Roles of IoT, Big Data Analytics, and Cyber-Physical Systems in a Sustainable Manufacturing

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Abstract. The convergence of big data analytics, cyber-physical systems (CPS), and the Internet of Things (IoT) is causing a fascinating revolution in the manufacturing sector. The convergence known as "Industry 4.0" is expected to bring about a symphony of sustainability, adaptability, and efficiency where machines move in time with real-time data. The maestro at this point is big data analytics, which translates these tunes to improve the whole thing from inventory control to machine maintenance. By permitting machines to separately adjust settings, act to fluctuating circumstances, and cooperate with one another, CPS bridge the gap amid the digital and physical worlds. This materializes into an astonishing ballet of intelligent automation. But regardless of this fascinating music, there are trials waiting in the shadows. Robust cybersecurity procedures are essential to address worries about data security and privacy, and continuous research and development is compulsory to manage the multifaceted integration and standardization of several technologies. Cautious planning and oversight are also compulsory due to ethical worries about algorithmic prejudice and job movement. The manufacturing industry is full of potential for invention and sustainability, even in the face of these dark clouds. Let us not be overwhelmed by the hindrances in the way of this uprising, but relatively use them to our benefit to generate a harmonious prearrangement of responsible solutions. Industry 4.0 will be protected to dance not just with data but also with beliefs, safety, and sustainability by means of continuing research, transparent communication, and investments in labor force development. This will pave the way for a upcoming in which humans and robots work collectively for an improved tomorrow. The main concepts of Industry 4.0 are outlined in this paper, along with its prospects, complications, and condition for an all-encompassing strategy.

1 Introduction

IoT has turn out to be an important part of modern production since it allows the interconnection of equipment and systems. It smooths real-time data collection and analysis, which progresses output and decision-making [1]. For example, IoT-based predictive maintenance in the manufacturing industry makes use of IoT sensors installed on perceptible possessions to advance manufacturing processes in the course of information input and decision-making that occurs on its own [1]. Hefty datasets can be extracted for understanding information by integrating big data analytics into manufacturing methods. This data-driven tactic take full advantage of productivity, lessens downtime, and enhances product quality. IoT has turn out to be an important part of modern production since it allows the interconnection of equipment and systems. It smooths real-time data collection and analysis, which progresses output and decision-making [1]. For example, IoT-based predictive maintenance in the manufacturing industry makes use of IoT sensors installed on perceptible possessions to advance manufacturing processes in the course of information input and decision-making that occurs on its own [1]. Hefty datasets can be extracted for understanding information by integrating big data analytics into manufacturing methods. This data-driven tactic take full advantage of productivity, lessens downtime, and enhanced product quality. Techniques like Bayesian inference engines and complex event processing are employed to fuse multi-source heterogeneous data, enabling efficient real-time data collection and processing [5]. A blend of AI, IoT, augmented reality, and machine learning is forming new manufacturing methods in Industry 4.0. This integration addresses challenges and impacts on society, job roles, and the manufacturing process [6]. The combination of IoT and service innovation in manufacturing leads to increased transparency and efficiency in industrial production as depicted in Figure 1. Intelligent forecasting tools are employed to manage industrial big data effectively [7].

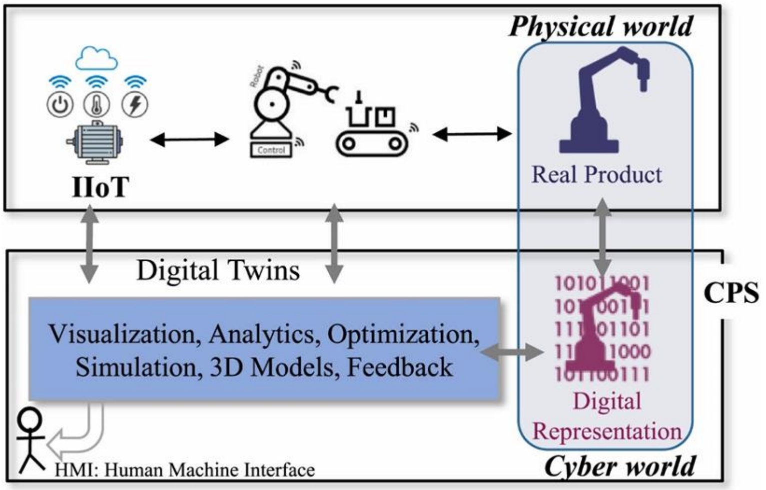

Fig 1. Illustration of IIoT, CPS, and DT for Real-world physical Assets and their Digital Representation

IoT plays a pivotal role in modern manufacturing industries by enabling smart and digital concepts. It encompasses the use of sensors, software, and various technologies to interconnect and exchange data, driving advancements in production and quality assurance [9]. Industry 4.0 integrates IoT with intelligent automation, big data, and artificial intelligence. This revolution brings technological innovation and economic growth but presents challenges like cybersecurity, skills mismatch, and management issues [10]. The integration of blockchain technology with IoT in manufacturing enhances security and promotes resilience, scalability, and autonomy as illustrated in Figure 2. It also offers new possibilities for timestamping sensor data and managing large datasets [11]. A subdivision of the Internet of Things, the Industrial Internet of Things (IIoT) emphases on automation, real-time data, and linkage in the manufacturing sector. It is projected to radically affect the enlargement of manufacturing enterprises by altering the way we work, play, and live [12].

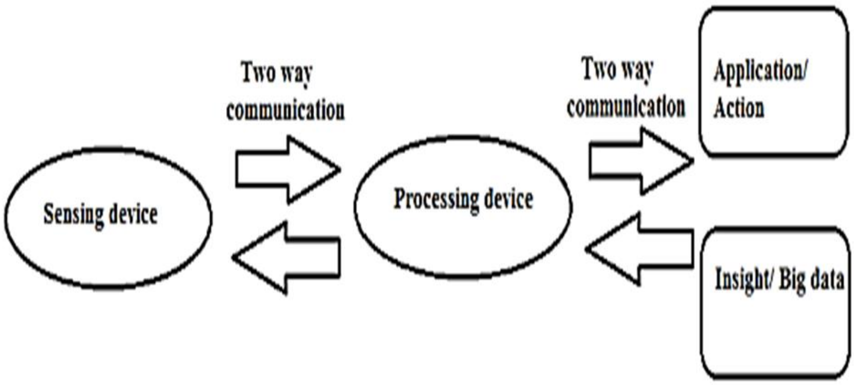

Fig 2. Building blocks of an IoT-enabled Smart Manufacturing.

IoT is important to manufacturing's sustainable development. It causes data and information switched by intelligent machines feasible, which is crucial for multifaceted system decision-making. This leads to improved efficiency and quality in production [13]. IoT offers small and medium-sized enterprises (SMEs) the opportunity to optimize production facilities and improve product quality by managing and monitoring production parameters in real-time [14]. Big data analytics is a critical component of Industry 4.0, driving advancements in sustainable industry applications. It aids in transforming large amounts of data into actionable insights, thereby enhancing strategic and operational decisions [15]. A bibliometric analysis reveals the impact of big data on continuous improvement in manufacturing. As industries embrace digital transformation, analytics has become a crucial tool for strategic decision-making in business management [16]. In the semiconductor industry, big data analytics is applied to optimize energy consumption. By analyzing machine parameters, predictive models for machine energy efficiency are developed, leading to significant energy savings [17]. Sources of big data is depicted in Figure 3.

