AIoT for Sustainable Manufacturing: Overview, Challenges, and Opportunities

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Abstract

The integration of IoT and AI has gained significant attention as an emerging means to digitize manufacturing industries and drive sustainability in the context of Industry 4.0. In recent times, there has been a merging of AI and IoT technologies to form an "Artificial Intelligence of Things" (AIoT) infrastructure. This integration aims to enhance various aspects such as human-machine interactions, operations in the field of IoT, big data analytics, and more. AIoT-based solutions offer numerous benefits to the manufacturing industry. These solutions improve efficiency, reduce waste, and enhance safety measures. By utilizing AIoT, manufacturers are able to achieve Industry 4.0 goals and increase productivity through automation, process optimization, and more informed decision-making. Additionally, the adoption of AI and IoT-based solutions in manufacturing companies has increased substantially. These solutions enable the early detection and prevention of defects in equipment, leading to the production of high-quality products. By minimizing waste, reducing costs, improving efficiency, and boosting productivity, manufacturers can further optimize their operations. Academic researchers and industry practitioners are currently prioritizing the development of highly advanced and streamlined AIoT-based solutions specifically designed for sustainable manufacturing. The primary objectives of this paper are (i) to provide a comprehensive overview of the domain-centric AIoT-based industry technology for sustainable manufacturing; (ii) to conduct a thorough survey of the existing research on AIoT-enabled manufacturing; (iii) to discuss the current challenges faced by AIoT in the context of sustainable manufacturing and explore the research prospects in this field. Therefore, this paper presents a systematic review of state-of-the-art AIoT-based techniques employed in industries for sustainable manufacturing and analyzes the key contributions and opportunities. Finally, the key challenges are explained for future research prospects.

1. Introduction

Manufacturing industries are transforming traditional manufacturing into sustainable and economically sound manufacturing practices by embracing digital technologies to utilize natural resources and minimizing negative environmental impacts more effectively [1]. Industry digitization and achieving Industry 4.0 goals are assisted by adopting new technologies, such as artificial intelligence (AI) and the Internet of Things (IOT) [2]. Using these emerging technologies in industrial manufacturing can improve product quality, machine efficiency, employee safety, and predictive maintenance and reduces overall energy consumption, negative environmental implications and production costs [3]. Moreover, concerns about air pollution and ecological implications are growing in relation to industrial production. AI and IoT-based intelligent systems enhance the resource and process scheduling of manufacturing, which implicitly reduces energy consumption and environmental pollutants. Additionally, the combination of AI and IoT to create the Artificial Intelligence of Things (AIoT) infrastructure can quickly identify the level of toxins in the air and make an appropriate decision based on an analysis of the data [4]. Incorporating an intelligent system in manufacturing industries also improves the safety of workers [5]. For example, a top supplier to the automotive sector, Bosch[1], uses AI and IoT in autonomous driving and safety systems for vehicles and trucks to achieve the Vision Zero goal of having no fatalities or serious injuries resulting from the digitization of automobile industries which assists the achievement of sustainable manufacturing goals. These examples demonstrate how using these emerging technologies is changing the world. This study presents an overview of AIoT for sustainable manufacturing and, state-of-the-art research, and discusses the challenges and future research directions.

1.1. Motivation

The AIoT infrastructure incorporates intelligent capabilities on IoT devices to improve IoT operations, big data analytics, and human-machine interactions. It represents an intelligent IoT infrastructure. The role of AIoT-based

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technologies in sustainable manufacturing is significant as it addresses the critical challenges of sustainability, especially in manufacturing industries, and is able to drive decisions on big data generated by various sensors in different industrial processes. Initiatives are needed to incorporate modern technologies to achieve sustainable manufacturing goals [6, 2, 7]. Recently, AI and IoT-based applications such as knowledge-based expert systems, intelligent scheduling, and fuzzy controllers have been introduced in different manufacturing industries to maintain the sustainability of manufacturing [2]. However, the demand for utilizing AI and machine learning technologies has increased in the last two decades in relation to analyzing the risk profiles of supply chain management [8]. Domain-centric AIoT-based sustainable manufacturing research is ongoing, and its progress in incorporating the technology in manufacturing industries is in the initial stage. The future of manufacturing is likely to be increasingly data-driven. Manufacturers can make better decisions and improve operations as more data is collected from various process segments using multiple sensors and analyzed for decision driven. However, it is hard to interlink them using traditional machine-learning approaches to derive real-time forecasting, monitoring, fault detection, and decision modification. AIoT is able to analyze big data from different perspectives and retrieve feature attributes from data using AI techniques to resolve this issue [9]. Therefore, AIoT is involved in the complete cycle of sustainable production, i.e., product design, process planning, sustainable machining, process scheduling, energy consumption, supply chain [10, 11, 8]. This study presents an extensive overview of the research on AIoT for sustainable manufacturing.

1.2. Objectives of the Study

The primary focus of this study is to determine why AIoT should be applied in industrial manufacturing to achieve sustainable manufacturing goals by maximizing resource utilization, increasing productivity and quality control, improving safety, and reducing adverse environmental effects. To accomplish these goals by managing the enormous volume of data generated from diverse industrial processes, it is essential to use AIoT manufacturing tools to advance traditional manufacturing models. Businesses are quickly discovering the advantages of employing sustainable production methods and strategies [12]. For instance, the perception that resources (raw materials, energy, water etc.) are limited and frequently non-renewable may impact business operations. Anthropogenic activities also progressively contribute to climate change, which can have adverse effects. Recent worries regarding the sustainability of corporate strategies that are narrowly focused on economic growth and pay little attention to avoiding negative externalities have also been sparked by the financial crisis. As a result, the demand for sustainable manufacturing from a wide range of stakeholders, including workers, investors, suppliers, customers, rivals, communities, governments, and regulators is rising. There are three pillars to sustainable manufacturing: economic, environmental and social [7]. This study follows the principles of sustainable manufacturing. The objectives of the study are as follows:

- To provide an overview of how AIoT can be used in different industries to make manufacturing more sustainable by optimizing energy use, reducing waste and improving product quality.
- To review the existing research on the use of AIoT in manufacturing.
- To discuss the challenges that need to be overcome to realize the potential of AIoT for sustainable manufacturing fully. The paper also discusses the research prospects for this area and identifies the key areas where further research is needed.

Although manufacturers have begun to notice how sustainability initiatives affect consumer behavior and help build their brand's value and image, there are still many obstacles to putting them into practice. Some manufacturing industries involved in sustainable manufacturing need more assessment tools for measuring and analyzing manufacturing performance, which can cause inefficiencies and inaccurate development tracking. Additionally, implementing AIoT for sustainable manufacturing requires access to research and programs focused on the sustainable development of manufacturing sectors, as more knowledge and assistance expand ideas and businesses' capacities to realize them. Manufacturers must create strategies that effectively address these issues and streamline the implementation of AIoT-based sustainable manufacturing methods.

1.3. Comparisons with Previous Surveys

There are two tiers of technology associated with AIoT. The first is computing technology, which involves big data, machine learning, computer vision, embedded computing, sensors and networks, and edge computing. The other is related to specific industrial domains and deals with predictive maintenance, process mining, and optimization. While

Table 1
Existing AIoT survey and their objectives

Reference	Focus
Chang et al. [26]	Edge computing powered AIoT
Zhang et al. [24]	AIoT architecture with edge, cloud and fog computing
Revathi et al. [13]	Agricultural production, crop monitoring
El Himer et al. [22]	AIoT for renewable energy, distributed energy resources
Ghoreishi et al. [20]	Eco-friendly business operation, circular economy
Bronner et al. [25]	Technological transformations of business, Product-as-a-service
Yang et al. [4]	AIoT for particulate patters monitoring, pollutant monitoring
Nishimura et al. [21]	Industrial automation, AIoT-based industrial controllers
Yu et al. [23]	Intelligent scheduling of manufacturing
Mao et al. [27]	Energy-efficient AIoT
Wazid et al. [28]	Blockchain technology incorporated in AIoT applications for security
He et al. [29]	Sustainable manufacturing using digital twin

this survey aims to provide a comprehensive understanding of sustainable manufacturing, AIoT-based solutions, and their implications and limitations based on our investigation of earlier publications, to the best of our knowledge, there is no survey to date dedicated to AIoT for sustainable manufacturing. Although several recent surveys focus on AIoT-based technologies, they focus on specific domains or problems, such as smart agriculture [13, 14], smart healthcare [15, 16], smart homes [17, 18], and smart environment [4], supply chain and circular economy [19, 20]), industrial control unit [21], renewable energy [22], and scheduling [23]. We are aware of some surveys on generic applications of AIoT [24, 25, 26]. For example, [24] thoroughly assesses AIoT and discusses how AI may enable quicker, greener, safer, and more intelligent IoT in a cloud-fog-edge computing setting. Another survey on edge-computing-powered AIoT further covers the sensor and network domains and presents a fundamental AIoT architecture [26]. This survey differs from previous relevant surveys by centering on AIoT for sustainable manufacturing from blended research, domains, and industry perspectives. To present a better state-of-the-art view, we summarize the most relevant AIoT reviews in Table 1.

