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Review

A Review of 4IR/5IR Enabling Technologies and Their Linkage to Manufacturing Supply Chain

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Abstract: Over the last decade, manufacturing processes have undergone significant change. Most factory activities have been transformed through a set of features built into a smart manufacturing framework. The tools brought to bear by the fourth industrial revolution are critical enablers of such change and progress. This review article describes the series of industrial revolutions and explores traditional manufacturing before presenting various enabling technologies. Insights are offered regarding traditional manufacturing lines where some enabling technologies have been included. The manufacturing supply chain is envisaged as enhancing the enabling technologies of Industry 4.0 through their integration. A systematic literature review is undertaken to evaluate each enabling technology and the manufacturing supply chain and to provide some theoretical synthesis. Similarly, obstacles are listed that must be overcome before a complete shift to smart manufacturing is possible. A brief discussion maps out how the fourth industrial revolution has led to novel manufacturing technologies. Likewise, a review of the fifth industrial revolution is given, and the justification for this development is presented.

Keywords: smart factory; traditional manufacturing; industry 4.0; edge analytics; cloud computing; manufacturing supply chain; cloud manufacturing

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1. Introduction

In the past few decades, there has been a decline in the dominance of traditional manufacturing. Traditional manufacturing is an industrial process that converts materials into a finished product using a labor-intensive low-end operation, low precision, average resource utilization and efficiency for economic value. The shortcomings of traditional manufacturing are articulated and documented in [1] when compared to other sustainable forms of manufacturing that rely on modern technologies and digital innovations. Over the last two decades, manufacturing has transformed into something complex, automated, and new. In their evolution, manufacturing systems must retain the ability to respond to disruption quickly while possessing a good control structure. Response to disruption involves intuitive knowledge about what to do in a changing situation, even when it has never been implemented before. Through the described manufacturing approach [2], flexibility and reconfigurability are introduced into traditional manufacturing systems. Reconfigurable manufacturing systems (RMS) and flexible manufacturing systems (FMS) are two popular central forms of such transformed manufacturing. Each of these forms of manufacturing possesses features that make them unique and distinct from traditional manufacturing. According to [3], a smart factory incorporates existing production/manufacturing into broadly existing and future communication technologies. An intelligent production environment integrates manufacturing technology [4] and cyber-physical systems [4–6] and creates more complex and detailed models than traditional architectures by integrating previously independent and disconnected systems. Another description of the smart factory relies on its creating connections between digital and physical environments [7] while enlarging the digital space through the Internet of Things (IoT) technologies to enhance the quality and precision of manufacturing processes [8]. This extension [7] exhibits superior information processing support structures in data analytics [5,9], cloud systems, and machine/deep learning. This intelligent system [10] outlines a context-sensitive industrial environment in which dispersed communication structures are used to improve production processes while allowing for minimal unpredictability. Adapting to various changes and conditions is also handled in such a system, mostly instinctively [11].

An intelligent system enables unrestricted real-time data access, collection, and distribution of relevant manufacturing information. Hozdić in [12] describes a production solution that meets current demands while integrating industrial and non-industrial partners, resulting in the efficient construction of a compelling and virtual organization. An intelligent factory is a manufacturing solution that will solve complex manufacturing problems in smart manufacturing facilities through adjustable production processes within changeable boundary conditions. The smart factory entails integrating smart manufacturing, digital technology, intelligent computing, and Big Data with physical production processes and operations, resulting in a more resourceful system for successfully managing manufacturing and supply chain. This system consists of appropriate hardware systems, such as controllers and sensors, which provide a significant amount and variety of manufacturing data, and software systems that establish communication, transmitting, processing, and requesting information. This approach also accommodates existing and future enabling communication technologies that provide significant benefits such as ultra-low latency, high reliability of connection, spacious bandwidth, ample data storage, and advanced computational powers.

In all the descriptions of intelligent/smart manufacturing, incorporating man, machine, material, method and technologies, and energy to ensure a comprehensive convergence model [13] and continuous improvement is crucial for implementing an intelligent/smart factory. Figure 1 depicts a convergence model that links all contributing elements to traditional production and enabling technologies.

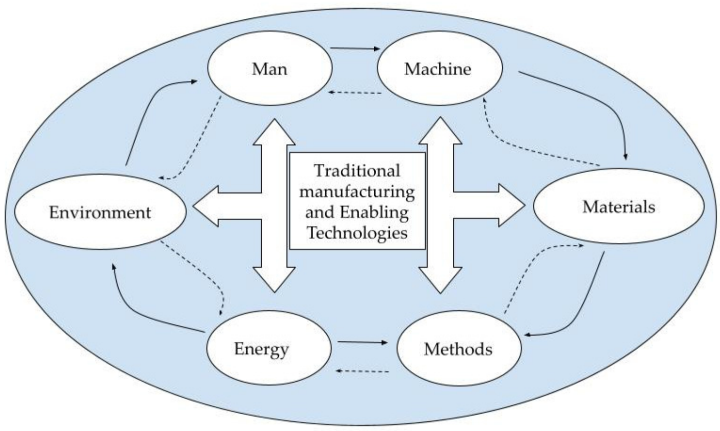

Figure 1. The Convergence model connecting all relevant elements to traditional manufacturing and existing enabling technologies that facilitate smart manufacturing.

In Figure 1, traditional manufacturing and all the enabling technologies have connectivity to all contributing factors such as man's knowledge, machines, materials, methods, energy, and environment in continuous communication. The contributing factors constantly talk and respond, establishing a mutual relationship that improves smart/intelligent manufacturing. The dashed arrows symbolize the response phase, a dependent type of association, whereas the full line arrows reflect the directed association between the contributing factors. All relevant components contribute to the "left–right up" arrow.

Many researchers have acknowledged Industry 4.0 (4IR) in sectors such as manufacturing, pharmaceutical, agricultural, etc. Many have also praised the innovations and underlined the impact of the technological driver on the supply chain. The full benefit of 4IR technologies can only be fully realized if and when these are integrated into the manufacturing supply chain (MSC). Despite this, little research has been conducted on the physical and digital factors at the heart of the MSC. Reference [14] has addressed radio frequency identification, Big Data analysis, IoT, Cloud computing, and blockchain and its relationship with manufacturing and supply chain. This paper will present an in-depth review and analysis of the literature and the current state of affairs in the MSC. The digital and physical drivers of Industry 4.0 will be the focus of our attention. The interaction between the 4IR enablers and the manufacturing supply chain will be examined in depth. IoT, IIoT, Big Data Cloud Computing, Advanced Robotics and Collaborative Robots, Artificial Intelligence/machine/deep learning, Big Data, and Cloud/Fog/Edge Computing are some of the enablers that will be considered. However, this study does not cover the final two biotechnological drivers: genetic engineering and neurotechnology. The literature retrieved from Google Scholar contains studies from various fields useful to current and future researchers studying the fourth industrial revolution. In this review, the following questions will be addressed:

- What is the present state of the supply chain for the manufacturing sectors?
- What approaches have researchers employed in describing the manufacturing supply chain?
- What does the literature suggest will be the proposed impact of the enablers of the manufacturing supply chain?
- What does the literature indicate as the gaps and the shortfalls of the fourth industrial revolution concerning the manufacturing supply chain?

The paper is divided into the following sections. We discuss smart manufacturing in Section 1. We will briefly review the history of each industrial revolution because we know that the fourth industrial revolution is at the heart of smart manufacturing. Section 2 provides an overview of the research methodology used to identify 4IR drivers and the literature on the manufacturing supply chain. In Section 3, each of the enabling fields and critical applications is briefly highlighted. Section 4 discusses the distinguishing characteristics of the five manufacturing systems. Section 5 addresses incorporating innovation into smart manufacturing. We consider the merits of the three integration approaches. The cost of innovation in the manufacturing sector is capital intensive and, hence, in Section 6, we discuss the advantages and disadvantages of applying intelligent manufacturing in any nation before discussing the justification of the advancement from 4IR to Industry 5.0 (5IR) in Section 7. In Section 8, we conclude the article.

2. Research Methodology

Each literature item found was reviewed based on a systematic literature review approach. This approach enhances and provides collective insights through the theoretical synthesis in a field and subfields. As a first step, a systematic search was used to initiate the review process. The search was conducted on only one public database, Google Scholar. The keywords used in the search were as follows: "Autonomous car" AND" Manufacturing" AND" Supply chain". Subsequent search criteria included "Additive manufacturing" AND" Manufacturing" AND" Supply chain"; "Advanced robotics and collaborative robots" AND" Manufacturing" AND" Supply chain"; "IoT" AND" Manufacturing" AND" Supply chain"; "IIoT" AND" Manufacturing" AND" Supply chain"; "Artificial intelligence/Machine/deep learning" AND" Manufacturing" AND" Supply chain"; "Big data and Cloud/Fog/Edge computing" AND" Manufacturing" AND" Supply chain"; "Blockchain" AND" Manufacturing" AND" Supply chain". For some sections of the search, "Supply chain" was replaced with "Logistic 4.0" or "Supply chain 4.0", "Big data and Cloud Manufacturing" AND" Manufacturing Supply chain."

Thereafter, a detailed review of the literature identified in the search was executed. Findings based on the detailed review work were summarized and presented in a meaningful manner. In the literature search, three concepts at a time were researched. They are supply chain management, traditional manufacturing and each of the enablers highlighted in the paper in turn. After that, the search was narrowed to the manufacturing supply chain (MSC) while keeping all the other search parameters. The number of articles identified was narrowed down by removing book chapters and website pages. Hence, the results were limited to conference proceedings, articles, articles in press and review papers. Consideration of abstract and conclusion of each article allowed relevance to be confirmed and /or duplication to be avoided. This resulted in a final list of articles for the review focusing solely on the interaction between enabling technologies and the MSC.

3. Industrial Revolutions and the Enablers of Industry 4.0

The increasing transformation of the economy away from the use of animal and human labor [15–17] towards a large-scale mechanized, high-tech, and automated system with adequate and new machines, power supply systems, and improved ways of performing work has been the hallmark of each Industrial Revolution (IR). Each IR has increased productivity and international commerce. Each nation's achievement is determined by the predominant energy resources available during each IR [18].