Big data analytics in manufacturing has advantages, but it also has drawbacks, such managing complicated and unstructured data. But these problems are addressed by technologies like Hadoop, Spark, and MapReduce [19]. Big data-driven technology guides decision-making in intelligent manufacturing. It unlocks the potential and hidden knowledge contained in industrial data, assisting businesses in making informed decisions across a range of manufacturing contexts [18]. AI backed by big data analytics improves circular economy capabilities and sustainable manufacturing practices. It promotes technology enablement and enhances the efficiency of the supply chain [20]. As a key component of Industry 4.0, CPS uses digital twins (DT) and cutting-edge communication technologies to improve manufacturing (See Figure 4). These technologies make it easier to integrate the digital and physical world, which improves industrial process monitoring, optimization, and prognostics [8]. Manufacturing execution systems (MES) have developed to fulfill new requirements in the context of Industry 4.0. All CPS components must now be seamlessly and securely connected by MES, which must also offer sophisticated automated solutions and use semantic metadata to improve interoperability [21]. The development of

CPS in Industry 4.0 brings with it both possibilities and constraints. To fully realize the promise of CPS in manufacturing, concerns including cybersecurity, capital investment, talent mismatches, and technological capabilities must be resolved [10]. Artificial Intelligence (AI) is essential to CPS operation, especially for industrial maintenance. AI solutions enhance a number of KPIs, which reduces costs and optimizes plant management in intelligent factories [22]. Digital twins, big data-driven tactics, edge-to-cloud service technologies, and virtual-real mapping and fusion are all components of the CPS-based smart factory concept. This method changes how production procedures are carried out, opening the door to creative ideas and instantaneous quality gains [23].

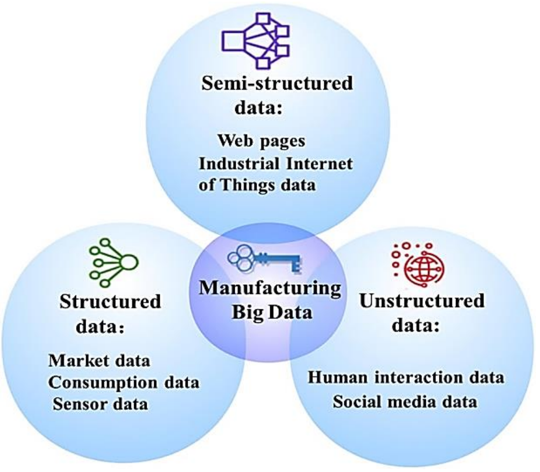

Fig 3. Sources of Industrial Big Data.

IoT is revolutionizing asset tracking in manufacturing by employing distributed ledger technologies like IOTA Tangle architecture. This integration improves production performance, increases information visibility, and copes with system complexity [24]. Big data analytics plays a pivotal role in Cyber-Physical Production Systems (CPPS), enabling production visibility and efficient real-time data processing. By using data stream processing approaches and complex event processing, CPPS can enhance production efficiency significantly [25]. The combination of service innovation and CPS is shaping the future of the manufacturing industry. Intelligent forecasting tools manage industrial big data, enhancing the transparency and efficiency of industrial production [26]. The fusion of AI, IoT, augmented reality, CPS, and machine learning is forming new methods of manufacturing in Industry 4.0. These technologies address challenges and impact various aspects of society and job roles [6]. IIoT, a sub-segment of IoT, focuses on interconnectivity and automation in manufacturing. It plays a crucial role in transforming how we live, work, and play, impacting the growth of manufacturing companies [10 -12]. Industry 4.0 introduces challenges in cybersecurity, skillset mismatches, and technological capabilities. To fully utilize CPS in manufacturing, it is imperative to address these difficulties.

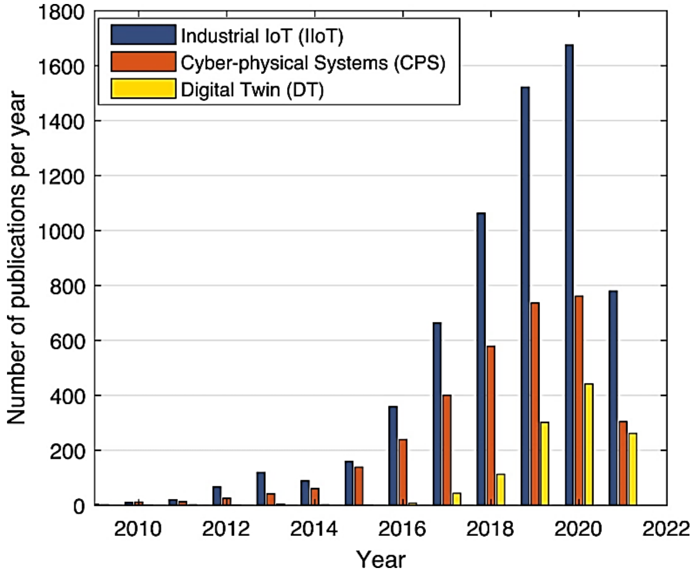

Fig 4. Research Trends of IIoT, CPS, and DT.

2 Literature Review

2.1 Concept of IoT

The phrase "Internet of Things" was initially used by Kevin Ashton in a 1999 presentation to Proctor & Gamble (IoT). He was a founding member of the Automatic Recognition Lab at the Massachusetts Institute of Technology [27]. He created RFID technology, used in barcode detectors, in the field of supply chain management. The Internet of Things is a new yet significant topic in technology, society, and the economy. The potential for revolutionizing our job and way of life lies in the combination of powerful data analytic skills and internet connectivity with consumer products, durable goods, cars and trucks, industrial facilities, sensors, and other everyday objects [27]. How would be the world without the Internet? We have never encountered such a situation; thus, it is hard to imagine. The Internet is becoming a need for everyone in today's world, both personally and professionally. Our daily lives involve interacting with many gadgets, including smartphones, wearables, mobile computers, and other smart objects. Emerging ICT and corporate systems technologies are significantly impacted by these and other Internet of Things-related technologies [28]. The growing interconnection of the Internet of Things (IoT) is changing our daily lives from routine jobs to revolutionary breakthroughs. Physical items, ranging from industrial gear to domestic appliances, are being integrated with sensors, software, and network connectivity to create a technological symphony that allows them to gather, share, and analyze data [29]. This pervasive network of "smart things" blurs the boundaries between the digital and physical domains by fostering historically unheard-of levels of automation, communication, and decision-making capabilities [30]. The term "Internet of Computers" was used early on in its history, then "Internet of People," and more recently, the term "Internet of Things" has come to be understood due to the quick advancement of ICT. To broaden the Internet and make it more accessible and individually identifiable, a variety of gadgets and smart things are included in the Internet of Things. "Anytime, anywhere" for "anyone" becomes "anytime, anywhere" for "anything," improving connectivity [31]. IoT-related technologies are now receiving a lot of attention in

ICT innovations and economic developments, as they are regarded as one of the future promise tactics and one of the most crucial infrastructures for their promotion. Enabling interaction and integration between the real world and cyberspace is the primary goal. Essentially, the Internet of Things functions via a complex interplay of technologies: sensors built into devices function as digital eyes and ears, collecting data on everything from location and movement to temperature and pressure [32]. This data is then transmitted through a variety of communication networks, such as Wi-Fi, Bluetooth, or cellular, to cloud-based platforms for processing and analysis [33]. This processing power, which is frequently fueled by artificial intelligence and machine learning algorithms, enables the IoT to not only gather data but also gain insights and make well-informed decisions [34].