1.4. Contributions

The key contributions of the study are as follows:

i. We overview why AIoT in industries is a promising tool from the perspective of sustainable manufacturing and provide a thorough analysis of AIoT's potential to support sustainable manufacturing.
ii. We survey the state-of-the-art research on AIoT-enabled manufacturing: the core integrated technology for achieving the goals of sustainable manufacturing is AIoT.
iii. Finally, we discuss the current challenges of AIoT-enabled manufacturing and future research directions through an extensive discussion. The key focus of the study is to undertake a thorough investigation of AIoT applications in the field of sustainable manufacturing.

The reminder of the paper is organized as follows. The background of the study is covered in section two, including the fundamentals of sustainable manufacturing, requirements for sustainable manufacturing, AIoT concepts and architecture, and AIoT market analysis. Section three discusses the systematic literature review (SLR) methodology with details on the research questions, the search keywords, and the sources used to retrieve the relevant literature. Section four details the state-of-the-art AIoT approaches for sustainable manufacturing, application areas, and AIoT-based industrial toolkits across sustainable manufacturing domains. A few open research problems and potential research directions for AIoT are discussed in section five to encourage ongoing research activities. Finally, section six concludes the SLR on AIoT for sustainable manufacturing.

2. Background

In this section, we cover the background of sustainable manufacturing, especially in terms of what sustainability can be achieved through AIoT technology. We also introduce AIoT concepts, architecture, and workflow.

2.1. Sustainable Manufacturing

Sustainable manufacturing refers to manufacturing economically sound products by properly utilizing raw materials and reducing energy consumption and emissions. It is also referred to as green manufacturing or eco-friendly

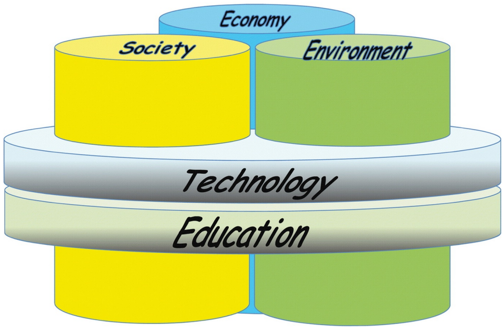

Figure 1: Three pillars of sustainable manufacturing [7].

manufacturing. The ability to efficiently utilize resources for industrial manufacturing can be termed as sustainable manufacturing. It helps develop goods and solutions that, due to technological advances, regulatory restrictions, and socially entirely consistent objectives, satisfy economic, ecologic, and social goals while enhancing the living conditions for individuals [7, 1, 30, 12]. Therefore, industries, the environment, and communities can all profit from sustainable manufacturing. To measure manufacturing sustainability, holistically, organizations or industries have to measure their sustainability from three aspects: the economy, society, and the environment. Technology and education are two essential elements for binding together the three pillars of sustainable manufacturing to maintain a socioeconomic balance, as shown in Figure 1. However, the three pillars of sustainable manufacturing are interconnected through human involvement: economic sustainability depends on production that balances the supply and demand relationship, social sustainability depends on safe and secure livelihoods, and environmental sustainability depends on conserving global ecosystems and natural resources.

The digital transformation of industries has played a role in utilizing resources and reducing energy consumption and emissions. In a world where renewable energy is produced from decentralized sources, such as solar systems [31], the AIoT can play an essential role in managing decentralized energy supply and demand. The manufacturing and energy sectors can be decarbonized by AIoT automation to improve resource use, scheduling, renewable energy adoption, decentralized trading, intelligent buildings, and recycling and waste reuse [25, 32]. However, digital gadgets and IoT infrastructures need energy to function. Two key concerns arise when considering intelligent technology incorporated into industry. Firstly, energy is required for operating technology-oriented infrastructure and information processing, and the other is changing production patterns and consumption according to market demand. These requirements can be assessed by AIoT solutions specifically for improving sustainability and implementing intelligent footprint assessments that will enable a sustainable economy with the aid of digital technologies. Industry 4.0 encourages the development of high-performance-wise production plants with fully optimized resource usage, including essential and productive resources like energy and water, as pillar product components like raw materials.

The main goals of sustainable manufacturing depend on three key characteristics: efficient production, improved safety and security, and agile manufacturing. To incorporate these key features while manufacturing industrial products, we must consider the following aspects for sustainable manufacturing:

- Avoiding negative environmental impacts such as pollution and emission while manufacturing products
- Reducing the cost of production by reducing the consumption of energy, raw materials, water, and other limited resources
- Recycling waste and the proper maintenance of disposable and hazardous waste
- Improving safety and security for workers and nearby communities

Industries are pursuing sustainable solutions to align with the objectives of Industry 4.0 through changes in products as per present market demand and automation of manufacturing systems. Currently, technology adaptation is rooted in sustainable productivity and social welfare as well as improving the environmental aspects of manufacturing [33]. Industries are going through a transition period to adjust to the fourth industrial revolution. Therefore, manufacturing

Figure 2: Elements of sustainable manufacturing and AIoT-enabled manufacturing support

industries are facing several challenges while shifting to the new trend considering the cost of production, present market demand, and environmental impacts. In particular, the key challenges addressed in the previous studies are the inadequate capabilities of industries to adopt advanced manufacturing technologies, sustainable processes, planning and scheduling, waste management, safety and security, and supply chain management [34, 2, 35, 36]. Researchers focus on addressing these issues and devising intelligent solutions using AIoT-based infrastructure. Figure 2 shows what sustainability can be achieved through AIoT-enabled manufacturing support.

2.1.1. Boost Productivity through Efficient Resource Management

The issue most identified by operations research and control groups is the management of manufacturing activities for sustainable production, particularly process and resource scheduling for sustainable manufacturing. Scheduling is the process of allocating resources (both technical and human) to tasks throughout specific periods to optimize one or more criteria [37]. By effectively utilizing resources to reduce energy consumption, sustainable process scheduling is primarily intended to minimize production costs in manufacturing industries. The environment is polluted due to excessive carbon emissions from industries. So industries must focus on efficient process scheduling to maximize the use of resources and minimize the negative environmental effects. Concurrently, they need to consume energy to produce goods to meet today's market demand. Therefore, balancing both sides, i.e., reducing energy consumption and manufacturing goods to meet market demand is a complex problem. This issue can be optimized by incorporating AIoT-based process scheduling. Although analyzing big data generated from process industries needs computational infrastructure, the comprehensive process scheduling provided by AIoT can be a sustainable solution.

2.1.2. Energy Management

AIoT-based manufacturing solutions reduce energy costs through resource and process scheduling [38]. When energy consumption is reduced, manufacturing costs decrease along with carbon emissions. Additionally, increasing grid efficiency, optimally utilizing renewable energy sources, and integrating AIoT to establish decentralized energy trade are all ways that AIoT can help with efficient energy management [22]. However, AIoT technology depends entirely on sensors, IoT devices, network connections, and data centers. To link the many connected devices, energy is required to maintain the functioning of the AIoT infrastructure. Research is being conducted to reduce the energy requirements for AIoT solutions [38, 39]. Furthermore, changes in consumer demands, behavior and technological advancements have increased energy consumption. Energy management is now a significant issue for sustainable manufacturing.

2.1.3. Safety and Security

Manufacturing industries play a significant role in balancing the supply and demand of the market. As previously mentioned, the key goals of sustainable manufacturing are: to reduce energy use and pollutant emissions during production, to monitor and evaluate the environmental footprint, and to control risks throughout life, which emphasizes