The first IR [9] is best described as an age of mechanization, steam engines, and hydraulic application. During the second IR, there was an increase in the use of science and electricity, while mass production was in its early stages. The third IR saw the introduction of digital technology, automation in manufacturing and electronic and informatics systems into nearly all processes. 4IR elevates the third industrial revolution and includes the Internet of Things, automation, machine learning, and cloud computing. Additionally, interconnectivity and real-time data acquisition are enabled. All previous IRs and their associated technological aspects and advancements are seamlessly incorporated into 4IR. The fifth IR addresses concerns about the dominance of the robot, and may eventually take over the manufacturing process in specific sectors [19,20]. In the fifth IR, an advanced human–robot interface [21–24] is used. Human characteristics such as creativity, craftiness, power, and imagination are superimposed on the complex automation, consistency, productivity, and speed of the collaborating robots [25,26]. Integration and interoperability are required attributes of all the parts that define each industrial revolution for optimal performance and efficiency, especially in 4IR and 5IR. In interoperability, interconnectivity across device system sets is possible. Through this process, acquiring the required volume of data to make informed decisions is realized during the production process [27].

In Table 1, each IR is summarized, and the ultimate goal stated.

Similarly, the various accomplishments realized directly impacted the economy while allowing for technological advancement through the eras [41]. Presently, the fourth IR is translating and transforming manufacturing. The categorization of technological drivers of the fourth IR [42,43] can be divided into three broad categories: physical, digital, and biotechnological drivers [44]. Table 2 shows how each of these broad categories can be subdivided.

Table 1. Stages of IR, energy sources, inventions, and final objective.

IR	Energy Sources	Inventions	Final Objective
1st	Coal and steam [28–30].	Steam engines [31].	Mechanization and centralized manufacturing.
2nd	Electricity, natural gas, and oil [28,30,32].	Lighting, telegraph, telephone, long-distance wireless communications, and steel production.	Industrialization [33].
3rd	Among others, a mix of energy sources: natural gas, nuclear power (energy) [30,32,34–36], coal and others. There is also a move towards renewable sources	Solid-state electronics [37], robotics, automated process; and programmable logic control.	Factory automation and computerization [38].
4th	A mix of previous and existing energy sources and a greater focus towards sustainable sources.	Cloud computing, IoT, IIoT and blockchain.	Digitalization.
5th	Most likely sustainable energy [39].	Massive IoT, Autonomous cars, Augmented reality, and virtual reality.	Customization and personalization [40].

Table 2. Technology-based drivers for the 4th IR and application fields.

Technological Drivers	Fields
Physical	Autonomous cars Additive manufacturing Advanced Robotics and Collaborating Robots
Digital	IoT IIoT Artificial Intelligence and machine/deep learning Big Data and (Cloud, Edge, and Fog) Computing Blockchain-powered digital platforms
Biotechnological	Genetic engineering Neurotechnology

3.1. Physical Technology Drivers

These drivers [20] are distinguished by their visibility, rapid adoption, and widespread application. This technological driver category is significant among the three specialized drivers. Autonomous vehicles (AV), additive manufacturing (AM), and advanced robotics and collaborating robots are examples of fields associated with physical technology drivers.

3.1.1. Autonomous Vehicles

AVs are self-driving, crewless vehicles that communicate and comprehend the intentions of other road users while close to other vehicles [44–46]. V2V [47] and V2P [48] are at least two technologies that permit autonomous vehicles to communicate with other road users in real-time. Sensors, cameras, light detection, range systems, and artificial intelligence enhance self-driving vehicles' performance [49]. The vision for AV began with the use of radio technology as early as 1920. However, it was not until the mid-1980s that the underlying computational and technological requirements for ensuring the vision's realization became obvious. The AV concept was based on current automobiles that were not self-driving. The initial phases, which included a significant amount of foundational research, relied on roadway infrastructures integrated with magnets and vehicle-to-vehicle communication. This was the initial method in developing an autonomous car. The second method in the foundational phase involved creating semi-autonomous and autonomous vehicles that relied on limited highway infrastructure. However, with advancements in sensor technology and computational techniques essential for recognizing and responding to other vehicles on the road, the next stage witnessed an acceleration in the development of autonomous vehicles. The fourth stage entailed expanded commercial development involving collaborative efforts between vehicle makers and academia. There was a breakthrough in the area of improved sensors and smart algorithms. This effort also resulted in a better knowledge of the autonomous vehicle's automation taxonomy system.

The autonomous taxonomy system [46] allows for five automation levels, ranging from a situation where the driver manages virtually all functions to a system where nearly all the systems are automated. The third automation level was attained in 2020 [50]. However, automation levels 4 and 5, which are simply termed high automation and full automation, require a remarkable enhancement, which is still being researched. The fifth automation level will require remarkable driving functionalities in information acquisition, localization, perception, planning, control (lateral and longitudinal), management and system architecture [51,52]. Areas of application for autonomous cars include logistics and agriculture.

The theoretical approach to autonomous vehicles involves modeling different scenarios using mathematical expressions to represent their performances. Most of the scenarios that involve sensible decision making utilize game theory, either cooperative or non-cooperative involving two or more players. More forms of game theory include non-zero-sum game theory, hierarchal game-theoretical planning, and the distributed game theory approach. Specific parameters must be considered, while the approach must be relevant and dependent on the structure and functionality to be addressed. Game theory can be used in speed management, lane changes, traffic congestion scenarios, freeway platooning strategies, pedestrian and driver interaction, security concerns for communication links and sensors due to intruders, and road intersections.

Autonomous Vehicles and MSC

In supporting the manufacturing supply chain or supply chain 4.0 [53], autonomous vehicles can be deployed between the supplier and the customer. Autonomous equipment can be used in the warehouse, increasing the efficiency and reliability of inventories and reducing the required human resources. Through autonomous vehicles, the quality of decision making is improved, and flexibility is introduced into the supply chain. IoT and sensors are required for the autonomous system to function. Industries and warehouses require automated guide vehicles and industrial conveyors for viable supply chain flow. From the factory to the warehouse, self-driving trucks and trains have been proposed. From the warehouse to the customers, autonomous trucks and drones would be helpful. Their practical deployment remains to be seen. The influence of AV on the manufacturing supply chain is discussed to support the case for its deployment in [54]. Bechtsis et al. in [55] devised a framework for generating highly tailored simulation tools that effectively integrate Intelligent Autonomous Vehicles (IAVs) in sustainable supply networks.

Further research proposed which autonomous equipment and vehicles could be applied in the supply chain process and considered their advantages and disadvantages [56]. In addition to this, the characteristics of the supply chain process and the benefits of applying specific tools of 4IR were emphasized. The flow path from the industry to the products, to the warehouse and to the customers was highlighted. By incorporating AGVs and SC management, Perussi et al. developed integrated and systematic methodological approaches to promote social, economic, and environmental sustainability in [57]. In the near future, researchers can investigate the dynamic interaction of swarm robots in a supply chain network inspired by nature [58].

3.1.2. Additive Manufacturing

Additive technology [59,60] or rapid prototyping [60] is a fabrication technology that typically uses layer-by-layer-based printing, which converts loose-based charges to a three-dimensional object based on available numerical data and models. Data acquisition and processing, additive fabrication, and post-processing procedures are part of the overall manufacturing process [61]. Additive manufacturing can draw on theoretical approaches and practical approaches, as discussed above. The theoretical approach is dependent on the input from the experimental viewpoint [62]. In the process of modelling, a simulation model (white box), black box, or grey box model can be used. With the grey box model, no additional experiments are needed to establish the relationship between parameters. Once the parameters and the influences over the theoretical approach are defined, all correlations are also established. Expected correlations and relationships between other parameters which are not apparent are also identified. Following the filling of the matrix, the listed correlations are assessed, finding the defining mechanisms that control each relationship. After that, the model process can commence.

Extensive and exhaustive reviews have been conducted on the comparative benefits of additive manufacturing over traditional manufacturing. Examples of traditional manufacturing are subtractive manufacturing and formative manufacturing [63], among others. Many criteria and metrics have been used to verify and validate the substantial advantages of additive manufacturing. The research focuses on designing low-cost machines, enhanced material changeability, efficient energy and material utilization is the primary driver behind the rapid growth of AM technology [64]. Construction advantages, high performance with a faster system, an improved supply chain and lower resource costs are advantages of 3D printing manufacturing. Similarly, 3D printing reduces waste and supports efficient short production runs, reduces lead time [64], lowers associated costs, reduces assembly error, designs products with complex parts, and results in more sustainable manufacturing processes. Additive manufacturing [65,66] reduces overheads associated with building object production planning. It also enables rapid market response by rapidly producing replacement parts on demand, jettisoning the need for stockpiles. It is now possible to customize on-demand products with numerous competitive advantages over the traditional manufacturing approach. Additive manufacturing structures reduce the geometrical complexity associated with customized design. Production of intelligent materials is, therefore, possible.

AM also provides new material alternatives, faster processing speeds, and greater autonomy. However, standardization and design guidelines for additive manufacturing still need to be researched. When compared to typical manufacturing machines, AM remains a prohibitively expensive investment [37]. Meanwhile, traditional manufacturing's low production efficiency is exacerbated by outdated production lines and technologies. The traditional manufacturing industry tends to cause much wastage of resources and severe environmental pollution where casting is concerned. Environmental pollution manifests in volatile organic and industrial water waste, particulate waste, a mixture of hazardous solid, all solid and liquid particles suspended in the air process. Despite all the advantages of additive manufacturing, it will not entirely replace the old prototype process; however, it will augment and reinforce it. Hence, Strong et al. in [67] have proposed hybrid AM, which includes integrating sequential order AM into traditional manufacturing processes to achieve the desired surface polish, dimensional tolerances, material qualities and to meet the required engineering criteria.