The range of IoT devices (See figure 5) is matched by the diversity of their applications. Our homes' smart thermostats adapt to our tastes, maximizing comfort and minimizing energy use [34-35]. Wearable fitness trackers keep an eye on our health and reveal information about our sleep and exercise patterns [35]. In cities, networked traffic signals enhance traffic flow, lowering congestion and pollution [36] . According to Lee et al. [37], intelligent sensors are used in companies to monitor machinery performance, anticipate maintenance needs, and avert expensive breakdowns. A multitude of enterprises and scholarly establishments have provided diverse estimations concerning the potential impacts of the Internet of Things on the economy and the Internet in the next decade. Huawei estimates 100 billion IoT connections by 2025. Additionally, by 2025, the Internet of Things may have an annual economic impact of \$3.9 to \$11 trillion. These elements include falling costs for devices, better cloud computing for storage, quicker speeds, and less expensive delivery. As a result, there are now more computers and other gadgets online. Additionally, it is projected that by 2025, the Internet of Things will account for 4% to 11% of the world's GDP [38]. The integration of smart objects is the most important aspect of the IoT vision. These things have intelligence, computing, sensing, remote monitoring, and control capabilities, and they are effortlessly connected to the Internet [39].

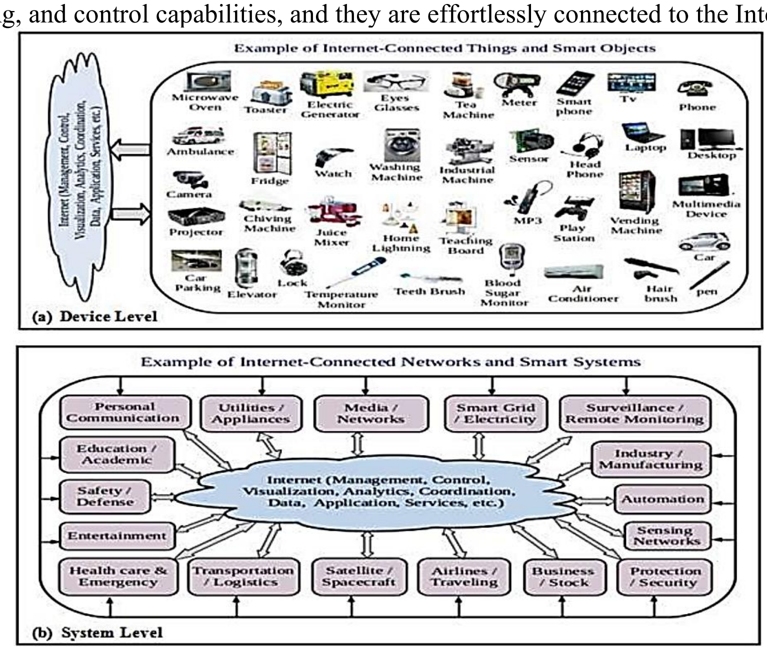

Fig 5. Internet of Things: Devices and Systems Level Interconnection.

2.1.1 Concept and Role of IoT in Manufacturing

The fundamental function of the Internet of Things in manufacturing is to gather and use data in real time, converting it into intelligence that can be put to use as illustrated in Figure 6. Vital characteristics including temperature, pressure, vibration, and energy usage are continuously monitored by sensors integrated into equipment, goods, and the entire manufacturing line. With the help of strong analytics tools and this data stream, the production process is vividly depicted, revealing inefficiencies, foretelling possible setbacks, and improving performance in previously unthinkable ways [40]. Imagine being able to predict equipment failure before it occurs, saving money on downtime, and guaranteeing efficient output. When anomalies occur, IoT sensors installed in machines may monitor temperature, vibration, and other vital characteristics and give out real-time notifications. This gives manufacturers the ability to plan maintenance, reducing downtime and increasing uptime [41-42]. Manufacturers can optimize production schedules, resource allocation, and preventative maintenance by harnessing real-time data from connected machines to discover and address inefficiencies. Significant drops in waste, energy consumption, and downtime may result from this [43].

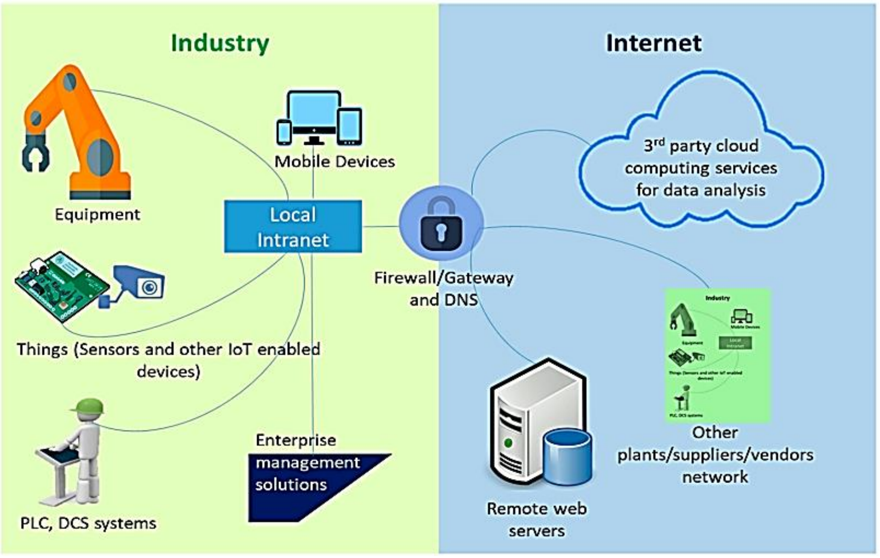

Fig 6. The industrial internet - The Internet of Things (IoT) enabled industry.

Manufacturers can optimize the whole production chain, from the acquisition of raw materials to the delivery of finished items, thanks to the interconnection that the Internet of Things fosters. Real-time tracking of resources and components revolutionizes supply chain management by guaranteeing ideal inventory levels and reducing inefficient overstocking [45]. Manufacturers can achieve just-in-time delivery and efficient production processes by establishing connections with suppliers and logistics providers, which gives them unparalleled access and control over the entire material flow. IoT data comes into analytics platforms with great strength, exposing production process inefficiencies and hidden trends. Due to the ability to alter temperature, pressure, and speed in real time, production runs may be optimized, waste can be decreased, and energy efficiency can be increased [46-47]. Across the use of networked sensors to track items across the supply chain, producers can obtain important information about product provenance, resource origin, and production history. Customers' trust can be increased and transparency increased as a result [48].

The Internet of Things not only facilitates optimization but also intelligent production, where data analysis drives ongoing development. In production data, machine learning algorithms can spot trends and abnormalities that provide insights for improving product designs, processes, and even individualized customization. Envisioning a manufacturing process that gains knowledge from its past iterations, adjusting its specifications to provide customized goods according to specific client demands [49]. Manual inspections, which are prone to inefficiencies and human mistakes, are a common component of traditional quality control procedures. IoT-enabled sensors can continuously check the quality of products during the manufacturing process, automatically identifying flaws and initiating remedial action in real-time. In the end, this raises customer satisfaction by lowering scrap rates and improving product uniformity [43, 50]. IoT can enable more effective and transparent supply chains as well as the creation of novel products by fostering tighter cooperation between producers, suppliers, and consumers. An architecture for sensory environments that is divided into four layers: the application layer, middleware layer, transport layer, and physical layer. As seen in Figure 7, a potential IIoT design for the manufacturing process is proposed [44].