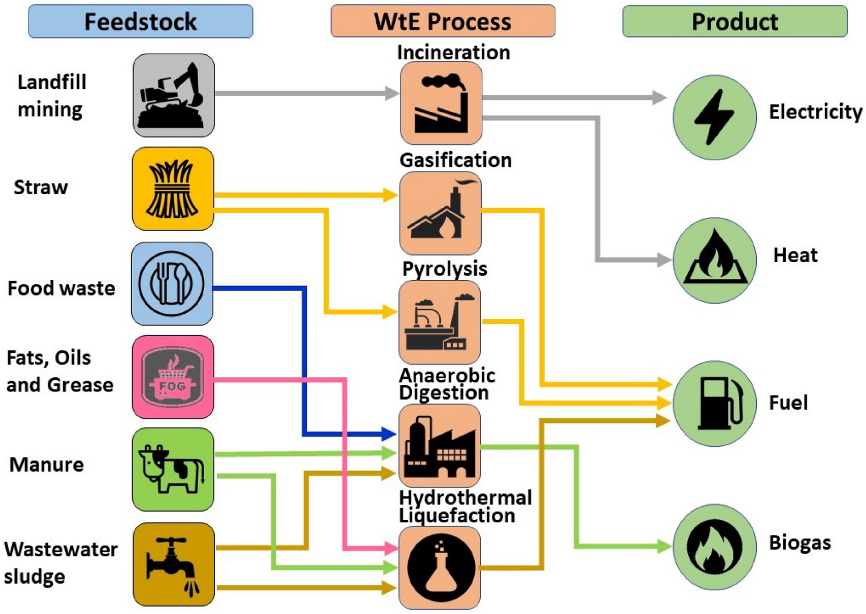

Figure 3: Sample prototype to reuse waste [49]

the need for stricter environmental regulations and improved accident prevention [40]. In any industry, employees involved in operations can face security threats while working in an unhealthy and hazardous environment. Additionally, many heavy workloads are beyond human capability. Using significant volumes of dangerous chemicals in the chemical industry causes spatial variability in chemical operations and the introduction of more strict safety and environmental requirements. Thus, many manufacturing industries are launching industrial robots, which increase productivity and reduce the risk to human operators [41, 42, 43]. Several wired, wireless, and remote communication protocols have been developed to solve this issue. Some researchers introduced remotely operated robots where the user operates the robot remotely. However, noticing every aspect of an industrial environment is a complex issue and can be dangerous. The AIoT and other emerging information technologies are extremely promising in relation to overcoming these challenges. An AIoT-based human-machine interface (AHMI) can be a solution in this regard as it enables users to monitor devices, control product quality, store documents safely on clouds, and issue instructions from a safe distance.

2.1.4. Waste Management and Recycling

The unrestricted dumping of manufacturing waste in public areas has become a significant concern worldwide. Exposure to toxic waste can result in cause adverse health effects and have a detrimental impact on the environment. One potential long-term approach to resolve these issues is an integrated waste management system [44]. Identifying and classifying recyclable, hazardous, and disposal wastes is a serious challenge. AIoT applications may be very beneficial as AIoT-based intelligent sensors can distinguish between waste comprising different materials and identify whether products made of the same substance have been chemically contaminated, maintaining the purity of the waste stream. Several waste management systems utilize such methods and IoT sensors to track how full garbage cans are throughout the city. Although every stage of waste management is essential, reusing and recycling garbage has resulted in the additional benefit of sustainable economic gain [45]. AI and IoT are being extensively researched for a sustainable waste management strategy with progress in research transforming urban and industrial garbage management [46, 47, 48]. Given limited resources, manufacturers should focus on waste recycling for manufacturing sustainability and to reduce environmental impact, as shown in Figure 3.

2.1.5. Employment and Social Sustainability

The public perceives that the traditional job market, especially in labor-oriented manufacturing [50, 51], will be adversely impacted if AIoT technology is widely used, with sustainable development becoming unbalanced, and the unemployment rate increasing [52, 53]. Hence, there is increased concern about how AI and IoT advancements impact jobs. Will automation, for example, significantly reduce the need for several workers and, as a result, impact the working capital and social performance of businesses? A study conducted in 2013 showed that 47% of total employment in the United States is at a high risk of automation [54]. Unquestionably, the rise in inequality, stalling labor demand, falling labor share in national revenue, and slower productivity growth are effects of advances in AI-driven automation technologies [55]. A report by PricewaterhouseCoopers (PwC) found that by the early 2030s, 30% of jobs in the UK, 38% of jobs in the US, 35% of jobs in German, and 21% of jobs in Japan could be automated. The net employment impact is unclear since new automation technologies will generate jobs, and there are practical obstacles to applying automation [56]. This finding sparked additional research on the expected effects of AI-driven automation on the economy [57]. The advancement of science and technology has resulted in enormous changes in society. Complex social adaptations have been driven by technological progress. However, research strongly suggests that, over time, AIoT advancement and industry automation both create a large number of new employment opportunities and increase demand for those that already exist, more than compensating for the number of jobs it eliminates [58, 59].

Therefore, sustainable manufacturing has become an increasingly important research topic to address global threats and increase technological adaptation for sustainable production. It is a pivotal element for industry conserving economic development, which is also a key objective in human development to balance social, economic, and environmental aspects [7]. Sustainable production brings socioeconomic balance to modern life and also addresses environmental issues. It is a holistic, sustainable development process that provides a balanced socioeconomic environment [30]. Therefore, sustainable manufacturing is one of the critical matters of the industrial revolution Industry 4.0 [2]. The process of manufacturing products considers economic development and minimizes adverse environmental implications while using energy and natural resources. It is also referred to as green manufacturing or eco-friendly manufacturing to increase productivity, employee safety, and community [60, 61]. According to state-of-the-art research on the fourth industrial revolution, [2], the digitization of the manufacturing industry can significantly improve resource and information efficiency, which is excellent for the environment [62]. Industry 4.0 technologies have a lower environmental impact, consume less energy and minerals, reduce hazardous chemicals, exhibit greater energy efficiency, reduce production costs, and enhance worker safety. Consequently, digital industrial innovation benefits mass production and environmental sustainability [63]. Therefore, the major concern of researchers is to ensure all factors of sustainable manufacturing are effectively incorporated into the industrial process. Researchers and industry collaborators have been working together to develop intelligent automation for the rapidly changing global market. As a result, automated manufacturing has begun to include smart solutions by integrating software and hardware to minimize production costs and negative environmental impacts.

2.2. Artificial Intelligence of Things (AIoT)

Artificial Intelligence of Things (AIoT) has significant potential for utilizing AI and IoT to make IoT applications intelligent [25, 65]. AIoT produces intelligent, interconnected systems where AI serves as the brain of the IoT devices. IoT devices gather and transmit data from various sources to enhance the AI learning process used for automation. The workflow of the AIoT infrastructure is shown in figure 5. Connecting IoT devices to sensors generate data from different sources, which is scattered and complex. Artificial intelligence can elicit responses and guide intelligent action by analyzing data from IoT devices. Digital technologies undoubtedly offer beneficial advantages to both industry revolution and societies. The AIoT typically impacts automated process scheduling and overall product output in industrial applications. The AIoT technology provides new opportunities in manufacturing industries that arise from developing innovative process industries, enhancing product quality, and ultimately increasing productivity and profitability. These factors are prerequisites for dealing with environmental issues and employee security for manufacturing industries. AI and IoT-based systems enable a new set of product functions and capabilities such as monitoring, scheduling, control, optimization, and autonomy [66] to boost operational efficiency, eliminate unplanned outages, reduce machine downtime, enhance product quality and service, improve risk management, and ensure high scalability (as shown in Figure 4). AIoT is currently employed as a digital technology for manufacturing data acquisition, process, and analysis to learn, predict decisions, and take action (as shown in Figure 5). The outcome is an upward spiral of value development for both areas: an increased number of IoT-based devices, increasing data volume, better AI algorithms, and growing IoT technology. The advantages include IoT devices with AI to function independently, such as logistics robots that move items in challenging areas like hospitals [25]. The overall flow of the AIoT infrastructure in industry practice for sustainable manufacturing is shown in Figure 6. To control and optimize manufacturing production in real-time, it is expected that AI and IoT technology, a digital replica of the physical system, will be employed widely.

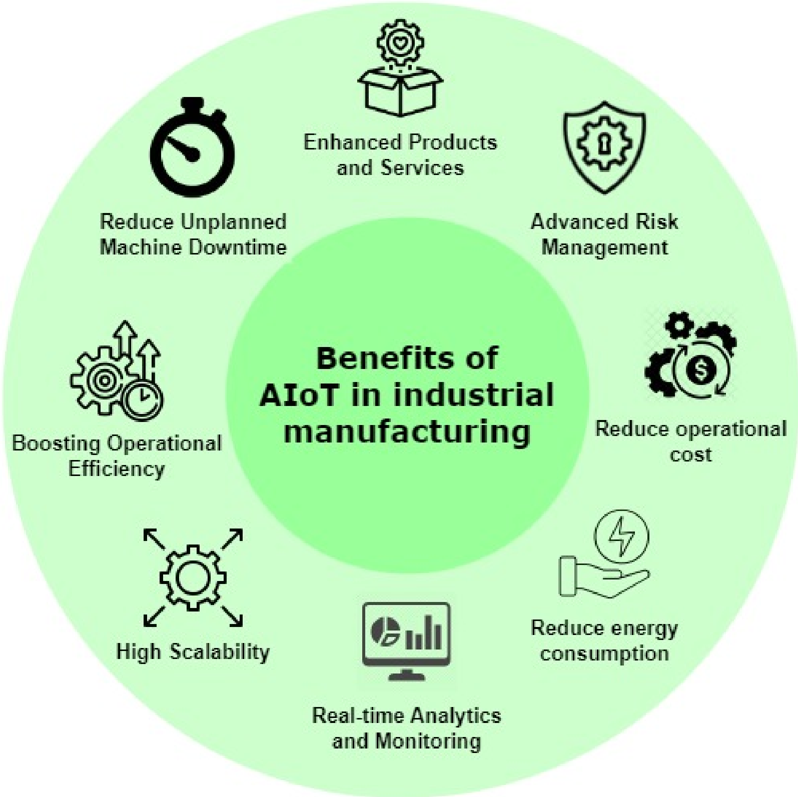

Figure 4: Benefits of AIoT in industrial manufacturing

Figure 5: Workflow of AIoT

AIoT technology creates an intelligent infrastructure for data analysis by integrating AI with IoT sensors and network systems. All applications and solutions utilizing AIoT rely heavily on real-time data. So AIoT technology has vast prospects for analyzing real-time manufacturing data. To develop an AI-based service function for industry, AIoT can significantly impact industrial automation and build smart homes, smart cities, and smart transpiration systems. The work in [67] recommends an AIoT-based system to track tunnel development in real-time. Their demonstration showed how AIoT infrastructure improves overall automation when working on a project, facilitates decision-making,

