency high speed internet
10	Virtual reality	Extended reality (AR, MR, Holography) and Metaverse

evaluated the impact of these technologies on social sustainability which must be a focus for future investigations. Hence, replacing industrial robots with cobots and adopting technologies such as IoE, AIoT, edge and fog computing, smart sensors, digital twins, 6G and beyond, and extended reality which either support the inclusion of humans or are highly environment conscious must be considered. A recent study has reported that although blockchain technology has numerous benefits in the way how transactions are handled, extending the network across all the supply chain partners would be expensive, consume more energy, and require enormous networking and computational power. The study has also recommended that reducing the size of the blockchain, block size optimization, and a lightweight blockchain to reduce transaction latency and computing power are the potential area for future research which can make the technology sustainable [5]. Hence, apart from performance aspects, optimizing and upgrading the existing technologies and inventing new technologies to consciously give importance to all the three sustainability pillars must be the future direction of scholars.

With more than two-thirds of the manufacturing industries yet to embrace Industry 4.0 and the onset of the COVID 19 pandemic further delaying it, there are possibilities that industries can directly leap into Industry 5.0 technologies. In addition, return on investment, security, privacy, scalability, regulatory compliances, and non-availability of skilled workers are a few other challenges to the implementation and adaptation of the technologies. So, industries could slowly start embracing one or the other key technologies that are critical to improving their process and may skip the others. The comparison of the evolution of Industry 4.0 into Industry 5.0 technologies is shown in Table 6.

The industrial revolutions are all about making products in a better way to meet consumer demand. However, some scholars have combined all the latest advancements in other fields such as bionics, synthetic biotechnology, genetic engineering, quantum computing, nanotechnology, smart self-healing materials, and Brain-computer interfaces as a few technology enablers of industry 5.0 [225–228]. Although these are some of the important technological innovations in their respective fields that use one or more digital technologies such as AI, their immediate application in an industrial environment is questionable. However, until a few decades ago even electronics and computers were considered naïve to production and manufacturing, but their union with machines has really kick-started the new industrial revolutions. Nevertheless, the new-age Industry 5.0 technologies can bring back the lost collaboration between humans, machines, and software systems and make the shop floor a sustainable place to work and the world a sustainable place to live. After all, we have only one place to live, and it means the world to us.

8 Conclusion

If the industry experts are to be believed the world is already in the midst of the fourth industrial revolution in which a myriad of disruptive digital technologies are married to various industrial machines and processes to collect data and establish a channel of communication between them to deliver products at a lower cost. The integration of the various intelligent machines and processes of an industrial unit with the help of new-age digital and computing technologies creates an eco-system that is connected, smart and agile. Besides, the entire supply chain is controlled, streamlined, and automated to collect, monitor, and optimize real-time data to enable high efficiency right from procuring raw materials till the product is delivered to the customers.

If Industry 3.0 was predominantly driven by computerization, then Industry 4.0 is driven by marrying digital technologies with physical systems that make them smarter and work independently without human intervention. However, from the discussion, it can also be implied that Industry 4.0 has focused on improving profits by concentrating solely on product quality and process efficiency using different digital technologies. But it has widely ignored the need for human intelligence and failed to acknowledge the impact of digital technologies on the environment and society. Like the previous industrial revolutions, the technologies of Industry 4.0 also have the destructive potential to promote automation and alienate humans from the factory shopfloor which could result in job loss and create inequality and imbalance in society. Hence the need to either give the technologies a miss or upgrade them to emphasize the inclusiveness of humans into the system and to focus on eco-friendliness is critical, both of which are expected to be fulfilled by the next industrial revolution.

While the small and medium scale enterprises are yet to realize the potential benefits of Industry 4.0 technologies, industrial leaders have already started envisioning what Industry 5.0 would look like. Their collective opinion echoes the need to bring back the human touch to digital technologies to deliver personalized products. If Industry 4.0 is about digitalization, then Industry 5.0 would be all about realizing the collaboration between the digital world, and the critical and creative thinking capabilities of humans, being agile to changing market conditions, and additionally emphasizing on sustainability. In addition, history has also shown that the previous industrial revolutions took decades or centuries to allow the emergence of disruptive technologies that industries adapt slowly before moving from one "revolution" to the other. It is aptly called a "revolution" because the level of innovation behind the technologies is capable of completely revolutionizing the entire industrial practices and not merely providing incremental improvements. However, if the prophecies of the leaders and scholars are accounted for, the next big thing would be the collaboration of humans with digital technologies with an additional focus on economic, social, and environmental sustainability. Hence it would be ideal to call the upcoming revolution as "Industry 4.0S" or "Sustainable Industry 4.0" rather than Industry 5.0. Nevertheless, with Industry 4.0 technologies gaining widespread acceptance in the large-scale multinational corporations of the developed nations and yet to step their feet in small and medium scale industries and developing countries, it is too early to call the upcoming transformation as Industry 5.0 without understanding what lies ahead in a few decades from now. It once again emphasizes that "Industry 4.0S" is the suitable connotation for the technologies.

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