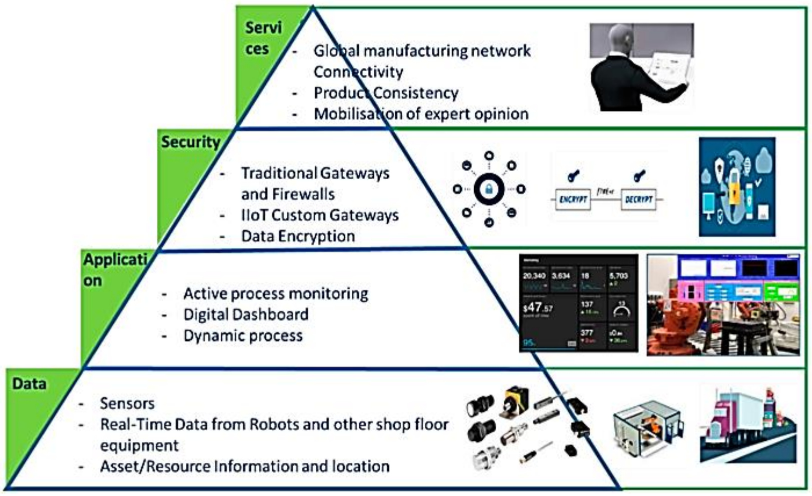

Fig 7. The proposed potential Industrial IoT (IIoT) architecture for the manufacturing industry

The typical IoT design will be a restrictive alternative in an industrial setting, necessitating more requirement-specific customization of the architecture. Although we refer to the lowest layer as "data," Figure 7 illustrates that the data generated from the shop floor will come from sources other than physical sensors. The information will include pictures and details about the operator, asset details, and sensor data. Therefore, it is insufficient to generalize the lowest layer as a sensing layer. The metadata must be applied to the data that has been gathered from multiple sources, and a first evaluation must be completed to draw conclusions or make predictions [44]. But even with its revolutionary potential, IoT adoption in manufacturing is not without its difficulties. Data security and privacy problems loom big, needing comprehensive cyber security measures and ethical data governance procedures [51]. Dealing with outdated systems and mismatched data formats presents integration issues that call for careful planning and interoperability solutions. Furthermore, the volume of data requires qualified workers who can decipher and utilize the knowledge gained from these digital streams [52].

2.2 Concept of big data analytics

At its core, big data analytics is the process of compiling, organizing, analyzing, and interpreting large, complex datasets. Unlike traditional data analysis techniques, big data tools and methods are designed to handle the "three Vs" of big data: volume, velocity, and variety [53]. Volume, which is sometimes expressed in terabytes or even zettabytes, describes the sheer amount of data. The term "velocity" refers to the big data's quick creation and streaming nature, which necessitates real-time analytical skills. Finally, diversity comprises the many types and architectures of big data, including structured data like spreadsheets and unstructured data like social media posts [54]. Big data analytics embraces the chaotic, unstructured universe of information, in contrast to its predecessor, which was limited to structured, well-organized data. Social media posts, sensor readings, financial transactions, genetic sequences, and other types of data are all included in the immense ocean of data known as big data, which is frequently described by its "three Vs" [54]. The initial challenge is this overwhelming amount. Big data overwhelms traditional data management techniques, making them unsuitable for analysis, retrieval, and storage. Utilizing the capacity of several computers, distributed computing frameworks such as Hadoop and Spark effectively handle and process these enormous datasets. Hadoop, for instance (See figure 8), has become a popular platform for big data analysis, enabling distributed storage and concurrent processing of enormous datasets [55].

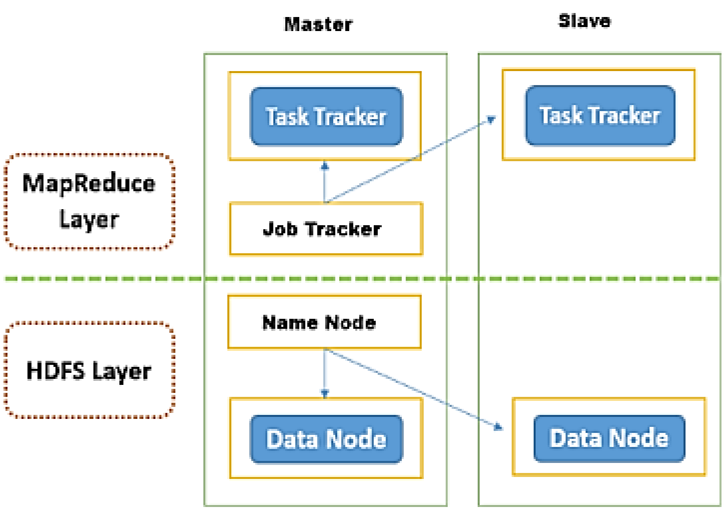

Fig 8. Hadoop Framework Components.

However, the attraction of big data is not limited to volume. Another level of complexity is added by the velocity or the quick inflow of fresh data. To catch fleeting ideas and make timely decisions, real-time analysis becomes imperative, requiring systems that can ingest and process data streams in near real-time [57]. And then, there's the diversity of data formats. Big data analytics requires navigating through multimedia, unstructured text, structured tables, and images to piece together knowledge from seemingly unrelated sources. To extract structure and meaning from these many data formats, methods such as picture recognition and natural language processing are used [38]. So how precisely do big data analytics results in real advantages? In the area of healthcare, for instance, evaluating patient data from electronic medical records and wearable devices might assist predict disease outbreaks, tailoring treatment programs, and optimize resource allocation [38]. Big data analytics can be used in the financial industry to identify fraudulent transactions, evaluate creditworthiness, and create customized financial solutions [58]. Big data research may offer businesses of all sizes with perceptive information on product trends, consumer conduct, and operative efficacy. These understandings can lead to more inventive product creation, more applicable marketing approaches, and lessened expenditures [59]. It's not easy to pass through the enormous ocean of big data, though. Data security and quality are vital apprehensions because wrong or compromised data can produce deceiving and possibly hazardous conclusions. Additionally, complex data processing and management techniques may be essential given that the sheer volume of data may be too huge for traditional analytical tools to hold [59]. Regardless of these challenges, big data analytics has the power to entirely convert a range of sectors.