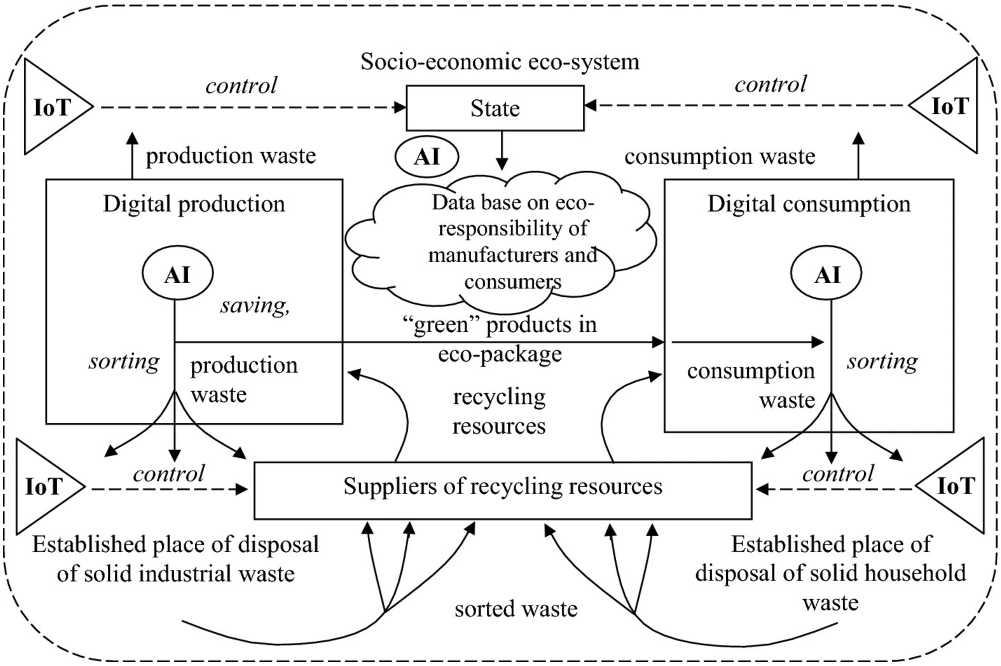

Figure 6: AIoT prototype in sustainable industrial practice [48]

and prevents accidents [68].The work in [69] presented a fast and energy-efficient framework for hybrid storage-class memory in an AIoT terminal. The authors demonstrated that the proposed system could, on average, consume 46.2% less energy than the conventional system. They utilized a sensor-based automated software manipulator to analyze the virtual storage of AIoT. The hierarchy for material flow management was implemented using AIoT in [70]. A novel two-step unsupervised error detection method that combines feature extraction and fuzzy clustering for typical AIoT was proposed in [71]. In [72] described how industrial AIoT was used to increase quality at an HP factory. The findings demonstrated the significant contribution this technology made to quality enhancement. The AIoT infrastructures are divided into two paradigms based on the challenges of AI model building and interfacing, IoT device connectivity, network communication, and data processing and computational strategy [64]: cloud-based AIoT and edge-cloud collaborative AIoT, as shown in Figure 7.

2.2.1. Cloud-based AIoT

Cloud-based AIoT devices can make decisions locally by accessing local and central data. However, they have access to start workflows in other connected systems. IoT devices can also send data to the cloud server. Both the training and testing models utilize cloud servers equipped with powerful and flexible computing and storage resources [64]. However, this cloud-based AIoT infrastructure may face significant challenges due to the existing network and the increasing volume of data created by edge IoT devices [73] and network capacity and communication delay between the devices and distant cloud [74]. Despite this, the scalability, flexibility, and integration capabilities of cloud-based AIoT devices can be the foundation for future intelligent applications. It can increase manufacturing efficiency as business needs to respond quickly and easily expand or reconfigure access control systems while needing to change threat levels.

2.2.2. Edge-cloud Collaborative AIoT

Edge-cloud AIoT computing shifts AI inferencing to edge-computing installed inside IoT devices and analyses a significant amount of the raw data locally instead of sending all the raw data back to the cloud for processing and analysis. The challenges raised in cloud-based AIoT may be mitigated through the edge-cloud collaborative AIoT approach. Therefore, edge computing can offer speed, reliability, low latency, and enhanced capacity using advanced AI models, even though traditional cloud computing is still necessary for training them. Large volumes of data generated from sensor-enabled conventional equipment are stored in the cloud database. However, difficulties arise when organizing and analyzing large amounts of data to gain information. The AIoT-enabled infrastructure must be seamlessly connected

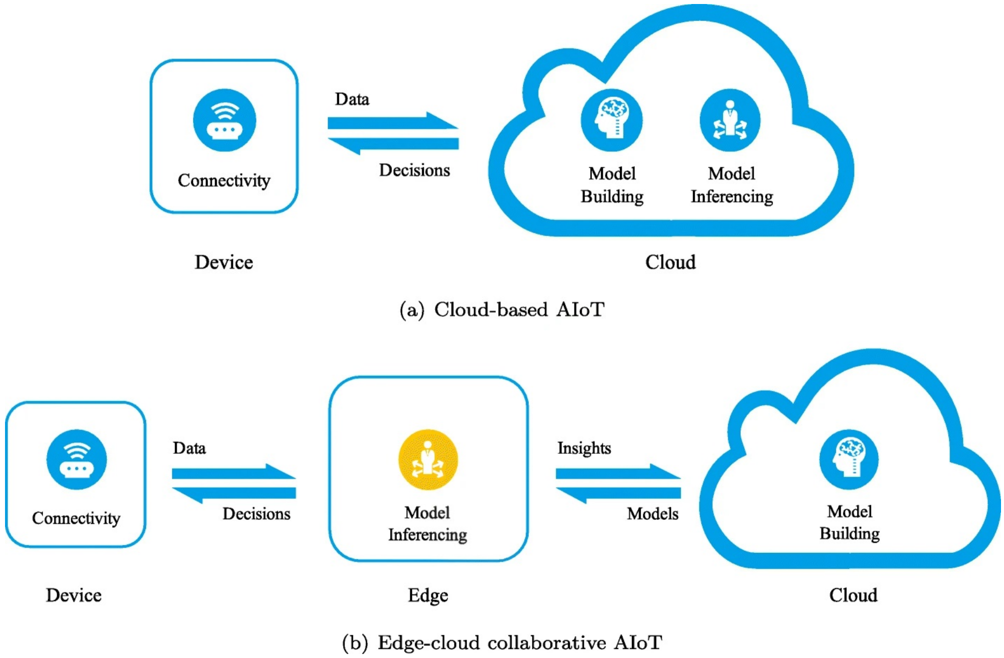

Figure 7: Two different paradigms of AIoT [64]

to the massive database to ensure the industry is artificially intelligent for economically sound manufacturing. To access databases and maintain continuous communication in relation to device-sensor-storage and vice versa, a networking infrastructure is essential for employing the AIoT system in real-time manufacturing.

2.3. AIoT market analysis

The growing use of AIoT technologies to improve decision making and the adoption of edge analytics solutions is expected to boost market growth. Figure 8 shows the global market trend for AIoT. According to the Global Market Insights research report [2], the global AIoT market is expected to grow from USD 9 billion in 2022 to USD 25 billion by 2032, at a compound annual growth rate (CAGR) of 20%. The market share of AIoT end-users in 2022 is shown in Figure 9. Moreover, a recent market research study by Transparency Market Research[3] found that the global AIoT industry was valued at 8.4 billion (USD) in 2022. The study also estimates that the market size will expand at a CAGR of 24.6% from 2023 to 2031, reaching 58.4 billion (USD) by the end of the forecast period. The increasing adoption of IoT devices and AI technologies is driving this growth.

3. Review Methodology

We conducted a systematic literature review of published scientific research articles using the PRISMA [75] methodology. Additionally, a multidisciplinary strategy was used to gather relevant papers in a bottom-up manner [76]. The publications were sourced from significant web databases rather than specific journals. Figure 10 depicts the procedure of retrieving relevant studies and their analysis. We utilized a three-phase SLR method for the study:

- *Phase-I:* We explored the top 5 online databases (as shown in Figure 10) to retrieve relevant studies. We identified 311 relevant studies for the SLR. Duplicate articles were removed at the end of this stage which left 265 articles for screening.