AM can be classified into two groups: additive metal technologies and additive non-metal technologies. Metal and metal alloys which can be melted and deposited on a substrate to construct layers that form the desired geometry are required for additive metal technologies, such as directed energy deposit and powder bed fusion. Stainless steel, steel, titanium, and aluminum are among the metals and metal alloys used. The fused deposition method [68], selective laser melting and sintering, and electron beam melting [65] are examples of additive metal technologies used in manufacturing. Non-metallic prototypes, such as paper, plastic, ceramic, polymers, and sheet, are used in additive non-metal technologies. Additive printing has applications in the automotive, aerospace, and medical fields.

Additive Manufacturing and MSC

The AM supply chain is a linked set of separate supply networks of commodities and services that cater to the needs of end-users of AM-produced items. Machine vendors, material makers, software providers, logistics operators, and research centres are all part of this supply chain. New supply chain models have materialized as a result of AM. Streamlined logistics, customer-managed inventory, 3D printing centres and design, research and development, and data management are just a few of them. Early adopters used AM's potential to rethink material sourcing, product distribution, and delivering items to end-users. The consequences of AM on supply chains are streamlining manufacturing processes, increased flexibility, lower pricing, faster demand responses, and the ability to decentralize production.

Alogla et al. in [69] established a theoretical model that connects AM traits related to flexibility to significant market disruption scenarios. Following the construction of this model, a case study was conducted to determine the influence of AM adoption on supply chain flexibility in terms of four key aspects: volume, mix, delivery, and new product introduction. This research provided new insights on the connection between supply chain responsiveness and AM, which will help researchers and practitioners in the future. An in-depth examination of the literature in [70] gives a detailed assessment of how the use of additive manufacturing may affect supply chain integration and firm performance. A developed model and simulation were used to examine the transformative implications of additive manufacturing on traditional supply networks in [71].

3.1.3. Advanced Robotics and Collaborating Robots

Robots are versatile machines equipped with various sensors that can fit to any manufacturing process or state. Robots are designed to replace or complement humans in dangerous and monotonous manufacturing jobs [72] with a high precision level. Modern collaborative robots are substantially different from traditional collaborative robots. Traditional robots are, in most cases, installed in a fixed position. Additional attributes are that they are challenging to engage with when it comes to learning and re-learning. Workers can only engage with traditional robots through programming, not through collaborating on tasks. The majority of these robots are separated from the workers by fencing. In terms of profit, it is more cost-effective to use them for medium- to large-scale jobs rather than little chores. These shortcomings of traditional robots prompted innovative research towards a superior alternative known as collaborating robots. The most adaptable and cost-effective solution proposed by academics and currently in use in the industry is based on the Human–Robot Interface (HRI) [23] or physical human–robot interaction [73]. As its name suggests, this interface aims to ensure safe communication, interaction, and cooperation between humans and robots. AI [74], sensor technology and computing power are crucial elements in the use of HRI. Safeguards are put in place to ensure that humans and robots communicate safely and at a safe distance. A common approach is kinesthetics teaching [75,76], where operators interact and configure the robot arm. With collaborating robots, the integration of humans and robots achieves high productivity in a shared industrial [77] working space. Other areas of use include domestic and industrial services.

Advanced Robotics and Collaborating Robots and MSC

Attaran in [78] conducted a literature review to discover current research and directions regarding how these technologies will improve and update the performance of digital supply chain. Customers will benefit from speedy and high-quality service since warehouse robots are more versatile and increase productivity while improving quality. Warehouse employees will have fewer monotonous duties to complete. Robots are already assisting logistics personnel in sorting centers and last-mile delivery. Unloading trucks, co-packing, choosing orders, inspecting stocks, and delivering things are just a few of robots' activities at warehouses. Through the management system, high-level responsibilities such as flow coordination, repairing of robots, and exception handling can be implemented.

Advances in computer vision and motion sensor technologies have resulted in collaborative robots, often known as cobots. These robots assist humans with dangerous or labor-intensive jobs such as lifting or transporting large things or hazardous commodities while being supervised by humans. By watching human movement, robots can be trained to generate smooth movements and even predict future movements and activities. Collaborative robots can also read product data from sensors and tags and make flexible decisions about where next to send a product coming towards them in the manufacturing line via the conveyor belt. Automated Guided Vehicles are examples of such cobots.

In [79], the research demonstrated robotics' significant potential in the manufacturing and machine tool industries. Use cases were investigated using cluster analysis and scored using criteria for effective robotics applications. This article examined the promises and challenges of robotics in the industrial business.

3.2. Digital Technology Drivers

Digital technology, according to [42], is the driving force behind the 4IR. This technological driver is the powerful force behind all connected ecosystems, whether in manufacturing, health, banking, transportation, or other fields. The establishment of a link between physical and biotechnological drivers via digital drivers results in digital transformation. IoT, IIoT, AI, Big Data and cloud computing, blockchain-powered digital platforms, deep/machine learning, Edge analytics, Fog computing, and network slicing are examples of digital drivers.

3.2.1. IoT

IoT is a structure in which everything in our physical world communicates with computers (exchanges data) via the widespread deployment of intelligent and self-configuring devices, sensors, and Internet-enabled devices [80,81], ensuring that industrial data is easily accessible. Kevin Ashton formulated the term IoT in 1999, proposing that everything has a digital identity and can be efficiently organized and managed by using a computer. According to the International Telecommunication Union's vision of IoT [82], connectivity must be realizable at any time, anywhere, by anyone and using any device. Context, omnipresence, and optimization are critical components of IoT. Context is defined as the possibility of the advanced object interacting with the current environment and reacting immediately to this change. Thanks to this distinguishing feature of context, all objects can be tuned to provide specific data about atmospheric and physical conditions. The concept of omnipresence represents the truth that advanced things are everywhere and that the connections formed between them will grow in the future.

The theoretical approach to IoT as an enabling technology was introduced in [83] by developing a mathematical model that depends on three parameters: trust, control, and feedback. In such a system, trust is modelled as a multilevel concept in terms of its autonomy. There are five levels of autonomy to which an IoT device can respond. The efficiency of each level is dependent on the interaction the user has with the device. With the trust model for the equipment described, a similar methodology was also applied to the user.

Through optimization, IoT systems can achieve full functionality, and the performance-enhancing internet-enabled object can be realized. Environment, buildings, factories, industry, roads, warning systems, water management, cities, energy, innovative manufacturing services, security, and health are applications for IoT solutions. IoT addresses the lack of urgent, inventive solutions in logistics and supply chain management. When IoT [84] solutions are developed, they will have low power consumption battery technologies, small footprints, and lightweight, high performance, and efficient systems.

Radio frequency identification (RFID), wireless sensor networks (WSN), middleware, IoT application software, sensor and detector technology, incorporation of intelligent elements [85], nanotechnology, Wi-Fi, Bluetooth, global positioning systems and cloud computing are some of the IoT enabling technologies required to deploy IoT-based solutions successfully. RFID enables automatic identification and data capture by utilizing radio waves, a tag, an antenna, access control, a server, and a reader. Tag applications can be classified into three types based on their power supply provision: active, passive, and semi-passive tags. WSN comprises spatially dispersed autonomous devices fitted with sensors that monitor physical and environmental conditions in collaboration with RFID systems. WSN's inherent strength is multihop communication. Location, temperature, electrical quantities, water pressure, and movement can all be measured. IoT middleware serves as a link between various applications, each with its interface. It connects sensors while also establishing reliable communications for other applications. The middleware also has the capability of analyzing, processing, and storing massive amounts of data. Hence, the IoT architecture comprises the sensing, access, network, middleware, and application layers.

IoT and MSC

Traditional supply chains confront several obstacles, including overstocking, delivery delays, and stock-outs, as well as uncertainty, cost, complexity, and vulnerability issues. However, developing a robust and modern IoT platform will ensure integration of the supply chain processes with external parties such as suppliers and customers for significant performance benefits. Many industries have adopted the supply chain operation reference model. However, this has not translated to an IoT-supply chain link. Conceptualised ideas and proof-of-concept are the predominant approaches used when discussing beneficial applications of IoT to the manufacturing supply chain. There has been little to no empirical research based on observation and measurement that sustains the hype around the capabilities of IoT.

IoT enables the design and modelling of intelligent storage warehousing services, order and inventory management capabilities, and transportation operations used in supply chain management. When IoT is introduced into the supply chain, improved inventory management, real-time supply chain management and logistics transparency are realized. Despite all these possibilities, the full capabilities of IoT for supply chain management are yet to be fully identified and explored because the technology is still in its infancy. As seen by the literature review, IoT has been brought to the attention of researchers. as an emerging technology and have mostly concentrated on imaginative research.

There are many research areas where work still needs to be carried out. Standardization [86], system architecture [87], management and self-configuration, quality of service, security, and privacy [88], identification and unique identity, interoperability and integration, and data processing are only a few of the topics that academics and industry are still working on [89].

3.2.2. IIoT

IIoT [90] integrates and extends the IoT and services (physical and virtual world) into the manufacturing process, resulting in an entirely intelligent, connected, and self-driving system [91]. In IIoT, sensors, actuators, controllers, and machines are connected through intelligent control systems that analyze and optimize the industrial process in a factory setting. With IIoT [92], the value provided, collaboration/networking, and human resources are all positively impacted. The interaction between customers and suppliers is built through collaboration and networking. Customers gain a better understanding of product engineering, required devices, and the design process. IIoT is divided into three categories based on usage and customer base: consumer IoT, commercial IoT, and industrial IoT. The Internet of Things (IoT) improves the collection of massive amounts of industrial data to help businesses and provide insight into achieving their operational goals. Data collection necessitates the use of sensors, actuators, controllers, and computers linked via the Internet. As a direct result, new business models and value chains are emerging. The IIoT technology stack [93] has three tiers: the edge, platform, and cloud IoT. Sensor devices are used in the edge tier to collect data from an array of sensors. The platform tier is an intermediary platform for pre-processing data. Before moving to the cloud tier, additional functions such as communication facilitation and offloading of processing functions are performed. Large-scale data computation is performed at the cloud tier via data analytics to generate insights and business value. Figure 2 depicts the protocol stack layer and its application and correspondence with the Internet of Things and services.