2.2.1 Concept and Roles of Big Data Analytics in Manufacturing

Comprehensive, various datasets are accumulated, joint, and inspected at the central of manufacturing big data analytics. Customer evaluations, data from the supply chain, machine sensor interpretations, manufacturing data, and even environmental factors are taken into account. By utilizing machine learning algorithms, sophisticated statistical techniques, and artificial intelligence to find concealed patterns, correlations, and trends, manufacturers can gain substantial perceptions from this huge data stream [41]. Big data turns into a powerful tool to combat inefficiencies aswas illustrated in figure 9. By analyzing sensor data from production lines in real-time, it is possible to identify underperforming equipment, locate bottlenecks, and adjust process settings to maximize output and reduce waste. Based on past data trends, predictive maintenance skills allow for proactive scheduling of equipment repairs before malfunctions cause production delays and reduce profitability [40]. Additionally, by examining product quality data alongside process parameters, producers can detect and alter variables affecting quality, leading to consistent output and fewer defect-ridden items [60]. Big data also creates a transparent network out of the previously opaque maze-like structure of supply chains. Manufacturers can see inventory levels, delays in transit, and changes in the market in real-time by combining data from suppliers, logistics companies, and even retailers. This enables them to proactively handle possible disruptions before they seriously impair operations, optimize sourcing methods, and dynamically modify production schedules based on demand estimates. An era of mass personalization is replacing the one of mass production. Manufacturers can use social media trends, buying habits, and customer data to understand individual tastes and customize products with the help of big data analytics. This promotes brand identification and consumer loyalty in addition to opening up new market sectors [61]. Analyzing large amounts of data can be a very effective way to green the factory floor. Manufacturers can discover areas for improvement and apply sustainable practices, such as resource recycling and energy-efficient production processes, by tracking energy usage, resource utilization, and waste generation. As a result, there are significant financial savings in addition to a decrease in the environmental impact [59-61]. As a result, there are significant financial savings in addition to a decrease in the environmental impact. For example, Siemens, a major player in the global manufacturing industry, used big data analytics to cut their water and energy use by 15% and 20%, respectively, in only a single year [61]. These kinds of instances show the concrete advantages of using big data for environmental sustainability and open the door to a more environmentally friendly manufacturing sector.

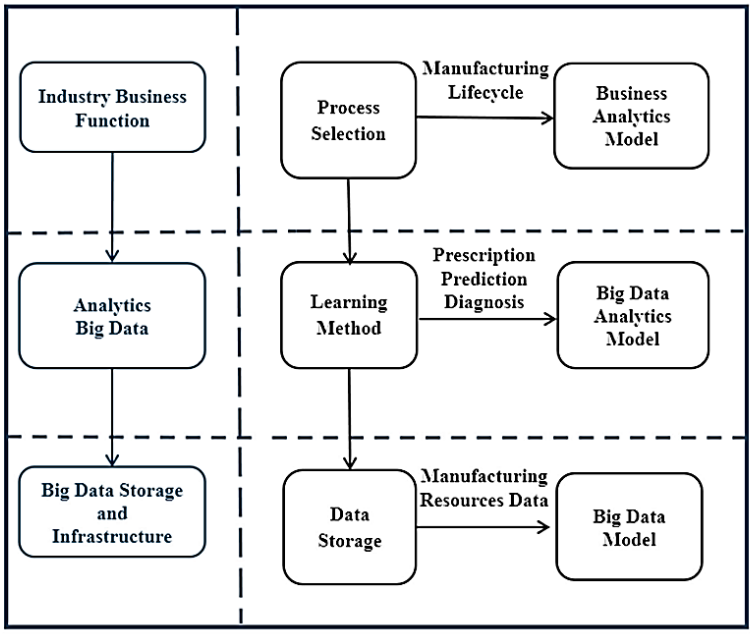

Fig 9. Big Data analytics management model

2.3 Concept of Cyber-Physical Systems (C.P.S)

Imagine a world in which the distinctions between the tangible and the computational are blurred as the digital and physical domains merge. Cyber-physical systems (CPS) as seen in figure 10, which bridge the gap between the virtual and the real through intricate networks of networked sensors, actuators, and computer algorithms, promise to bring this reality to life. According to Lee et al [41], these intelligent systems sense and react to the physical world in real time, dynamically altering their activities based on data and situations that are continually changing. Cyber-physical systems (CPS) are a paradigm shift in the way humans engage with the real environment. They create a bridge that unites the virtual and the real by bridging the gap between the tangible world of machines and processes and the computational realm of computers [60-61]. Imagine a future where self-driving automobiles effortlessly navigate city streets in real time, where smart grids dynamically alter electricity distribution based on demand, or where sensors implanted in bridges monitor the structural integrity of the structure. These are but a few examples of CPS's revolutionary potential, which can completely change a variety of sectors, including manufacturing, transportation, and healthcare [54, 61]. A sophisticated network of computational components (sensors, actuators, and controllers) embedded within physical systems is the fundamental component of a CPS. These elements continuously collect data about the physical environment, process it using complex algorithms, and then exploit this knowledge to impact the physical world using actuators. By constructing intelligent systems that can react, anticipate, and even learn, CPS's smooth feedback loop enables it to adjust and react to changing conditions in real time [57-60].

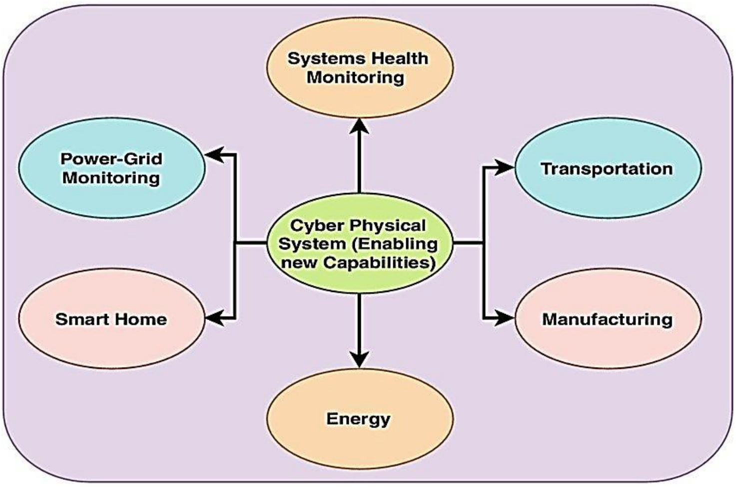

Fig 10. Applications of Cyber-Physical systems

2.3.1 Concept and Role of Cyber Physical Systems in Manufacturing

Manufacturers may now automate crucial operations that formerly required human involvement thanks to CPS. Based on sensor data, predictive maintenance algorithms foresee equipment breakdowns and initiate proactive repairs to avoid expensive downtime and production interruptions. Data-driven real-time process optimization enables dynamic changes to production parameters, guaranteeing constant quality and removing faulty items before they are introduced to the market [60-61]. Moreover, CPS facilitates adaptable production lines that can, with minimal human intervention, adjust to shifting market demands and product designs, promoting agility and responsiveness in a dynamic marketplace [34,45]. Manufacturers may now optimize production processes with previously unheard-of precision thanks to CPS. Real-time data from sensors implanted in machines, tools, and workpieces enables for continuous monitoring and adjustment of process parameters. Predictive maintenance algorithms, based on past data patterns, can foresee equipment failures and plan preemptive repairs before breakdowns affect output. The implementation of a data-driven approach results in considerable improvements in overall efficiency by minimizing downtime, reducing waste, and optimizing resource utilization. CPS also gives way to mass customization, which is a paradigm change in the manufacturing industry. Manufacturers can customize items to meet specific needs and preferences by incorporating client data and preferences into the production process. According to Müller et al. [61], this degree of customization not only increases consumer pleasure and loyalty but also creates new business prospects that were previously unattainable through mass production. CPS is cautious regulators of quality, guaranteeing reliability and reducing errors. Manufacturers can spot and fix anomalies in real-time and keep defective products off the market by combining sensor data from production lines with quality control systems. Furthermore, sophisticated data analysis methods can assist in pinpointing the underlying causes of problems with quality, enabling focused process enhancements and ongoing quality improvement [22]. For becoming green on the factory floor, CPS can be a very useful tool as illustrated in figure11. By monitoring energy usage, resource use, and trash generation in real time, manufacturers may discover areas for improvement and apply sustainable practices like resource recycling and energy-efficient manufacturing methods. This results in major financial savings as well as a reduction in the impact on the environment.