- *Phase-II:* After completing Phase-I, we examined the preliminary study list to exclude unrelated articles by

[2] www.gminsights.com/industry-analysis/aiot-market
[3] www.transparencymarketresearch.com

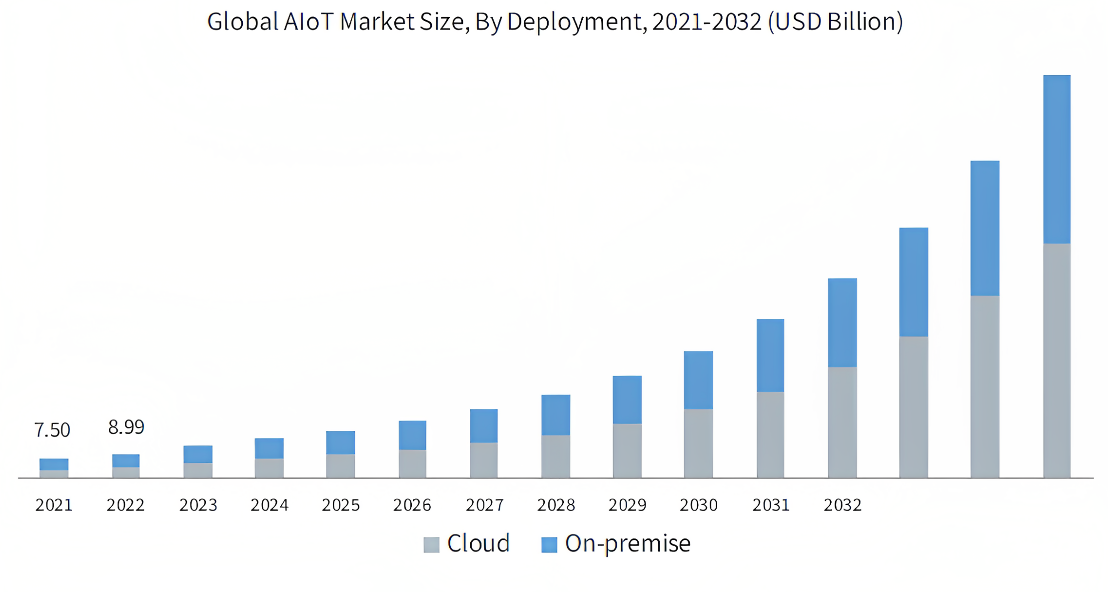

Figure 8: Global AIoT market size (Source: www.gminsights.com)

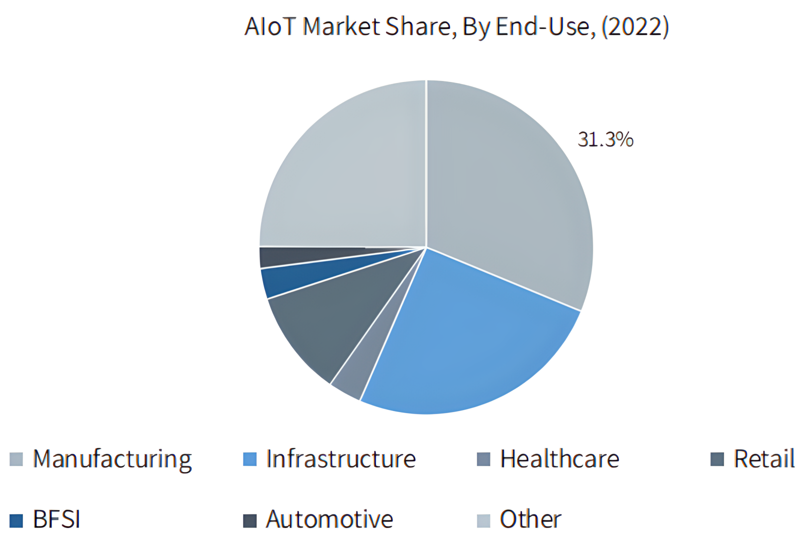

Figure 9: AIoT end-user market share-2022 (Source: www.gminsights.com)

carefully scrutinizing the articles' titles, abstracts, and keywords. Then, we removed unrelated articles from the list.

- *Phase-III:* Finally, we selected 146 articles from the 311 articles to prepare the SLR (as shown in Table 2).

The SLR provides an unbiased and realistic summary of the state-of-the-art research on AIoT for sustainable manufacturing and elucidates the current challenges and prospects of AIoT in sustainable manufacturing. Therefore, the outcome of the SLR can provide fruitful directions for AIoT-based technology adaptation in sustainable manufacturing.

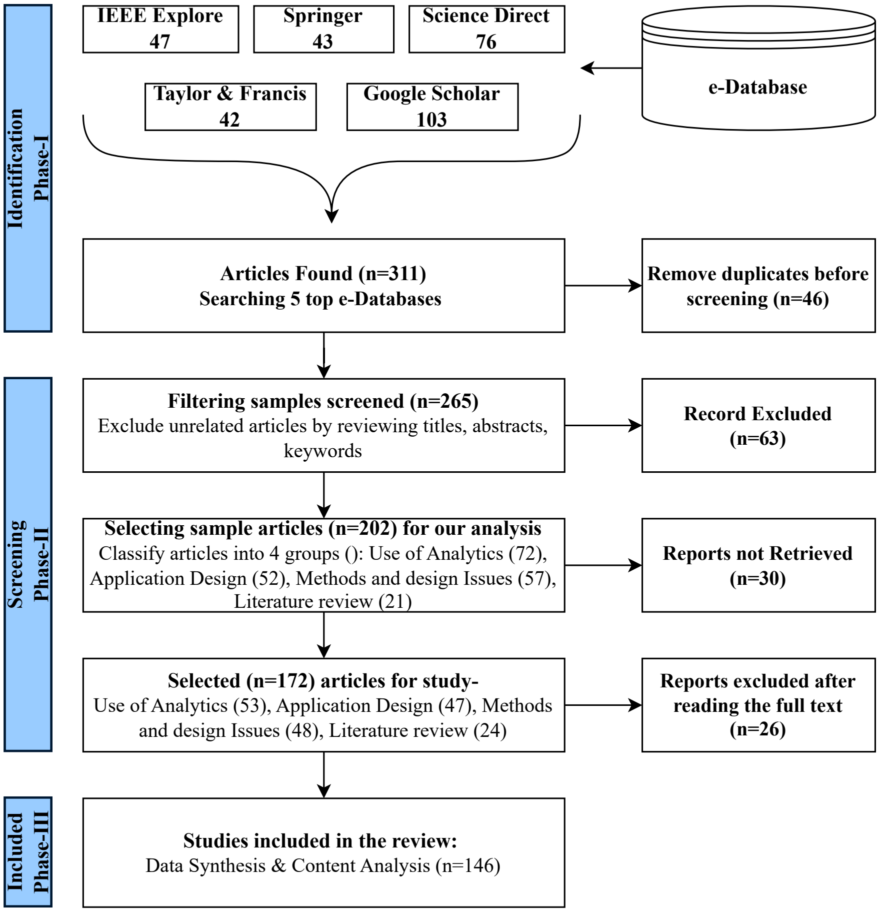

Figure 10: Review methodology for relevant study collection and analysis

Table 2
Search engines and number of studies

Search engine	Preliminary selection of studies	Final Selection of studies
Science Direct	76	48
IEEE Explore	47	30
Springer	43	24
Taylor & Francis	42	16
Google Scholar	103	28
Total	**311**	**146**

3.1. Research Questions

The primary purpose of the SLR is to answer the following three research questions regarding AIoT for sustainable manufacturing:

- *RQ1:* Why is there a need to adopt AIoT-based automation in manufacturing industries?
- *RQ2:* What contributions have been made in the emerging AIoT research field?
- *RQ3:* What are the major challenges facing AIoT technology that need to be further explored to achieve sustainable manufacturing objectives?