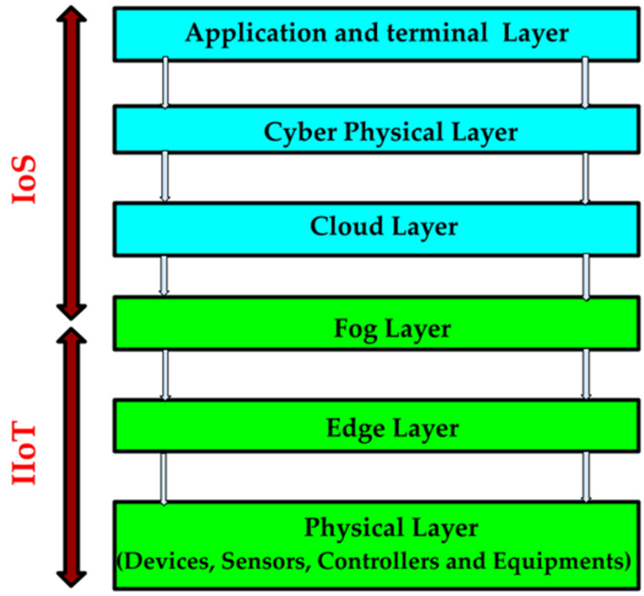

Figure 2. Interface between Internet of Services (IoS) and Industrial IoT (IIoT), and its interface with network architecture for the smart factory.

In Figure 2, the existing link and interface between IIoT and IoS can also be seen through the protocol stack [4], consisting of the physical resource, network, cloud application, and terminal layers. The fog layer is located between the IoS and the IIoT. Devices, sensors, controllers, and other types of equipment are part of the network and physical layer, linked to the edge layer, where critical computing exercises are carried out near the devices. The edge layer reduces the amount of computing that takes place at the cloud layer. The application and terminal layer are critical components of smart manufacturing network architecture because they form the interface through which instructions are initiated. These instructions are then forwarded through the cyber-physical and IoT layers. Business, E-services, and web services are examples of IoS. Service discovery is typically linked with the application and terminal levels, whereas execution might occur from the cloud and beyond. As a result, execution is generally dependent on IIoT.

Some pending difficulties must be addressed in the essential infrastructures that rely on IIoT, such as SDN, edge computing, fog computing, and blockchain. These issues include security and privacy concerns around the cyber-physical systems, scalability, and IIoT systems metrics such as energy, cost, and bandwidth [94,95].

3.2.3. Artificial Intelligence

AI is the "science and engineering" that involves developing computer algorithms that execute specific tasks mimicking [96] and enhancing human intelligence capacity [97,98]. Learning, interpreting, and using the data provided correctly [45] to achieve specific goals are realized through this process. In 1950, Alan Turing explained the method of mimicking intelligent behavior and critical thinking in machines to enable them to reason similarly to humans [99]. However, it was not until six years later that John McCarthy described artificial intelligence as "the science and engineering of creating intelligent machines" (robots). The evolution of AI can be divided into three stages: the initial, industrial and explosion phases. During the first phase, AI was used to solve algebraic applications and problems, prove geometric theorems, and learn English. The second step entailed developing machines that could engage in human–machine interaction, translation, and image recognition. In contrast, the third phase processed and analyzed data using a theoretical framework and machine learning methods.

With AI, the system flexibility, efficiency [4], and intelligence of any system is improved. Some of the branches of artificial intelligence include automatic learning, expert systems, computer vision, fuzzy logic, swarm optimization, neural networks, deep learning, Natural Language Processing, discriminant analysis, Heuristics, pattern recognition, machine learning, probability theory, and Intelligent agents. The designer of AI [100] must observe specific rules. These rules include:

1. AI design must benefit humanity;
2. Increasing the effectiveness of AI must not jeopardize human dignity; and
3. It must be possible for a human to reverse the unintended consequences of the AI design algorithm.

Before AI [91] can be fully deployed in any country, the need for "regulation with respect to algorithms and organizations, employment and democracy, and peace" must be considered. AI is used in financial services and the automotive industry. Figure 3 depicts the interplay between AI and other intelligent computational techniques. Artificial Intelligence's theoretical approach can be seen in the application of various domains to the supply chain. Artificial neural networks, rough set theory, machine learning, experts' systems, fuzzy logic, agent-based systems, and genetic algorithms are examples of AI categories.

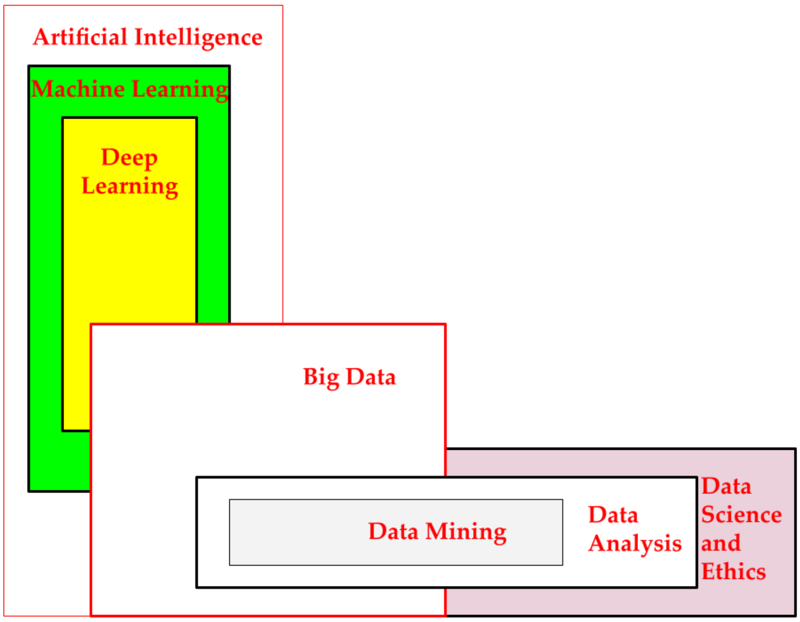

Figure 3. The interplay of Big Data, AI, and data science.

AI and MSC

There are many studies of Artificial learning with supply chain management (SCM), but only a little work has been carried out on manufacturing SCM. Other developments of AI with SCM are in the proposal [101], conceptualising [102], and design stages. Other researchers have engaged in empirical studies. With these drivers, the AI manufacturing supply chain is expected to improve transparency and accelerate decision-making. In addition, in [102], Woschank et al. present a conceptual framework based on the findings of a systematic literature review helpful in launching future research drives in the field of artificial intelligence (AI), in Smart Logistics.

AI can also be used to provide a system for the adequate inventory calculation of patterns of defective products in manufacturing. This technique aids transactional relationships between players such as integrates customers, manufacturers and suppliers, thus maximizing company profitability, ensuring operational inventory management system and timeous supply of product, as stated by [103].

3.2.4. Big Data and Cloud Computing

Big Data represents high velocity, wide variety, high volume and multifaceted data sets that are difficult to represent using typical data processing methods. Vision, verification, validation, and value are other essential features of Big data [104]. The use of Big Data reveals hidden patterns, unidentified correlations, market trends, preferred customer choices, and other helpful information needed by organizations to make more informed business decisions, all of which are revealed by datasets. A data analytics engineer can use a unified platform with predictive analytics and visualization tools to extract the necessary information. Its applications include, but are not limited to, smart grid, E-health, IoT, IIoT, transportation, and logistics [105]. Predictive analytics can result in cost savings, improved customer service, better pricing, and marketing personalization. Cloud computing provides on-demand access via the Internet to a shared pool of computing resources such as software, infrastructure, and computing platforms. As a result, while IoT and IIoT generate massive amounts of data, they also provide a new way of doing business and make additional room for much-needed innovation [106]. Cloud computing is a legitimate platform for hosting Big Data workloads such as data storage, management, processing, analytics, and security [107]. Figure 4 depicts an integrated view of Big Data and its added value.

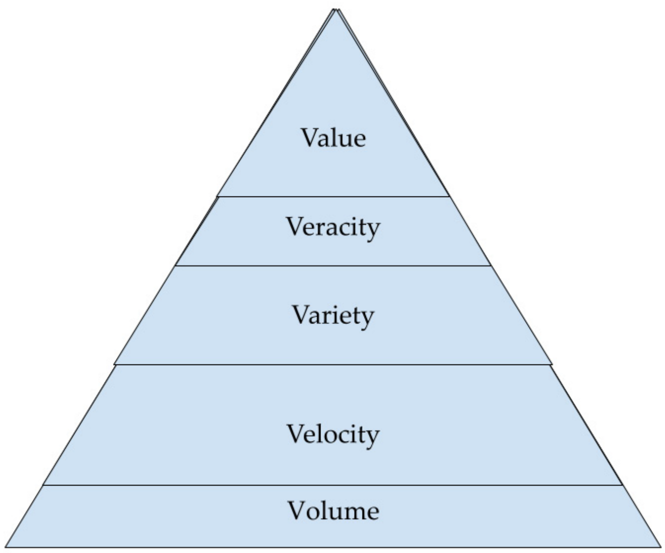

Figure 4. Overall dimensions of Big Data.

Big Data is beneficial in obtaining data for strategic decision-making. It is possible to categorize it based on how the data is used. The descriptive (issue identification), predictive (trend projection and forecasting), and prescriptive (recommendation) are the first three categories that jointly offer an opportunity of making alternate decisions to improve the overall performance of a business [108]. Jain et al. in [109] raised several concerns about supply chain management for Big Data.

Cloud computing provides a method for processing and storing large amounts of data created by communication. Multiple virtual servers are used for data storage, backup points are built using the servers, and self-synchronization is possible. Traditional data has specific properties that distinguish it from Big Data. Big Data is measured in petabytes and zettabytes, whereas little data (traditional data) is measured in megabytes and gigabytes. In terms of data sources, Big Data comes from numerous and dispersed sources, whereas traditional data is centralized. The following categories represent the issues associated with Big Data and cloud computing: security, data set integrity, data processing, and data management [110].