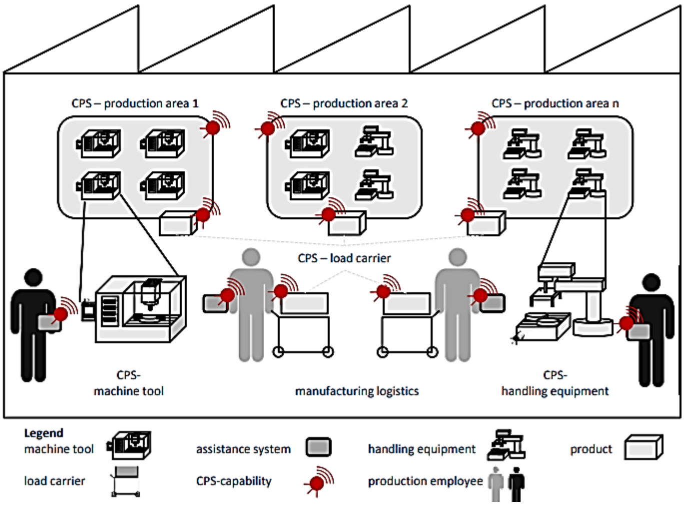

Fig 11. Scenario of the Cyber-Physical Production System.

2.4 Interconnectivity of IoT, Big Data Analytics, and Cyber-Physical Systems in Manufacturing Process

National economies have been transformed globally by digital breakthroughs. A new, intelligent, data-driven, and learning economy is being ushered in by these rapidly evolving and expanding technologies. Empirical data indicates that the digital sector contributes less than 10% of value added, income, or jobs to the majority of economies. Digital change is essential in this regard, and guaranteeing broad and equal developmental payoffs is the main issue [1-2, 33-34]. The digital economy is characterized by the widespread use of information and communications technology (ICT) in conjunction with the use of e-business, e-commerce, and foundational infrastructures. The breadth of this concept has gradually grown with the advancement of digital technologies [2-3]. The fourth industrial revolution, or "Industry 4.0," is largely defined by the digitalization and automation of industry. A significant change is now taking place in the manufacturing process, which will have a significant effect on future developments for the Internet of Things. Technological innovations such as robotics, 3D printing, machine learning, networking, data analytics, and others are transforming industrial processes and diminishing the necessity of human labor and judgment [4]. By leveraging digital technologies, manufacturing may decrease human error, shorten time to market, and accelerate the rate at which industrial processes can adapt to new information. Industry 4.0 refers to the confluence of operational and information technology, as well as the real-time interdependence of process and analytics.

The remarkable advancements in Cyber-Physical Systems (CPS) and the Internet of Things (IoT) have created a strong platform for the development of novel ideas like Industry 4.0, the Industrial Internet of Things, and the digital economy. In 1999, the phrase "Internet of Things" made its debut, and at the same time, relevant specialists discussed the potential future appearance of an IoT-based environment [5]. The concept of the CPS was primarily driven by systems engineering and control, while the Internet of Things originated in the RFID context and emerged from a networking and IT perspective. Artificial intelligence science gave rise to the notion of the Digital Twin. CPS reduces energy use and carbon gas emissions while increasing building energy efficiency. The system's functions include detecting humidity, temperature, and other actuators like water heaters, fans, and HVAC systems. To minimize accidents and increase safety, cars can connect via CPS to exchange data on traffic, location, and road issues.

By combining designed and physical systems, CPS creates a close connection between the real world and the cyber realm. Conversely, the concept of the Internet of Things (IoT) emerged from computer science and internet technologies, emphasizing physical component integration, interoperability, and interconnection inside the Internet environment [6, 54-60]. We could build computer systems that can communicate with people more readily by combining novel ideas like cloud computing, IoT, AI, and machine learning. In the modern day, the digital economy has the ability to predict people's actions in the marketplace and their purchasing patterns [7]. These days, digitalization is evident throughout all industry sectors. The term "information technologies" or "digital transformation" has been used to refer to a very broad range of topics, including digital literacy, the use of social media by individuals, the transfer of public services and digital media into electronic environments, and businesses that incorporate all of their assets and brands. In other words, a more comprehensive understanding of digitalization itself is responsible for transformation rather than technology or computers alone [8, 22]. Analog information has been transformed into digital information via the digital revolution, allowing for automated processing. Digitized information can be reliably reproduced and moved more easily between various media and over great distances. Keep in mind that this has important organizational and engineering ramifications [8]. Interoperability is the aim of standards-setting, although it doesn't always require the development of new technologies. However, standards development has ramifications for value capture and is also aimed at developing technology.

The manufacturing sector has encountered difficulties in obtaining aggregated production data for analysis as well as in combining many PLC (programmable logic controller) data sources produced by various brands that regulate sensors and actuators. The actual manufacturing line consists of several machines that are coordinated by different PLCs to achieve a shared goal. To accomplish the targeted aims, many PLC brands must coordinate with one another and exchange data. For many years, automation components like controllers, sensors, actuators, and visualization technologies have been a part of operational technology. The development of IT creates chances for the integration of IT and OT, utilizing IT for OT. OT software includes monitoring and control software, such as SCADA (Supervisory Control and Data Acquisition) and ERP (Enterprise Resource Planning) for key manufacturing operations. Using operational technology to gather data is merely the first step in applying information technology for analytics in the industrial sector [9, 35, 37, 40]. Big data analytics platforms, which can be used for analytics, data storage, and visualization, enable the collection of field device data. Two well-known data communication protocols that are used in the collection of data in smart manufacturing environments are OPC Unified Architecture (OPC-UA) and Modbus. These protocols enable batch or real-time production data collecting (or in some instance both). Through data communication protocols like OPC-UA, Modbus, and MT Connect, big data analytics systems can gather production data in real-time; alternatively, software tools like Apache Hadoop can gather data in batch-oriented and real-time modes [10,53-54].

It should be noted that IoT gateways are frequently necessary for big data analytics systems powered by the Internet of Things in order to complete data integration and collecting. These gateways provide several essential functions, including protocol translation, encryption, data processing, management, filtering, and wireless networking of distant and antiquated industrial equipment [10]. Consequently, techniques for leveraging open communication standards and encouraging smooth device and system integration must be developed [10]. Adopting the right machine learning models and carefully adjusting their hyperparameters are key components of the big data analytics shift. Furthermore, the performance of machine learning solutions is heavily dependent on the quantity and quality of data that is gathered as well as the effectiveness of data pre-processing; for this reason, big data platforms with organized data models and effective data management are necessary [11-12]. A growing number of serverless computing-enabled cloud-native analytics and data visualization products leverage autonomous scalability without requiring infrastructure management. Power BI on Microsoft Azure and Amazon Quick Sight by AWS are two excellent examples of how to extract insights from large datasets [12]. Success in creating KPIs and comprehending a wide range of manufacturing-related performance measures has been seen to need a methodical approach. As a result, the solution must be adaptable to take into account modifications as it moves through the various implementation phases. When performing basic computations in the control and sensing layer, the authors adhered to the practice of making small adjustments to the control code [12, 56].