We include RQ1 to comprehensively understand AIoT and its importance regarding the objectives of the manufacturing perspective. RQ2 summarises the current state-of-the-art regarding the main advantages of using AIoT technology

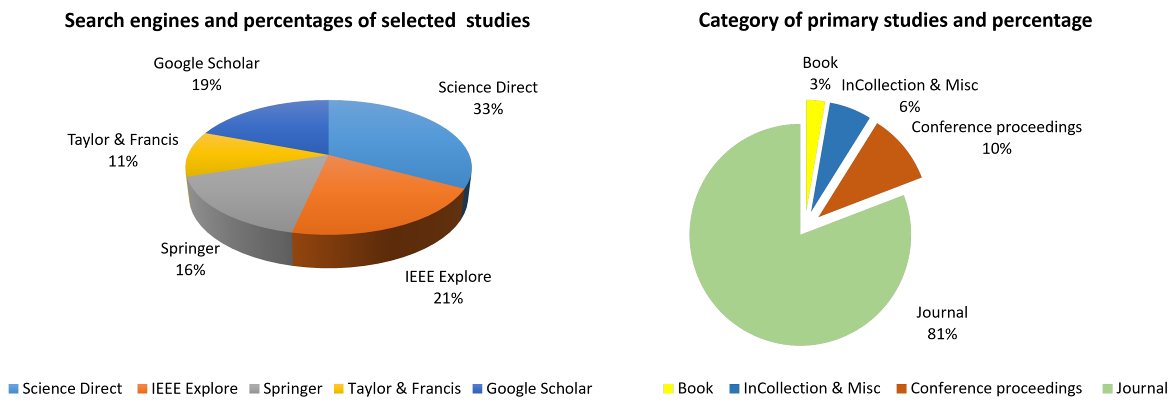

Figure 11: Source of the selected articles and their categories

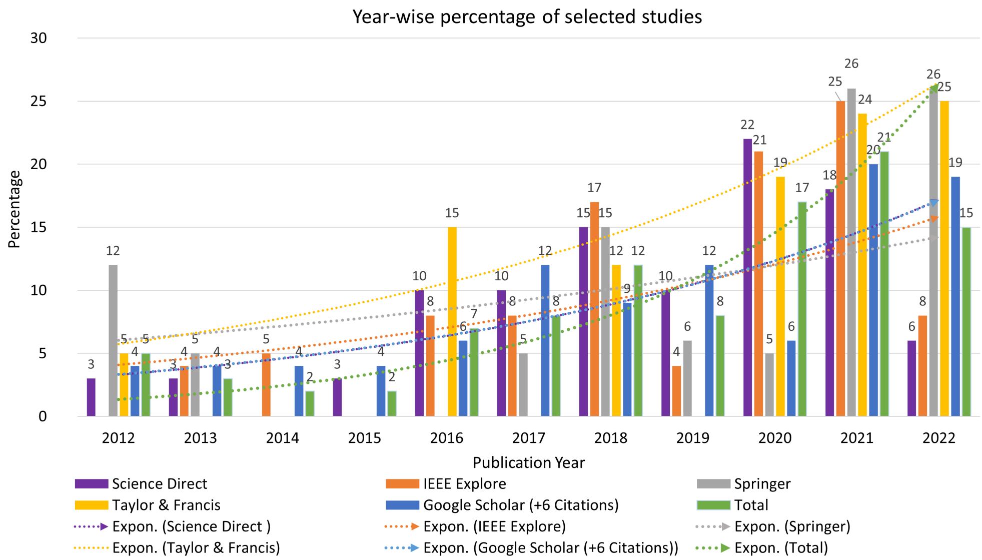

Figure 12: Publications by year

in industrial manufacturing. It is suggested that RQ2 explains the scope of AIoT applications in various manufacturing domains. Finally, we anticipate identifying unsolved issues and research possibilities in response to RQ3 based on the answers to the earlier questions.

3.2. Search Keywords

We focused on the literature topic and the most appropriate and specific synonyms while searching for relevant articles in the databases. We used the primary alternatives and the "OR" and "AND" operators to locate the most relevant works in the literature, as indicated in Table 3.

3.3. Literature Resources

We explored the following renowned databases namely Google Scholar, Springer, ACM Digital Library, Scopus, Science Direct, IEEE Explorer, Wiley Online Library, and Taylor & Francis to retrieve relevant publications. The percentage of articles retrieved from the databases is as follows: Science Direct (32%), IEEE Explore (18%), Springer (14%), Taylor & Francis (11%), and Google Scholar (25%), with most of the studies being journal articles (as shown in

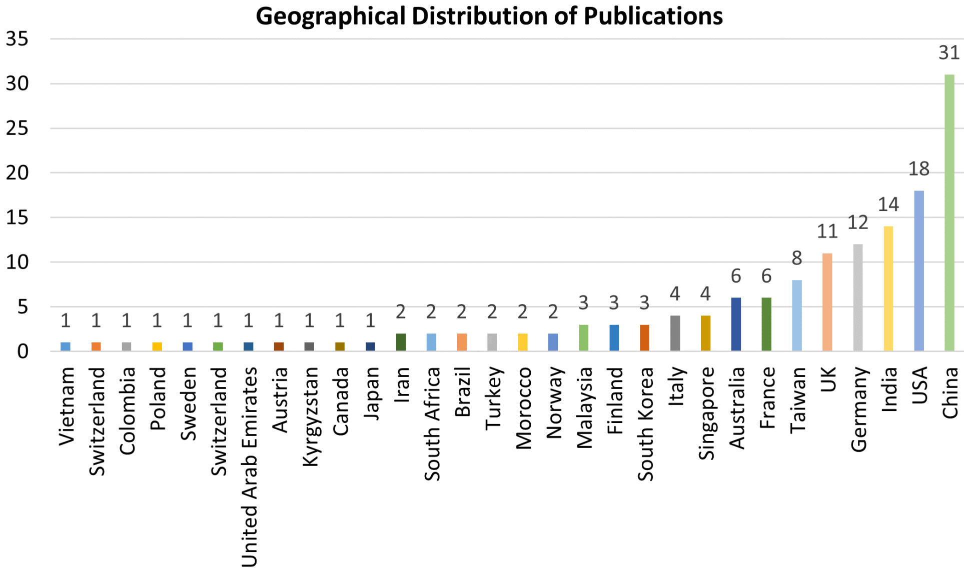

Figure 13: Publications by geographical distribution

Table 3
Search keywords for inclusion and exclusion of research studies

ID	Keywords
1	("AIoT" OR "Artificial Intelligence of Things") AND ("Sustainable Manufacturing" OR "SM")
2	("AIoT" OR "Artificial Intelligence of Things") AND ("Sustainable Manufacturing" OR "Industrial Manufacturing")
3	("AIoT" OR "Artificial Intelligence of Things" OR "Artificial Intelligence and IoT ") AND ("Sustainable Manufacturing" OR "Industrial Manufacturing")
4	("AIoT" OR "Artificial Intelligence of Things" OR "Artificial Intelligence and IoT ") AND ("Sustainable Manufacturing" OR "Industrial Manufacturing" OR "Manufacturing")
5	("AIoT" OR "Artificial Intelligence of Things" OR "Artificial Intelligence and IoT ") AND ("Sustainable Manufacturing" OR "Industrial Manufacturing" OR "Green Manufacturing")
6	("AIoT" OR "Artificial Intelligence of Things" OR "Artificial Intelligence and IoT ") AND ("Sustainable Manufacturing" OR "Industrial Manufacturing" OR "Smart Manufacturing")

Table 4
Top 10 venues of selected primary studies

Venue Name	Publisher	Papers
IEEE Internet of Things Journal	IEEE Inc.	5
EEE Transactions on Industrial Informatics	IEEE Computer Society	5
IEEE Access	IEEE Inc.	5
International Journal of Production Research	Taylor and Francis Ltd.	5
Procedia CIRP	Elsevier	4
Journal of cleaner production	Elsevier	4
Renewable and sustainable energy reviews	Elsevier	3
Future Generation Computer Systems	Elsevier	2
International Journal of Information Management	Elsevier	2
Technological forecasting and social change	Elsevier	2

Figure 11). The search phrase was developed by utilizing the extensive search possibilities provided by each entity of these databases. We restricted the search to articles published between 2012 and 2022. The sources of the selected studies are depicted in Figure 12 for a clear understanding of the growing research trend.

3.4. Metadata Analysis of the SLR

We extensively analyzed all 146 selected studies to obtain answers to our research questions. We compiled the following details from each study: a complete reference, an overview, the type of contribution such as methodology

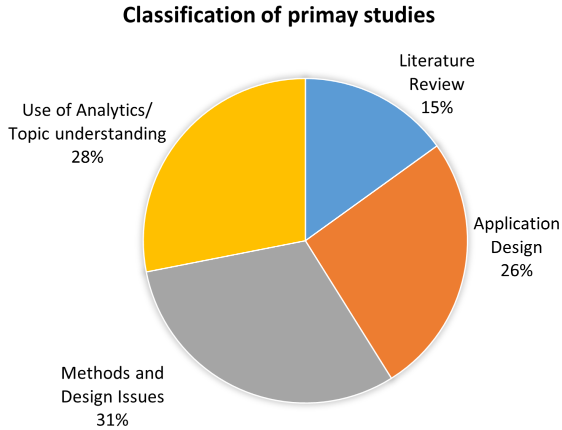

Figure 14: Classification of selected studies

design or resolving issues, the specific applications, and suggested challenges. As shown in Figure 11, 81% of studies were from reputed journals, with the most published in ScienceDirect/ Elsevier. Table 4 lists the top 10 venues of these studies. We also established a connection between each study's nation of affiliation of its first author. As illustrated in Figure 13, it is interesting to note that all 146 primary research came from only 30 countries, with China, the USA, India, Germany, and the UK leading the trend.