The theoretical approach to cloud computing involves the mathematical modeling of a process. Problems that have been modeled mathematically include, amongst others, the cloud federation problem [111], resource management in cloud computing [112], benefits of cloud computing [113], and user behavioral trust problems [114]. In resolving these problems, game theory (evolutionary), genetic algorithms, and Nash equilibrium have been deployed to model each problem, depending on input parameters. Performance metrics have also been identified to check how each proposed solution compares against the traditional/existing approach. In terms of the supply chain lever in cloud computing, the system must create greater profitability and efficiency while providing customer satisfaction. With cloud computing, it is necessary to find a model that suits each organization. The big question is whether all organizations need cloud computing. This question would best be defined by looking at the "pros vs. cons". While each corporation can obtain its own cloud computing solution, a further option is also the federated cloud [111] (albeit a third-party solution), which is helpful for organizations that cannot afford such a solution or whose cloud solution does not satisfy all their needs. With the federated approach come exposure and loss of control of system and data, and risk of data lock-in with the vendor, despite the cheaper form of service offered. If a business process is complex or compatible, or synchronized into the IT structure of a company, there is no need to adopt cloud solutions [115]. Figure 4 shows the overall dimensions of Big Data.

Big Data [100] has five dimensions: value, veracity, variety, velocity, and volume [116]. With increased velocity comes the possibility of increased volume and variety. The volume of data indicates the quantity of data to be processed. Velocity refers to the rate at which new data is generated and acquired, whereas variety refers to the data structure. Various types of data can be used, including unstructured, semi-structured, and structured data [117]. The term "veracity" refers to the data's credibility—its accuracy and high quality. With this level of validity, meaningful analysis and results can provide valuable insights to the organization. Value is achieved when a massive amount of data can be converted into information used to achieve business goals. Big Data can demonstrate customer behavior and desires and optimize business processes and operations most effectively. Some of the challenges in Big Data and its analytics include difficulties in data representation, data pre-processing and storage, integration, cleaning, and compression.

Cloud Computing, Big Data and MSC

SC is defined as a linked sequence of actions associated with the planning, coordinating, and controlling materials, parts, and finished goods from suppliers to customers. During these tasks, two distinct flows can be considered: material movement and information flow. A better flow of information, on the other hand, may well lead to a better/optimized flow of materials, boosting the efficiency and effectiveness of the supply chain operation [118].

Many authors have written on Big Data and supply chain management, but authors who have narrowed it down to MSC are limited in number. Based on available knowledge and available statistics, an initial idea of MSC and Big Data analytics was briefly described [119]. Other ideas about the supply chain have come from theoretical studies and conceptual design; further research work focused on empirical studies and framework development [120]. While previous studies, including those referencing MSC, have primarily focused on developing conceptual frameworks for Big Data analysis (BDA) in various situations, they have failed to investigate the nature of BDA hurdles. The advantages of using BDA, as well as MSC policy on BDA adoption [121]. Data collection methods, Big Data processing technologies, data transmission, data storage, data-enabled and application are likely to be critical components of the supply chain [119].

Cloud computing is a necessary tool for managing Big Data since good data processing would enhance the efficiency and effectiveness of supply, as highlighted in [118]. So far, there has been no work on cloud computing and MSC. Recent research has focused on cloud manufacturing and the supply chain. Much consideration of the impact of cloud/fog/edge computing has been directed at supply chain management but not at MSC.

3.2.5. Blockchain-Powered Digital Platforms

Blockchain [122,123] is a distributed ledger technology (database) in which transactions are grouped, recorded in blocks [124] over the same time intervals and arranged according to specific rules. The blocks are encrypted in this system, and connection to the previous block, which determines the entire blockchain transactional history, is cryptographically reflected in the latest block [125]. Blockchain-powered platforms provide trustlessness, flexibility, reliability, increased security, privacy, decentralization, permissionlessness, and complete transparency. Service-oriented middleware [126] like Man4Ware [127], with blockchain capabilities integrated within a single platform, can provide a powerful environment for creating and operating multiple smart manufacturing applications. Examples of smart manufacturing blockchain-enabled services include blockchain-powered (BP) business-to-business (B2B); BP IIoT [128], BP IoT [129], BP Big Data analytics [130], BP Geographical information system [131], BP electricity auditing system [132], procurement management, cost management, BP recruitment, and certificate management platform [133]. BP is also used in sales [134], advertising [135], sharing economy [136], micro-controls [137], Gig Economy [138], on-demand and supply chain manufacturing [139], and product certification [140].

The immutable, decentralized, and secure qualities of blockchain technology improve asset transparency, security, authenticity, and auditability in industrial supply chains. There have been theoretical discussions in this area, but no practical approach has mapped a holistic manufacturing supply chain with blockchain technology [141,142]. Much research has been performed by mapping blockchain technology onto distinct phases of the manufacturing supply chain. Interoperability, privacy, and disintermediation are technological issues that have yet to be addressed in the application of blockchain to the MSC.

Blockchain and MSC

Bose et al. [143] identified future uses, examined potential difficulties and opportunities and proposed a methodology for deploying blockchain throughout the MSC. They proposed using blockchain technology (BT) in conjunction with physically unclonable functions and identity-based encryption to address various counterfeit issues within the integrated circuit MSC, such as overproduction, intellectual property piracy, and harmful design change to gain unfair advantage; this would improve resilience against certain adversarial motives. In [144], Khanfar et al. explained the potential contributions of blockchain technology to manufacturers' economic performance, thereby broadening our grasp of blockchain applications in supply chains. In [145], Vafadarnikjoo et al. investigated the challenges to BT adoption in MSC. Subsequent to this investigation, it is now possible to offer an action framework for BT validation while aiding industrial managers and specialists by successfully integrating blockchain technology in their supply chains. In [146], Xu et al. proposed a design plan for an Ethereum blockchain-based management system for the MSC. The system's architecture and operation mode and the functional modules inside it were detailed. The potential benefits of BT in the MSC and the vision for the future blockchain-MSC were put forward by Abeyratne et al. in [142]. The use of BT in the global supply chain network was demonstrated through the manufacturing of cardboard boxes. In [147], Blockchain's decentralized transactions were highlighted as having the potential to impact MSC significantly. Mondragon et al. investigated the potential of BT in the composite materials supply chain, focusing on producing structures and components that employ semi-finished materials and transit and storage at a constant temperature.

The materials used in this review provide a glimpse of the possibilities of using blockchain in the MSC. The blockchain's impact and benefits on MSC have also been demonstrated. The difficulties that would be encountered in the deployment of blockchain on the MSC have also been discussed. A framework and architecture for use with MSC have also been developed. However, no research has as yet demonstrated the full practical implementation of Blockchain on MSC. This technology is clearly still in its infancy, with many research gaps still to be filled.

3.2.6. Machine and Deep Learning

Machine learning is an artificial technique that uses computers and software to make accurate data predictions. Learning is implemented through repeated practising, to perform the same action better and better. Through such a process, experience can be gathered by the machine. Supervised learning and unsupervised learning are two well-known machine learning subfields. The remaining subfields are semi-supervised and reinforcement learning. In supervised learning, patterns are used to forecast the label's values on additional unlabelled data, while unsupervised learning is used when dealing with data with no historical labels. Figure 5 depicts the distinction between deep learning and machine learning in terms of application.

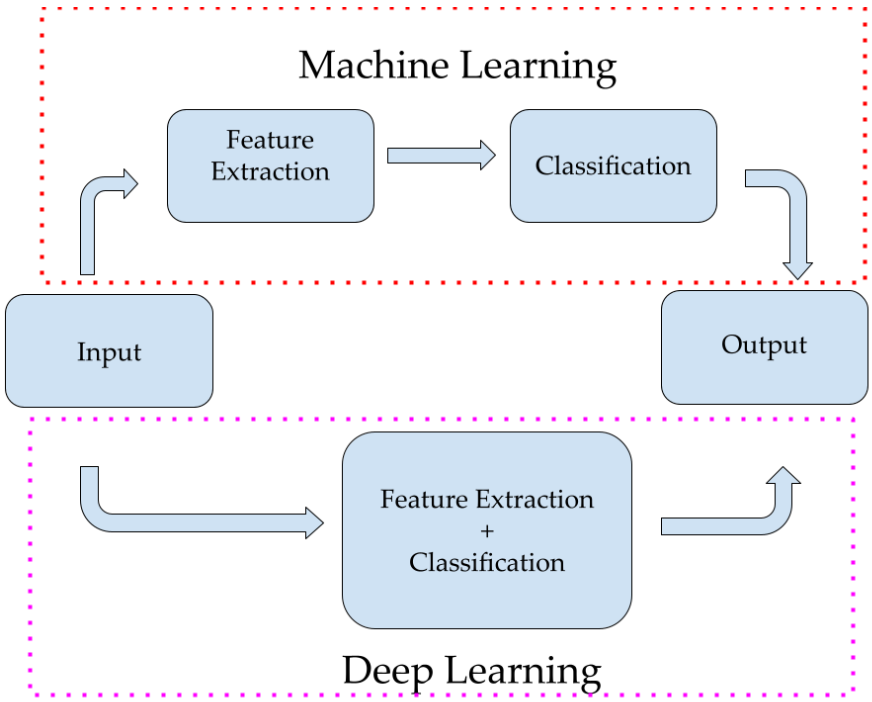

Figure 5. Sample application of machine learning and deep learning in the automotive industry and the distinction between both approaches.

The distinction is related to how feature extraction and classification [148] are performed. This operation can be performed in conjunction with or independently of each other. Feature extraction is a dimensionality reduction process that reduces an initial raw dataset to more adaptable groups for processing. Feature extraction is essential because large data sets contain many features that require many computing resources to process. Classification is a method of recognizing objects and categorizing them.