Modern technologies like IoT, AI, ML, cloud computing and analytics, and cloud computing are being incorporated by manufacturers into their operations and manufacturing facilities. Industry 4.0, sometimes referred to as smart manufacturing, is the integration of physical production and operations with intelligent digital technologies such as big data and machine learning to create a comprehensive and networked corporate environment [12-13]. A new generation of physical process integrations with computer and networking processes is referred to as "Cyber-Physical Systems." It is the merging of the real and digital realms. With the help of CPS, we can design, create, improve, and maintain smart systems that help people, companies, and communities [13]. CPS can influence technology in many different Industry 4.0 contexts. For CPS engineers to modernize the various antiquated systems of Industry 4.0 infrastructure, they must become specialists in technology. Innovative technology may proliferate when it is incorporated into physical frameworks for essential infrastructure [13, 45]. CPS is made possible by the growing use of sensor technologies. Because factories are spread out and connected, customers can choose from a range of service providers for different stages of the manufacturing process. Massive amounts of different data are frequently generated by Industry 4.0 technologies [14, 32]. Both a strong data security policy and a practical fix for this issue are required. Establishing and developing secure data standards is essential. Providing the protocols, networking, and technology necessary for the smooth integration of physical and virtual systems is the aim of CPS technology [14]. With the help of CPS, we may design, create, enhance, maintain, and upgrade intelligent systems in areas that help people, companies, and communities. CPS may have an effect on technology in a variety of businesses and organizations (see Figure12) [15].

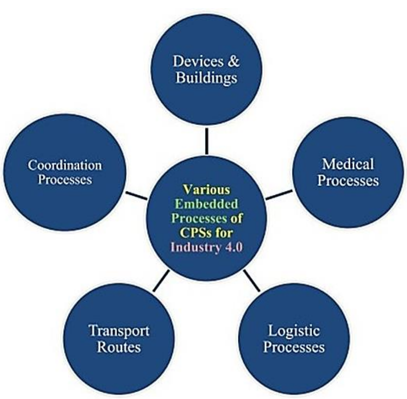

Fig 12. Typical CPS with Embedded Processes for Industry 4.0.

Networking and computerization are the first two processes. Integration of computer, networking, and physical processes is still far from perfect. Real-time observation of specialized records and processes is made possible through the use of sensors and digital models. By using digital models, industries may identify, comprehend, and monitor events in addition to monitoring them, so achieving the fourth degree of transparency [17-18]. Regarding the present trend of data exchange and production automation, which includes cloud computing, cognitive computing, IoT, CPS, and the building of smart factories. Developing innovative CPS applications requires a solid foundation of a well-designed communication network with guaranteed quality of service. When CPS entities are built correctly, they can interact with each other without any problems; the network only acts as an open facilitator [18].

Intelligent manufacturing, often known as smart manufacturing, is a complete concept of manufacturing that attempts to optimize production and product relations by fully leveraging state-of-the-art information and manufacturing technologies [19]. Intelligent manufacturing is seen as a crucial future viewpoint in both research and application since it adds value to a range of products and systems by fusing cutting-edge technology with traditional products in manufacturing and services. Product service systems will continue to supplant traditional product kinds [19]. Using the intelligent manufacturing system (IMS) is one way to implement this theory as seen in Figure 13. It is thought of as the next generation of manufacturing systems, developed by applying new models, forms, and methods to transform the traditional manufacturing system into an intelligent system. In the era of Industry 4.0, an IMS that utilizes service-oriented architecture (SOA) via the Internet to provide end users with collaborative, configurable, flexible, and changeable services makes feasible a highly integrated human-machine manufacturing system [20]. Real-time data collection and sharing amongst various production resources, such as workers, tools, supplies, and tasks, is in fact an aspect of manufacturing facilitated by the Internet of Things. Wireless communication protocols and ID (radio frequency identification) are two crucial technologies that provide the real-time data collection and exchange. RFID technology allows for the seamless integration of material movements and related information flows, such as the visibility and traceability of various industrial procedures, with physical manufacturing flows [21]. The manufacturing industry is gradually transforming into a "big data environment." While the Internet of Things (IoT) has made data collecting easier with the help of smart sensors, there is still the question of whether this data can be processed appropriately to deliver the correct information at the right time for the right purpose. Larger datasets that could be too complicated for traditional data processing technologies exist in big data environments [22,41]. For instance, hundreds of variables need to be watched over in the biopharmaceutical production chain to guarantee output, quality, and accuracy [23, 52].

Under Industry 4.0, IMSs are able to generate massive amounts of data in real time. To transform a manufacturing mode into intelligent manufacturing, cloud-based collaborative manufacturing, and customizable production, such data are necessary to accomplish intelligent analysis and decision-making. The objective of Industry 4.0 is to fully utilize CPS technology and principles in order to build a "smart/intelligent factory" [24]. Effective data use promotes increased agility and deeper interaction with other parties, including logistics and supply-chain management organizations, in addition to increasing production efficiency [25]. The efficiency and quality of a manufacturing system are greatly impacted by its dynamics. In data-driven models, information or knowledge integration, data mining, and data analytics are used to fully utilize historical or current data for system diagnosis or prognosis [26].

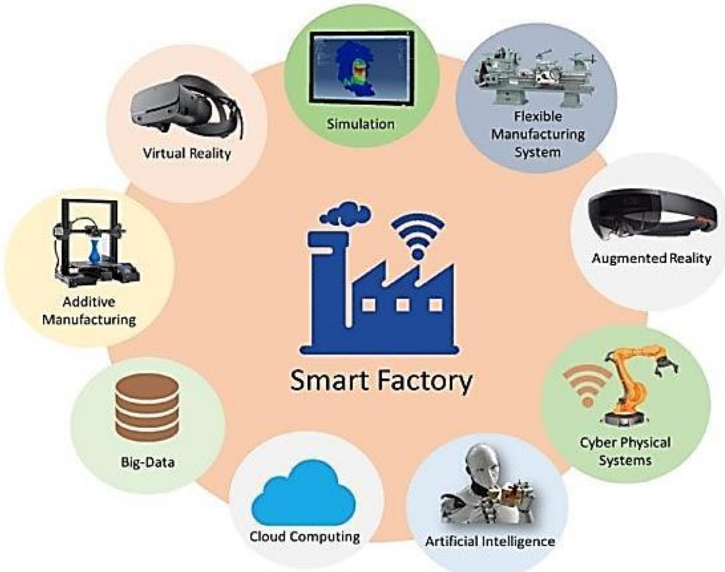

Fig 13. Components of Smart Manufacturing System.

The development of IIoT and IoT has been shown to be essential in improving the production system with smart manufacturing systems. Numerous manufacturing system studies have revealed that numerous industries aim to modernize their operations through the implementation of intelligent manufacturing systems. The incompatibility of their current systems and machinery with the new technology is a challenge for a smart production system [28]. The Internet of Things (IoT) paradigm is transforming industries into "cyber-production systems" that are completely aware of the production conditions and are able to be flexible and adaptive. To decrease the amount of data generated and communicated, innovative methods of data processing and filtering should be taken into consideration [29, 37, 59].