The selected studies were classified into four groups based on the paper contribution: use of analytics (41), application design (38), methods & design issues (45), and literature review (22), as shown in Figure 14. The results show that 15% of the publications are literature reviews, approximately 33% of the publications make new methodology contributions and solve existing design issues, and 26% & 28% discuss the application design and use of analytics, respectively.

4. AIoT for Sustainable Manufacturing: State-of-the-art

Manufacturing industries will enforce sustainable production to increase productivity as well as to achieve the objectives of Industry 4.0. Many technologies, such as the IoT, AI, cyber-physical systems (CPS), big data, intelligent sensors, and 3D printing, have advanced to the point where they can now be used in the manufacturing industry. Some of these technologies have already been incorporated to design task-specific applications. AI and IoT are the two technologies that are utilized the most frequently in smart factories, which control whole systems using data received from sensors installed on every piece of equipment in the facility [77, 78]. The demand to extract essential information to drive decisions from big data accumulated in various industries such as food manufacturing, chemical goods manufacturing, and healthcare is steadily increasing. Improvements made to the manufacturing industry with a consistent focus on automation, robotics, and complex analytics increase efficiency. For sustainable manufacturing goals, the AIoT enables the establishment of the manufacturing ecosystem and synchronization with several information systems [79]. This section details AIoT approaches, application areas of AIoT in manufacturing, and AIoT-based industrial toolkits.

4.1. AIoT Approaches to Sustainable Manufacturing

In this section, we explain the state-of-the-art AIOT-based research for sustainable manufacturing. We introduce intelligent process scheduling for resource management, predictive maintenance and fault diagnosis to enhance productivity and reduce machine downtime, intelligent energy management for the efficient use of energy, and supply chain management to manage the life cycle of manufacturing products from design to production and distribution.

4.1.1. Intelligent Process Scheduling

In sustainable manufacturing, intelligent process scheduling is a challenging issue. AI and IoT tools can solve this problem in several ways. The arrival rate of data packets varies dynamically in the IoT ecosystem, which consists of different types of sensors. The system's dependability and quality can be seriously compromised if data packets are

Table 5
Existing research on process scheduling and energy consumption

Reference	Problem Addressed	Proposed Approach and Methods	Significance
Liang et al. [82]	Resource load scheduling and device connections problem at the edge of AIoT	Hybrid resource scheduling architecture; Edge computing, a linear weighting strategy, multi-objective algorithms	Reduce the AIoT processing delay and energy consumption
Zhu et al. [38]	Resource management and energy consumption	Intelligent edge computing framework; Reinforcement-learning, online scheduling problem	Reduce energy consumption
shi et al. [83]	Network congestion and energy consumption	AIoT architecture for crop monitoring system(CMS); Edge computing, Deep reinforcement learning (DRL)	Optimize task scheduling and reduce energy consumption
Vermesan et al. [84]	The optimization problem in the microcontroller for complex DNS computation	Real-time AIoT scheme; Edge computing: Micro Edge, Deep Edge	Improve system optimization and product quality, reducing energy consumption
Rustia et al. [85]	Data unavailability and insufficient knowledge about integrated pest management (IPM)	Intelligent and Integrated Pest and Disease Management (I2PDM); Edge computing	Sustainable and data-driven IPM
Mun et al. [86]	Quality and production cost	Power monitoring and load classification system; ANN	Improve the quality control of manufacturing lines, efficient load scheduling, and reduce energy consumption
Hu et al. [87]	Lack of efficient and intelligent manufacturing system	iRobot-Factory; Edge Computing	improving productivity and efficiency and reducing production cost and energy consumption
Feng et al. [88]	Analysing high-dimensional and unbalanced data for real-time quality prediction	Integrated Quality Prediction model; Random forest, SMOTE-Adaboost, Edge Computing	improving quality prediction and accuracy

not processed following the QoS requirement. The Q-learning scheduling approach is used to schedule data packages generated by several sensor nodes [80]. Due to the wide range of product functionality, scheduling algorithms frequently need to be modified to satisfy the needs of industry. An approach has been proposed that combines machine learning and the Monte Carlo tree search (random search) to deal with re-entrant flow-shop scheduling problems with the requirement for eliminating problem-specific knowledge [81].

The logistics industry is also experiencing an increase in scheduling issues. To tackle a production scheduling challenge in a manufacturing plant, a scheduling problem is approached using Google's Deep Mind DQN Q-learning algorithm [89]. A neural network (NN) is trained to anticipate the action once the problem is given as a Markov decision process. In addition to this prediction, the DQN algorithm, a reinforcement learning technique, links choices to better actions. Tensorforce reinforcement is implemented using NN for order dispatching [90]. The hyperparameters, reward function, and state representation are all given in-depth descriptions. Additionally, these publications are aimed at engineers who need to learn more about ML and reinforcement learning. In [91], the author used a similar strategy for task scheduling in a smart factory. Reinforcement learning and Q-learning models are utilized to deal with a real-time scheduling issue. A reinforcement learning-based scheduling framework is proposed in [38] to develop energy-efficient AIoT systems. Details of some of the research on AIoT-based industrial resources and process scheduling is shown in Table 5.

4.1.2. Predictive Maintenance and Fault Diagnosis

Predictive maintenance refers to the physical status of industrial equipment and determining when necessary maintenance tasks are needed to extend the equipment's service life while reducing the risk of failure. AI and IoT applications are growing due to developments in data collection methods, algorithms, and processing power. AI algorithms are frequently employed for predictive maintenance and machine fault diagnosis to enhance productivity and reduce machine downtime. The timely diagnosis of machine faults helps manufacturers to decrease machine downtime and failure. As a result, manufacturers can provide products promptly and cost effectively and maintain a high level of product quality. However, predicting machine faults in advance is challenging; much of the time spent during downtime is spent finding faults rather than making repairs or undertaking the maintenance. Several fault detection approaches have been introduced using machine learning techniques such as ANN [92, 93, 94], BN [95, 96, 97], HMM [98, 99], SVM [100, 101]. With the advancement of IoT technology, data storage, and internet speeds, factories are becoming smarter and process big data to increase manufacturing performance through AI-based predictive maintenance. AIoT supports intelligent predictive maintenance to boost machine efficiency and enhance industrial productivity [102]. Some

Table 6
AI-methods for predictive maintenance and fault Diagnosis

Reference	Methods	Applications
Fang et al. [103]	Hybrid	Predictive maintenance and measure processing time left over during production
Wang et al. [102]	Deep Learning, BRNN	Intelligent predictive maintenance
Glaeser et al. [104]	CNN	Fault diagnosis
Liu et al [105]	CNN, Hybrid	Machine health monitoring
Carbery et al. [106]	RF, and XGBoost	Applying predictive analytics framework to the Bosch and SECOM datasets to identify faults
Susto et al. [107]	SAEF	Predictive maintenance
Zhang et al. [108]	CNN, Hybrid	Intelligent process fault recognition and diagnosis
Paolanti et al. [109]	RF	Predictive maintenance
Usuga et al. [110]	CNN, Hybrid	Estimating the length of manufacturing machine failures

AI-based predictive maintenance and machine health diagnosis approaches are shown in Table 6.

4.1.3. Intelligent Energy Management

Energy consumption and emission reduction are two crucial objectives for industry in today's environmentally conscious society, particularly energy-intensive manufacturing businesses. AI and IoT technologies have advanced quickly and can now be used in the industrial sector, creating opportunities to design and build dynamic decision support systems to enhance energy efficiency. Energy is a fundamental requirement in industrial operations for a variety of functions. With the growth of the balanced economy, the industrial sector now consumes roughly half of the energy used worldwide [111]. AI and IoT have made it possible to collect data on energy usage from manufacturing processes and the real-time status of resources. Real-time production management can improve energy efficiency using these industrial data. Multi-source production data are becoming easier to acquire and more commonplace due to the expansion of AI and IoT technology into the manufacturing sector. Real-time monitoring of the energy consumption status of manufacturing processes enables the resulting data to be mined and knowledge to be discovered. As a result, inefficiencies in energy consumption can be addressed, such as the energy used while a machine is idle or often transitions between shutdown and operation. The work in [112] proposed a real-time energy efficiency optimization method (REEOM) for energy-intensive manufacturing industries to apply AI and IoT technology to enhance energy efficiency. Ontology modeling, multiagent technology integrations, and load-balancing systems have been proposed to achieve effective dynamic resource management and reduce energy consumption [113]. Intelligent manufacturing is enabled by dynamic resource management through AIoT-based manufacturing, which offers a solution to complex resource allocation issues in present production situations and reduces energy consumption (as shown in Table 5). Energy-intensive manufacturing industries are forced to boost production with efficient energy use and decrease their associated environmental impacts due to rising energy prices, intensifying competition, new environmental legislation, and concerns over environmental issues.