In deep learning [148], a time and cost-effective machine learning approach enables computers to learn from practice and solve problems. Machines can recognize patterns using deep learning, reach a reasonable conclusion, and recognize the opportunity for maximum success in any situation. Patterns are built successfully on the volume of data available, and the more data the network can train, the better it can learn how to perform the task successfully. Deep learning allows for the maximum efficiency and accuracy associated with the human brain. This subset of neural networks (NN) makes it possible to achieve multilayer computational NN.

Machine/Deep Learning and MSC

The supply chain in manufacturing has yet to be examined. The most relevant work was completed in [149]. De oliveira [149] presented a machine learning-based methodology for lead time forecasting in the pharmaceutical supply chain, where minimizing long wait times is critical to providing adequate healthcare services. Because of the complexity of production processes and the substantial variety in data, forecasting lead time is a challenging field of study. Another piece of work carried out in this field was a master's thesis that looked at lead time forecasting in manufacturing [150]. Apart from these two articles, little has been written about the interaction between machine learning and MSC. Although machine learning applications are still in their infancy, their potential to improve supply chain performance is highly appealing. Some academics have developed AI-related models that have been evaluated and confirmed as helping optimize MSC; hence, using AI in supply chain networks clearly provides firms with competitive advantages.

3.2.7. Edge Analytics and Fog Computing

The discovery of Edge analytics [151] resulted from the inability of the cloud-based IoT analytic [152] services to support real-time responsiveness. Edge analytics [153] plays a significant role in handling the extracted data volume. Through Edge analytics [154,155], computational-intensive analytics workloads are shifted to the Edge, and management services are also provided in support of the analytics while minimizing cloud loads. As a result, it is sensible to move analytics workloads to the Edge and offer an edge analysis management service. Edge analytics allows IoT devices with limited resources to offload AI applications requiring high computational power [156] to the network edge for further execution. Edge analytics places a premium on speed and decentralization. Increased computational power on sensing and actuator nodes, switches, and peripheral devices can be used for analytics with the shift to the Edge. This capability ensures that network traffic and latency are reduced. Despite this advantage of IoT, the unprecedented amount of data generated by IoT and its innovative applications in traditional systems, cloud computing, and even edge/Fog computing necessitates this information's storage, processing, and analytics. Edge computing can reduce the traffic load on the core network, allowing for network balance. The goal of Fog computing is to overcome these restrictions of cloud computing. High energy consumption and computational power, and increased processing latency are addressed by incorporating Fog computing. Similarly, sending large amounts of data to the cloud for storage, which is critical for efficiency in processing, saturates network bandwidth. Hence, Fog computing is a distributed prototype [157] providing cloud computing services to the network edge while also being closer to end-user devices [158].

Edge Analytics and Fog Computing and MSC

Little has been carried out with regard to the practical applications of fog computing in the manufacturing supply chain. Fog has been used to manage perishable supply chains [159], logistic supply chains, and to increase organizational agility. In [160], supply chain awareness, connectivity, logistics, smooth supply, and integration were all considered. To explore the influence of Fog computing on the supply chain, it has to be added by either designing or using an existing multi-layered model. Through multi-layered models, it is possible to generate accurate data that helps to improve supply chain management processes and consumer satisfaction.

Table 3 shows the various layers and sub-layers of Fog computing and the function of each layer.

Table 3. The various layers and sub-layers of Fog computing, as well as their functionalities.

Layer	Sublayer	Functions
Transport and Security	Transport layer Security layer	Pre-processing data to the cloud. Check against a security threat. Encryption/decryption functions.
Network	Temporary storage Pre-processing Monitoring	Connection point to transport and security. Storage of data temporarily (Microdata centre) Re-ordering of data. Activity monitoring, i.e., resource and service allocation. Resources provisioning.
Physical/Virtualization	Physical layer	Capturing and forwarding of data for upward processing generation and collection of data.

The physical layer in Table 3 is for end devices such as sensors, actuators, and applications that enhance their functionality. These components rely on Edge and cloud resources for communication. The network for communication with Edge, i.e., devices, gateways, and cloud services, are typical examples of such devices. The resource-management layer oversees the entire infrastructure, ensuring service quality. The previously established applications have an impact on Fog computing programming models in order to supply end-users with smart services [161]. Fog computing features include location awareness, scalability, mobility support, real-time interaction, and interoperability. Figure 6 depicts the relationship between cloud, Fog, and Edge computing.

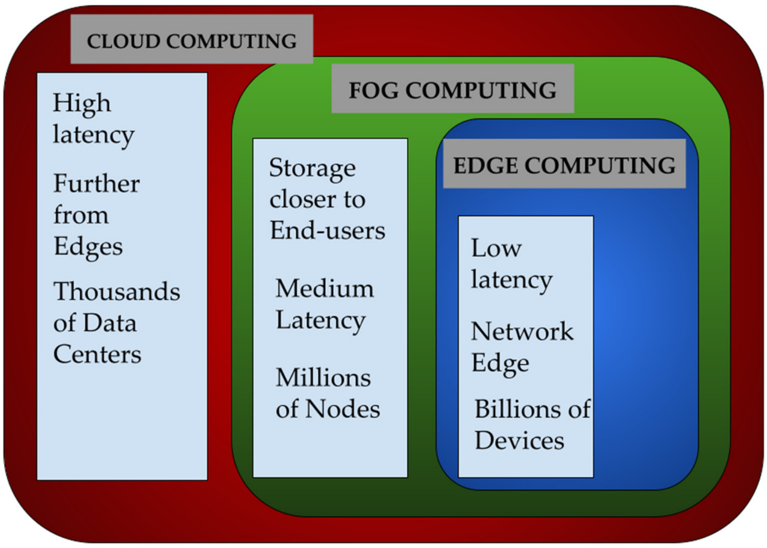

Figure 6. Hierarchical architecture and structural relationship between Cloud, Fog, and Edge computing.

4. Approaches to Manufacturing Technologies

Manufacturing is concerned with developing economic capabilities that meet customer needs while also improving efficiency, performance, and delivery in any society. Manufacturing is also defined as adding value to raw merchandise through labor, machinery, chemicals, formulation, or biological processes, thereby introducing extrinsic value before it is sold. Manufacturing dates back to ancient times, but significant advancements and transformations have influenced the changing scopes of manufacturing over the last five decades. Artificial intelligence, virtual reality, IoT, IIoT, and 3D printing, among other advanced technologies, have shaped manufacturing in several ways. The enormous volume of data and storage possibilities have contributed to lowering production costs, introducing precision and safety, increasing the speed of operations, minimizing errors, and allowing for prognosis. The six manufacturing categories are intelligent manufacturing, cloud-based smart manufacturing, IoT-based smart manufacturing, flexible manufacturing, reconfigurable manufacturing, and traditional manufacturing.

4.1. Intelligent Manufacturing

A factory may automate a production line so that robots can carry out various manufacturing stages without human intervention. Computer vision (cameras) and sensors can automate much of the testing and quality control processes. This type of manufacturing is widely known as smart manufacturing [90]. A smart factory has many advantages, including high correlation, deep integration, and massive data volume. The opportunity to yield a customized product [7] with variations can be efficiently realized in the smart ecosystem, and returns on over-invested capital are possible. Similarly, the manufacturing process becomes more stable, and added flexibility is possible. This process demonstrates a high level of interoperability.

4.2. IoT-Enabled Manufacturing

This type of smart manufacturing is based on collecting and distributing data in real-time among workers, machines, and related jobs. Radio-frequency identification (RFID) and other wireless communication standards are required for data collection. RFID tags and readers are embedded in shop floors, assembly lines, and manufacturing machinery. These devices provide timely, accurate, and consistent information about distributed manufacturing resources and rapid identification of all the building and floor disturbances. Similarly, real-time manufacturing [91] information is readily available between the manufacturing system layer, workshop floor layer, and machine layer, allowing the best manufacturing system decisions to be made.

4.3. Cloud-Based Smart Manufacturing

In Cloud-based manufacturing [92,93], existing advanced, networked, and decentralized manufacturing technologies which can provide computing and service-oriented frameworks [94] for manufacturing are supported by intelligent computing, IoT, and virtualization. Cloud-based manufacturing can also be described as a knowledge-based, service-oriented smart manufacturing system that operates successfully through cloud computing. Cloud-based smart manufacturing has been found to be beneficial in blockchain, robotics, and health care. To function appropriately, Cloud-based smart manufacturing types of equipment/machines must be intelligent, connected, and have a context-aware metering system. Physical resources, local servers, and cloud servers are the three layers of a cloud-based smart manufacturing architecture. The physical and local servers (hardware and software required in the manufacturing process) are connected to the factory network. On the other hand, the cloud servers are internet-based and connected outside the smart factory's boundaries. Flexibility, cost-efficiency, and product scalability are some of the benefits of Cloud-based smart manufacturing.

4.4. Flexible Manufacturing Systems

Flexible manufacturing processes (FMS) deal with uncertainty, allowing manufacturing facilities to modify, or in some cases reverse, decisions made in previous periods. Once clients provide information needs that must be met, companies can adapt to the future demands of the manufacturing process. The system's robustness allows it to adjust whenever something changes. Changes could appear as strict operating requirements, a shortening in the product lifetime [162], reallocation of capacity to another manufacturing process without equipment replacement or major retooling, and an increase in the range of goods supplied. Flexible production can be conducted continuously as the intelligent sensors provide the necessary data to realize the self-optimization process. Adapting to dynamically changing conditions is enabled by continuous run-time and self-optimization of operations in terms of efficiency, availability, energy consumption, reliability, flexibility, and computational requirement. Highly skilled workers oversee the system and ensure that the problem-solving skills deployed can be used to address any system failure autonomously while supervising the machine and robot renewal process. FMS's main advantage is its ability to manage time [163], machines, and robots with great flexibility. It can also ensure mass customization and more excellent demand responsiveness [164].