3 Summary of Findings

IoT is revolutionizing the manufacturing sector by enhancing asset tracking and data transactions. The use of IOTA Tangle architecture exemplifies the potential for distributed ledger technology to improve production performance, information visibility, and manage system complexity [30 – 33]. Big data analytics within Cyber-Physical Production Systems (CPPS) has emerged as a key driver for production visibility and efficiency. It enables real-time data collection, processing, and visibility, significantly enhancing production processes [34]. The integration of service innovation and CPS is shaping the future manufacturing industry. Intelligent forecasting tools and big data analytics are increasing transparency and work efficiency in industrial production [35-37]. The amalgamation of AI, IoT, augmented reality, CPS, and machine learning is forming new manufacturing methods. This blend addresses societal and occupational challenges, reflecting the transformative impact of these technologies [38]. The advent of Industry 4.0 brings challenges like cybersecurity, skillset mismatches, and technological adaptation. Addressing these challenges is crucial for the successful integration of IoT, big data analytics, and CPS in manufacturing [39]. Industry 4.0, which highlights automation and interconnectedness in manufacturing, hangs severely on IIoT. It is altering the way we work, play, and live, and it is having an influence on the progress and increase of manufacturing businesses [42–44]. Whispering a steady supply of data on temperature, pressure, vibration, and manufacturing rate, the persistent IoT serves as the pervasive sensor network [45]. Once raw and overlooked, this masterpiece of data is now translated by the big data analytics maestro, who uses intricate algorithms to find concealed patterns, project trends, and extract useful insights that progress the whole thing from inventory control to machine maintenance [46]. By linking the gap between the digital and physical realms, CPS permits machines to participate in an enthralling autonomous dance. hardware and software are wholly combined by these intelligent systems, permitting machines to interrelate with one another, modification of settings in real-time, and reply to fluctuating circumstances [47]. Visualize autonomous drones measuring equipment, robots amending assembly lines on the stain, or production lines continually changing to meet ultimatum—all motivated by the song of the data. Manufacturers may now reach extraordinary levels of production, efficacy, and sustainability thanks to this technological ballet. Algorithms that forecast apparatus complications before they occur make analytical maintenance a certainty by cutting down on downtime and expensive repairs [48]. By continually adjusting production lines to condense waste and optimize supply use, adaptive production permits factories to tango to the beat of request [49]. Moreover, customized manufacturing turn out to be achievable, letting producers to have capacity for precise consumer inclinations and generate one-of-a-kind goods that express their needs. This fascinating concerto is not without complications, though. Strong cybersecurity gauges are required to avoid undesirable contact to sensitive information due to data security and privacy subjects. Also, continuous research and development are desired for the tough integration and standardization of many technologies all through high-tech manufacturing systems [51].

3.1 Challenges and Limitations

Undeniable hindrances and limitations cast doubt on Industry 4.0's positive future [52–54]. The agreement of the data work is endangered by uncertainties about data security and privacy, notwithstanding the assurance of transformative effectiveness. Manufacturing systems are easy mark for bad actors due to the enormous quantities of sensitive data these technologies gather round; this possibly will expose secluded information, cause disturbances to operations, or even outcome in physical injury [32]. Moreover, the continuing surveillance of devices and measures gives rise to effective confidentiality bothers around employee spying and likely data misuse. fostering trust and avoiding misuse entails durable data governance and security mechanisms [55]. It takes expertise to incorporate these technologies across complicated production ecosystems effortlessly. One main hindrance is the heterogeneity of systems with dissimilar compatibility stages and data setups; to overpower this, open standards and interoperability solutions are desired to bridge the communication differences [40, 56]. An added major hindrance to deployment is the absence of a staff with CPS operation expertise, cybersecurity, and data analysis. For implementation to be operative, it is imperative that this skills difference be closed by intensive training and educational creativities [57 Hindrances of an operational and technical character can hinder the way in the direction of Industry 4.0. Processing data in actual is still a technical problem that entails high-performance computer infrastructure and active algorithms to sort across and turnover from the huge amounts of data that are being produced [58]. Additionally, in specific circumstances, constraints in edge computing capabilities make it more tough to sort out and scrutinize data on-site in real-time, which might suspend vital decision-making [58]. Not to mention the financial and scalability matters that can dishearten smaller enterprises from implementation the Industry 4.0 revolution. For larger usage, scalable and moderately priced solutions must be established

[59]. It's significant to systematically discover the ethical consequences of these technologies as well. Automation of jobs via CPS and AI may interrupt existing workforces, imposing destructive reskilling and the creation of new opportunities to offset adverse effects. In addition, the likelihood of algorithmic bias in big data examination calls for thoughtful preparation and error to assure fairness and inclusivity in the measures involved in making conclusions. Finally, it is impracticable to ignore how Industry 4.0 will disturb the environment. The growing number of sensors and devices being used adds to the manufacture of e-waste, presenting a new ecological problem that calls for suitable recycling and dumping methods. Besides, there is a need for research and advancement into energy-efficient solutions because the growing request for smart devices and data processing can result in complex energy usage [60].

4 Conclusion

The flowing together of CPS, big data and IoT has Industry 4.0, an uprising in manufacturing, is the result of the conjunction of IoT, big data, and CPS. Machines will dance to the beat of real-time data in a period of matchless efficacy, adaptableness, and sustainability, based on this symphony. But amongst the enthralling composition, there are trials waiting in the shadows. Cautious thought must be given to data security, incorporation challenges, ethical matters, and environmental difficulties. A harmonious corporation between accountable results and technical advances is essential to fully understand the capability of Industry 4.0. To incapacitate these obstacles, proactive workforce development investments, open communication, and continuing research are important. We can guarantee that manufacturing in the future is ethical, ecological, safe, and intelligent by finding this equilibrium. Rather than being intimidated by the shadows, let us use them to create an innovative symphony that will make sure that everyone benefits from Industry 4.0's data-dancing.

An important turning point in the development of the industrial sector has been reached with the integration of big data analytics, cyber-physical systems (CPS), and the Internet of Things (IoT). These technologies form the foundation of Industry 4.0, which ushers in a new era of smart production that is marked by increased adaptability, efficiency, and decision-making skills. IoT technology have improved production performance and increased system visibility in manufacturing by redef ining asset monitoring and data transfers. The potential of IoT to secure and streamline manufacturing processes is further highlighted by the introduction of distributed ledger technologies such as IOTA Tangle.

Manufacturing procedures have changed as a result of the capacity to process and analyze enormous amounts of data in real-time. Big data analytics helps manufacturers anticipate maintenance needs, streamline operations, and obtain deeper insights—all of which result in major cost and efficiency benefits. The integration of computational and physical capabilities in manufacturing is based on CPS. They improve real-time control and monitoring, which raises production efficiency and lowers errors. The future of smart factories depends on the advancement of digital twins and other CPS technologies Despite the many advantages, there are drawbacks to integrating these technologies, including the requirement for significant capital investments, mismatches in skill sets, and cybersecurity threats. To fully utilize the potential of these technologies, producers must overcome these obstacles. The constant development and smooth integration of big data analytics, CPS, and IoT will determine the direction of manufacturing in the future. These technologies will become more and more important in creating an intelligent, connected, and sustainable industrial landscape as the manufacturing sector develops. Adopting new technologies is only one aspect of the journey towards smart manufacturing; another is adjusting to an

industrial ecosystem that is changing quickly and where agility, innovation, and teamwork are becoming critical success factors.
This succinct conclusion summarises the main points of the discussion, underlining the opportunities and difficulties presented by Industry 4.0 and stressing the necessity of an all-encompassing strategy that takes responsible solutions and technology breakthroughs into account. Recall that you can modify your conclusion to better suit your requirements or include a call to action to encourage more investigation into this fascinating field.

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