4.5. Reconfigurable Manufacturing Systems

Reconfigurable manufacturing systems (RMS) [165–168] incorporates the merits of both dedicated manufacturing lines and FMS. RMS [169] improves the response of the entire manufacturing system to unanticipated changes in production demand by reacting quickly to market changes and adjusting production systems efficiently [4]. Changing machines to match the new throughput requirements while simultaneously complementing each available configuration is a cost-effective way to reconfigure an existing system [9]. Thus, RMS has the edge over FMS since it can abruptly change conditions with lower and reasonable capital investment. RMS's crucial characteristics are scalability, customization, integrability, modularity, and diagnosability [170].

4.6. Traditional Manufacturing

Traditional manufacturing separates automated processes from one another, necessitating numerous human interventions to handle transitions from one phase to the next. Because there is no connectivity between machines and across the business process, human workers in manufacturing must examine unrelated datasets and issue reports to identify problems and potential areas for improvement. Traditional manufacturing applications are decoupled. Traditional manufacturing cannot monitor and control automated processes and sufficient functionality, scalability, elaborate manufacturing, and well-organized connectivity with demand and supply diagnosability [90]. The consequence of staying with traditional manufacturing on a large scale includes factory closures, short-time work, reduced production, and demand, impacted supply material chains, and closures. Reusing the same system is impossible in traditional manufacturing. Increased maintenance costs of these legacy instruments, which are prone to reoccurring breakdowns, are prevalent in the conventional manufacturing line. In such a system, there is limited visibility [6] of operation systems and productivity data. A form of traditional manufacturing is the dedicated manufacturing system (DMS) [171], in which a rigid structure of manufacturing optimized for a specific product is designed. DMS is not designed to meet varieties and sudden increases in demand. In Table 4, the differences between traditional manufacturing and smart manufacturing represented. In this perspective, traditional manufacturing refers to a production-oriented culture with a local focus and stepwise international expansion. In contrast, smart manufacturing refers to develop strategies and management processes motivated by new ideas and the concept of opportunity [172].

Table 4. Differences between traditional manufacturing and smart manufacturing.

Traditional Manufacturing	Smart Manufacturing
A stand-alone, manual, isolated process with separate systems that are not capable of automated monitoring and control.	A dependent, strongly related, and closely linked system that continually communicates and collaborates is backed by automation, monitoring, and control capabilities.
Humans are in charge of machine operation and control.	Machines and robots interact with, without or with little human intervention.
There is no plan to develop an action through equipment that learns from processes; therefore, gathering, evaluating, and updating information is carried out manually.	It is possible to collect, analyze, update, and develop an action that learns from data-driven processes.
The manufacturing line is fixed, and the system must be shut down before any reconfiguration occurs.	The production line is dynamic and can be maintained without being disconnected from the power supply.

Table 4. *Cont.*

Traditional Manufacturing	Smart Manufacturing
The production process is centrally managed.	Decentralized production processes.
A less productive, flexible, sustainable system. Enterprise competitiveness suffers as a result of wasteful resource utilization.	More competitiveness is achieved by increased productivity, flexibility, sustainability, and efficient resource usage.
A considerable number of inexperienced operators are engaged. As a result, the factory's production line has increased labor costs.	At a lower cost to the manufacturing, a workforce skilled in developing and operating intelligent devices is brought on board.
There is a lack of self-optimization and reconfiguration production systems to learn and respond to shifting demand patterns.	Self-optimisation and reconfiguration, production systems that learn and adjust to changing demand patterns, are available.

5. Integration for Innovative Industries

Since the inception of 4IR, industries have seen a shift of ideas, with many ideas discarded and innovative ideas embraced. The ability to promote and advance the concept of integrating various systems, collaboration between different robots and interoperability among organizations remains the core strength of any intelligent manufacturing system [172]. Based on the strengths mentioned above, the efficiency and feasibility of modern product creation processes are not driven solely within one business boundary but are ensured by integration across boundaries. This approach is a reality for businesses all over the world.

The three key features [10] that can be considered as implementing 4IR are described in the following sections.

5.1. Horizontal Integration

Horizontal integration [173] is the automated coalescing of various information technology systems in multiple production stages across firms in different geographical locations. These companies may offer the same or similar services. Working on the process and the system concurrently until the product is completed is advantageous for horizontal integration. Customer relationships are strengthened, and each company transforms into a service-based smart factory. Horizontal integration improves the ability to sense the needs of customers. Other companies which provide additional services that meet customers' needs can be added to the board of directors to increase customer satisfaction and benefits. The integration with customers and other value-added service providers grows as more content is added to meet customer satisfaction. As a result, customers' values are added to the services provided. Horizontal integration strategies increase market share while decreasing competition, enhancing the firm's reputation, and improving cost competitiveness. Value-added networks are critical to ensuring the profitability of horizontal integration. A broader market base is realized.

5.2. Vertical Integration

Vertical integration [174–176] is best described as integrating hierarchical subsystems within an organization, thereby creating an FMS and RMS within the organization. Vertical integration aims to achieve growth by acquiring other companies either for distribution or manufacturing services. In vertical integration, IoT, artificial intelligence, cloud computing, and Big Data are intensely incorporated with information technologies and automation [177]. These are combined to improve the intelligence used in manufacturing and the machines/collaborating robots involved in the process. Due to this integration, intelligent devices within the organization that are autonomously configured can adapt to different manufacturing processes. Integration can benefit retailers and consumers as well as suppliers. Some of the objectives include product flexibility and complete customization.

Vertical integration benefits include cost-cutting while delivering work at higher efficiency and profitability and lowering transaction costs by eliminating redundant service channels. Firms can also control input quality and design flexibility to improve product quality and control.

5.3. End-to-End Digital Integration

In end-to-end engineering integration [173], an established value chain can adequately cater for and lead to the creation of customized and automated products and services. The chain of activities could involve customer requests, product submission, approval and design, product development, production planning, production engineering, and product delivery and maintenance. With end-to-end, product integration fulfils promised lower costs, more excellent reliability, safety, reusability, and better sustainability. Its strong point is that end-users do not need to choose from a pre-defined range of products specified by the manufacturer but can blend individual functions and components to meet their unique needs. This integration model requires identifying customer value based on customer requests. After this, the value stream mapping process allows the creation of a detailed picture of all production steps. Subsequently, the standardized process around best practices is established, creating an automated mechanism, seeking to perfect the manufacturing process, and implementing technology improvements based on the large chunk of data gleaned at the intelligent factory. Figure 7 is a diagrammatic description of the three forms of integration.

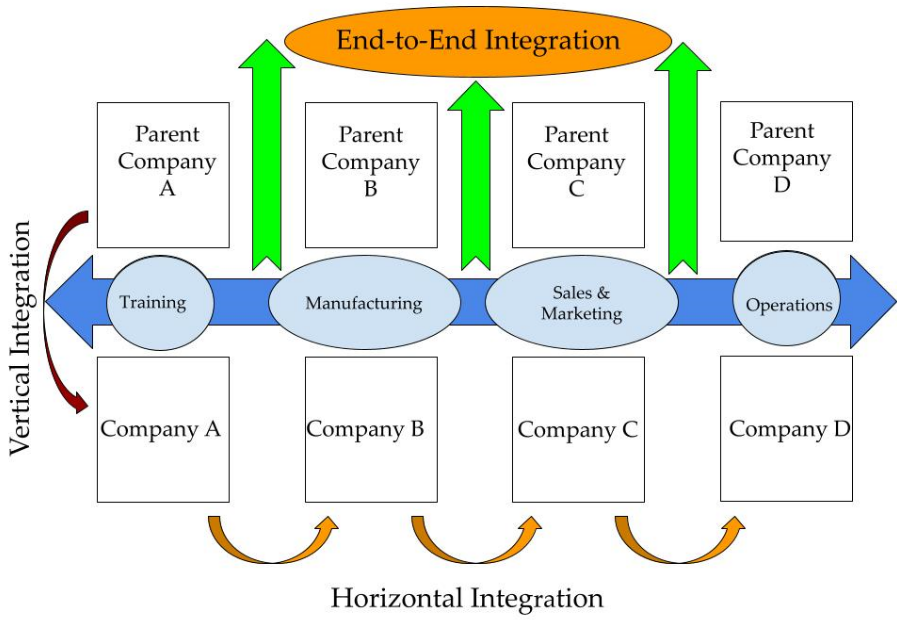

Figure 7. Sketch of the three integration types and their association.

6. Impact of Smart Manufacturing

The advent of 4IR is having different effects on diverse areas of the manufacturing industry. Its impacts can be assessed based on each main area of application and the enabling technologies [178] that presently constitute the 4IR ecosystem [37]. Its impact can also be defined based on the drivers of 4IR transformation, such as production processes and services, business models, markets, governance, industry, organizational structures [179] and the environment. The immediate effects include enhanced employment and social equality, economic development, and added industrial manufacturing benefits to the supply chain and industry. The following are the generalized impacts of smart manufacturing.

6.1. Productivity and Efficiency

Productivity and efficiency have been the system's leading symbols in smart manufacturing. Productivity and efficiency are achieved through the extensive value chain network based on digital integration and an intelligent approach to manufacturing. Machines/collaborating robots can act autonomously and efficiently in the manufacturing space during this process. As a result, the process and supply chain are more efficient, and customer demands are met without delay. Similarly, the industrial cost required in the factory's production, logistics, and quality control sectors is significantly reduced [180].

6.2. Revenue Growth (Profitability)

Maximizing business profitability is central to every business. The growth of profits primarily determines its long-term survival, and it strives for long-term sustainability. A novel opportunity for cost savings and revenue growth emerges with significant capital investment in the smart manufacturing process and value chain. The invention of the smart manufacturing process has also improved competitiveness. With a large market, leverage, and liquidity, any smart factory can achieve revenue growth in a matter of years. Revenue growth and profitability will be achieved through massive sales and process automation.

6.3. Employment

Even though smart manufacturing has increased the use of automation and robotics, employees still have opportunities to play a significant role on the manufacturing floor. Specific low-skilled jobs will inevitably be eliminated with 4IR. Experts, a new working class, will be required to realize the smart factory's objectives and goals. Many workers will need to be trained in information and digital technologies, AI, cybernetics, Edge/Fog/Cloud computing, additive manufacturing, virtual reality, and data analytics [9]. Collaboration between robots and humans will result in the full deployment of Industry 5.0, which is on the horizon. New business opportunities [181] for companies directly or indirectly involved in developing new products and services using intelligent technologies will increase the number of new jobs created. Low-skilled employees [182] might thus take advantage of this opportunity to advance their careers. New jobs are expected to be created by using smart technology to introduce new products and services. However, it is unclear how this may be accomplished in a smart manufacturing space despite career advancement possibilities. One may also take a transitionary approach from traditional to smart manufacturing—a gradual approach supported by change management.

6.4. Sustainability and Energy Efficiency (Energy Saving)

Sustainability [183] is the emergence of a strategy to preserve productive capacity and the value chain for the indefinite future. Sustainability [184,185] comprises transforming resources into economically valued goods by operating environmentally friendly processes. With sustainability, we have become aware of social, economic, and environmental dimensions of growth [186,187]. These dimensions of growth have been central arguments in 4IR and its application to the smart industry. Improving energy efficiency by encouraging more energy-saving and lower consumption of natural resources is made possible by strategies for sustainability. Low energy utilization can be achieved in a smart factory by first understanding its operations and energy consumption, developing an energy strategy, and upgrading the equipment to be more energy efficient. A single or multi-aspect approach can be used to achieve low energy utilization. The overall layout of the factory, production line, and primary production equipment must be examined when considering a multi-approach to energy efficiency. Advanced automation and energy-saving goods must be employed to ensure that manufacturing equipment is both productive and efficient in energy usage. Power management and energy efficiency require careful planning and consistency to be successful.

6.5. Quality Management

Since the smart manufacturing process is an automated one, this offers an opportunity to monitor the quality of the production lines. Production quality can be real-time, with quick decisions being made about customer demands. Quality management is further enhanced through the three forms of integration: vertical, horizontal, and end-to-end integration. In smart manufacturing, quality control is realized with itemized integration forms, and less post-process quality inspection is required. With quality management, more goods are in demand, and the time of goods in the market becomes minimal.

6.6. Supply Chain Management

The existing approach to supply chain management is based on the traditional approach, which has not addressed critical issues such as the loss of key suppliers and the unavailability of essential spares for any machine. This complete reliance on the deterministic approach [188] towards handling the supply chain has not yielded the best results, especially during the COVID-19 pandemic. This low performance is because social behavior patterns do not have a repeater pattern and are unpredictable. Because the world's situation is rapidly changing and increasingly multifaceted, looking at exit supply chains and the decisions of innovative supply chain managers as a guide for development is insufficient. Smart manufacturing offers advantages such as cost-cutting opportunities, increased process transparency, procurement process optimization, and flexibility, but especially at the production and supply chain management stages. A smart supply chain is a new integrated business system that spans inaccessible, local, and lone-company applications all the way up to a supply chain that is global [189] intelligently implemented. Smart supply chain management is self-organizing and self-optimizing at all times. Interconnectivity, precision data collection, real-time communication, intelligent decision-making, and efficient and responsive processes are also advantages of such a system.

7. Justifying the Advancement from Industry 4.0 to Industry 5.0

The manufacturing industry is currently undergoing transformation and development as a result of 4IR. The convergence of IoT, IIoT, automation, cyber-physical systems, advanced analytics, cognitive computing, and AI has transformed industrial-scale production. It has resulted in cost savings in the manufacturing process. It is distinguished by effective resource utilization and the incorporation of business partners and customers into the business process. Despite these advantages, there has been little or no consideration of any potential downsides to this change. This section will focus on deficiencies of 4IR that are critical for the future growth of the fifth industrial revolution (Industry 5.0).

7.1. Symmetrical Innovations Systems and "Extreme Integration without a Safe Exit Strategy from Networks"

The goal of Industry 4.0 is to connect the unconnected until everything that requires a connection is connected. Similarly, it is projected that developed countries' competitiveness will improve by developing new business models and additional means of revenue generation. However, highly integrated continuous are prone to systemic hazards such as complete breakdown of network if one of the components fails. If left unchecked, networks can build power systems that can lead to hegemony. Reduced creative outputs and system scale vulnerabilities are characteristics of a system where connectivity and interconnectivity of everything are not controlled and managed correctly.

Most approaches to invention include identifying a problem and finding a solution to the problem. However, it has been only a few people who have been able to identify and resolve problems. With 4IR, a high-tech sector, the number of people who have a thorough understanding of technologies is limited. As a result, inventions are asymmetrical in nature. On the other hand, symmetric innovation provides possibilities of increasing the knowledge base for the greater benefit of society. Through new symmetric innovation models, 5IR will seek to democratize knowledge co-production. People will be introduced to the principles of democratic public control and ownership over intellectual property, research, and development. More information will be extended to the public commons through the democratized knowledge surrounding 5IR, a linked and intertwined system.

Symmetrical innovation systems have been proven to be the basis of the next-generation innovation paradigm, 5IR [190]. These have a built-in sustainability strategy for entry into entrenched and hyperconnected networks such as 5IR as well as "safe exits". Extreme integration at any cost and hyperconnectivity, on the other hand, pose system-scale risks that have thus far not been addressed. Because a safe product cannot be built, a system must fail safely, be left safely, and be evacuated safely [191]. Likewise, the central proposition of "safe exit" [192] is that anything that occurs in a hyperconnected space [193], such as the 4IR, must not impact exit pathways needed at any time. Therefore, symmetrical innovation systems must become the foundation of 5IR.

7.2. Filter Bubbles, Technology, and Society

Filter bubbles [193] are states of intellectual isolation that emerge due to over-integration and exposure to information and ideas that strengthen a particular technological ideology. Filter bubbles have resulted from the over-integration of 4IR. The total reliance on one dominating technology, such as 4IR, will enable a technological monoculture beneficial to the production system. However, this can lead to a restricted and primarily scientific way of thinking and of knowledge, which could be a method of silencing rival narratives in the manufacturing environment. This is the outcome when we fail to consider how our beliefs impact other defining aspects of research and society. Scientists and engineers who contribute to the technologies enabling 4IR may be unaware of social and human power dimensions. In the long term, filter bubbles will, therefore, jeopardize the predicted 4IR traits of transparency, efficiency, and innovation. Industry 5.0 has the opportunity to capitalize on this weakness and turn it into a creative advantage.

In comparison with the vast numbers of technical studies on 4IR and its enablers, little emphasis has been placed on the effects of 4IR on at least two of the key drivers of sustainability (society and environment). Studies on ethical and unethical decisions and on 4IR policies which will define its global dominance are also lacking, possibly due to its initial proponents being primarily critical solution-seeking professionals rather than scholars from the social sciences and humanities. To remedy this deficiency, people from various sectors must be brought on board so that 5IR can be built on this innovative edge. 5IR involves various fields of technology that must be examined holistically by researchers in all fields. This research must concentrate on each technology, as well as on its relationships with and impact on people and the environment.

8. Conclusions

This paper discussed earlier industrial revolutions as well as the current industrial revolution. The article began by outlining the history of the industrial revolutions. The conversation then switched to the topic of assistive technologies for intelligent industrial processes. Alternatives to traditional manufacturing were offered, with examples of how they have progressed and are now being applied in smart factories. Each manufacturing system's merits and downsides were analyzed. The topics of smart manufacturing system were considered. The enabling technologies, as well as their applications in various spheres of life, were discussed. With the advancement of the smart industry, the need for security measures to ensure the cyber-physical and digital drivers was outlined. Intelligent manufacturing, technology enablers, and essential enablers are all critical. The literature identified the difficulties associated with the full deployment of technological drivers in the manufacturing supply chain. Much of the research surrounding the MSC has justified its importance to the 4IR and demonstrated the MSC's potential influence in 4IR. This technique has provided the necessary confidence for further work on conceptualization, frameworks, and more empirical studies. However, it must be stated that, in terms of the manufacturing supply chain, we are still a long way from actual-world implementation of the drivers.

There is a need to build systems that can accommodate all MSC components when the drivers presented in this study are considered. Research should be prioritized to address creative techniques that strengthen the path towards comprehensive practical implementation and deployment of the MSC while employing 4IR enablers. Future studies of this magnitude must be focused on a single issue rather than a group of themes. Before consulting central databases such as Google Scholar, EBSCO, IEEE, Scopus, and others, high-quality journals that focus on the 4IR drivers and manufacturing supply chain, with a particular emphasis on the manufacturing sector, must first be considered. One of the natural advantages of such an approach is that it will ensure that private investors, the government, and society all have a comprehensive view of the solution. This concept may positively or negatively impact people, as some may embrace it while others may reject it. This strength allows symmetric innovation, which is at the heart of 5IR, to be demonstrated to society.

The function of intelligent manufacturing systems in 5IR and its integration with MSC is still unexplored territory. Because 5IR is still in its preliminary stages, the role of IIoT in manufacturing is uncertain. Current gaps in reconfigurable and flexible manufacturing systems must be filled. Unresolved security and interoperability issues in smart manufacturing must be investigated. Once 5IR is fully operational, the issues raised will become even more critical. This paper concludes with a brief but insightful prediction and justification of the next industrial revolution. Future research would consider integrating risk management into the MSC with explicit consideration of 4IR enablers. Additional areas of future research would focus on the framework regarding the exit strategy and symmetrical innovation that is the cornerstone of 5IR.

In terms of the work's limitations, the analytical framework offered was created utilizing information from literature and research experience without contacting any industry specialists. Similarly, some review articles may have inadvertently been excluded due to the process used to choose articles. For similar tasks in the future, more databases should be examined. Another method for expanding the area of the material studied is to broaden the keywords used in the search to include synonyms as keywords. Research that looked at the manufacturing supply chain and the essential enablers for 4IR must also examine the risk of deploying any of these enablers because the MSC is susceptible to disruptions. An end-to-end link is essential for the 4IR enablers in the manufacturing supply chain to work efficiently. Because the current purpose of the supply chain is to ensure the integration of operations from suppliers to customers, the research performed thus far does not address the need for connectivity across each stage of MSC.

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