Instead of using fossil fuels as a source of energy, manufacturing industries concentrate on renewable energy to mitigate energy resource limitation and emission issues [114, 115, 22]. AIoT-based Distributed Energy Resource (DER) systems can boost renewable energy production and distribution [22]. However, various renewable energy sources such as wind turbines, solar panels, and transformers are difficult to access and are located in remote areas. By utilizing AIoT, predictive maintenance may foresee equipment breakdown and schedule preventative maintenance in advance. AIoT enables DER systems to reduce operational expenses by minimizing unplanned downtime. When machines and IoT sensors are connected through a network, it is significantly more advantageous for DER systems than the traditional disconnected operation style. AI, in addition to IoT connections, accelerates DER development by predicting outcomes, autonomously optimizing system operations, and automatically discovering flaws. Hence, through the use og AIoT, DER systems can be described as "green energy systems". The main advantages of using AIoT in DER systems are boosting operational efficiency and reducing downtime.

4.1.4. AIoT-based Supply Chain Management

AIoT can analyze continuous data streams and identify precise patterns for making decisions. AI and machine learning can also predict operational circumstances and identify factors that need to be altered for the best results. The IoT provides data on which processes take too long and are redundant and which ones may be changed to become more efficient. To modernize supply chain management and improve value creation across all industries, emerging Industry

4.0 technologies are the main drivers in these areas [116]. Consequently, AIoT can also make the traditional supply chain management system smart and more intelligent. However, most supply chain decision-makers need help to obtain sufficient data in terms of quantity and quality to meet demands. Difficulties are mainly caused by the time-consuming process of locating and validating reliable data sources, followed by the challenges of cleaning and classifying the data into smaller chunks [116]. The shortage of high-quality data also creates an obstacle due to the low level of data transparency. To be more precise, some AI techniques, such as decision trees and scorecards, are simple to understand. However, other AI techniques, like neural networks, are still mysterious and challenging to understand, making it difficult for practitioners to understand the rationale behind the decisions made by AI methods. In addition, a lack of adequate and scalable storage is a problem for supply chains that must deal with such large data clusters [117]. Furthermore, adopting AIoT solutions is difficult to incorporate immediately due to current challenges such as resource constraints and initial installation costs. However, it is clear that most of the AIoT research in supply chain management is conceptual and is still in the early stages of development, lacking the successful application of AIoT infrastructure.

4.2. Application Areas

There are several manufacturing areas[4], such as food and beverage manufacturing, agricultural manufacturing, textile and apparel, footwear and accessories, pulp and paper products, chemicals and plastics, metal, machinery and equipment, etc. [118], where AIoT technology can be incorporated for sustainable manufacturing. This section introduces some of the manufacturing sectors where AIoT technology can be used to increase productivity and efficiency.

4.2.1. Food and Agricultural Manufacturing

The food and agricultural industry is going through a significant transformation by adopting new automation technology to improve efficiency and safety and prevent production disruption. Technology development has increased intelligence at the edge, enabling IoT devices to make better decisions with high performance, low power processing, and built-in security. AIoT enables production optimization, waste reduction and maintenance, and environmental sustainability to develop intelligent and adaptive industrial applications. The adoption of AIoT solutions in the food and agricultural manufacturing industry has assisted in overcoming production and execution-related issues by minimizing the possibility of human error and moving manual labour to an automatic system that is essential for the quality of products. AIoT can be used to improve the quality of food and agricultural production, which can lead to increased customer satisfaction and economic benefits. Therefore, the manufacturing industry can benefit from using AIoT in predictive quality analytics and predictive maintenance and identifying machine failures that reduce productivity.

The manual labour system is automated using sensors, cameras, and actuators built into autonomous machines. AIoT-based systems can track, monitor, and manage waste throughout its life cycle, including collecting data on waste generation, transportation, and disposal to identify opportunities for recycling and reuse. With various sensors, IoT devices, and edge technologies, AIoT systems can monitor food quality and safety, and AI-based food safety solutions help forecast food product concerns. Data from sensors are collected, labeled, and analyzed using AI algorithms. Food and agricultural manufacturing facilities are adopting capital-intensive machinery to enhance and optimize their utilization of machines and resources. Examples of AIoT-based research are detailed in Table 7.

4.2.2. Chemical Manufacturing

Sustainable manufacturing in the chemical industry aims to maximize production by ensuring safety requirements and reducing abnormal chemical incidents. Therefore, chemical processes should be smart to avoid safety incidents and maximize productivity. Abnormal situations and safety management in chemical industries have been researched for more than two decades to gain and utilize operational knowledge to address complicated abnormal circumstances that are challenging for operators to identify and prevent. AIoT can provide significant support in this regard to improve safety and productivity. Several conceptual AI and IoT-based (digital twins) intelligent frameworks have been introduced in [124, 125, 126] for chemical process scheduling, control and optimization, and predictive maintenance. In [70], an AIoT-based intelligent linkage service for a material flow management approach was proposed using deep learning to resolve manual loading, labour waste, and safety issues. The Chemiscal[5] introduced an AIoT-based application to improve the efficiency of chemical synthesis.

AIoT technology integration in the chemical industry has distinguished research prospects to accelerate chemical goods production. One of the significant aspects of AIoT technology adoption in chemical industries is to boost

[4] https://business.gov.au/planning/industry-information/manufacturing-industry
[5] https://www.chemiscal.com/index_en.html

Table 7
AIoT for food and agricultural manufacturing

Reference	Problem Addressed	Proposed Approach and Methods	Significance
Vermesan et al. [84]	The optimization problem in Soybean Manufacturing	Real-time AIoT scheme; Edge computing: Micro Edge, Deep Edge	Improve system optimization and product quality, reducing energy consumption
Chen et al. [119]	Pests identification from image data	Pests Detection; YOLOv3	Assisting farmers in advance with pests control and operations, reducing crop damage from agricultural pests and raising crop yield
Liu et al. [120]	Food Safety	Proposed 5 layers Internet of Agricultural Things (AIoT) Architecture	The architecture supports the entire management of the food life cycle from production to sale, Trace and trace products, decentralized supply chain
Wang et al. [121]	Inability of farmers to use the existing agricultural information interface	Intelligent IoT-based smart greenhouse application	Replaces the traditional, unfriendly operation interface for farmers
Li et al. [122]	Technology adaptation in agriculture	AIoT platform for Smart Agriculture	Pests detection, intelligent plant disease monitoring,
Shi et al. [83]	Network congestion and energy consumption problems in traditional IoT-based crop monitoring system	AIoT architecture for crop monitoring system(CMS); Edge computing, Deep reinforcement learning (DRL)	Optimize task scheduling and reduce energy consumption
Coppola et al. [123]	Environmental issues due to wine and champagne production	Deep edge AI solution using intelligent sensors, DNNs, LoRaWAN technology	Optimize product quality and reduce energy consumption and deployment costs.

sustainable manufacturing aligned with Industry 4.0, which will influence the future manufacturing process. Therefore, the fundamental research principle of chemical industrial automation is to significantly enrich the use of AIoT across the entire manufacturing process to reduce energy and material use and enhance safety, environmental sustainability, and economic productivity.

4.2.3. Textile and Apparel Manufacturing

The textile and apparel (T&A) industry has also undergone a revolution as a result of AI and IoT, which encompasses a wide range of activities, including design support systems, fashion recommendation systems through sensory evaluation, intelligent tracking systems, textile quality control, fashion forecasting, decision-making in supply chain management or social networks, and fashion e-marketing [127]. Environmental experts have recently expressed severe worries about textile manufacturing, which contributes significantly to global pollution. The slow implementation of sustainability solutions in the textile sector is having negative social and environmental repercussions. IoT sensors and AI algorithms can generate more effective interaction among T&A manufacturing to speed up production. Managing the product life cycle and improving preventive maintenance, re-use, and recycling operations are made possible using data to track and trace product development. Such technologies can assist in up-cycling and recycling used clothing through digital platforms, helping preserve the value of the products while lowering the use of virgin materials. IoT and AI have the ability to speed up prototyping, make predictions, and reduce the number of flaws in the garment business. As a result, sustainable manufacturing is boosted by lowering prototyping waste and increasing and optimizing energy efficiency.

Exchanging accurate data and information among the various processes of T&A manufacturing is crucial to achieving sustainability. This improves resource efficiency and optimization and speeds up material recycling and circulation operations [128]. Furthermore, AI and IoT can assist in the management and optimization of warehouses. Data on product availability in storage facilities and warehouses is transferred to management, which helps in estimating consumer demand and, as a result, reduces the occurrence of unnecessary manufacturing. Products are created in an intelligent manner based on IoT, blockchain, and AI according to market demand. Since these items can be traced, it is possible to monitor their whole life cycle and personalize, improve, and upgrade them in response to user demand [128]. T&A manufacturing can be aided by the use of RFID tags that store all pertinent data about the components and chemicals in the products. RFID tags make it easier to track product availability in stores and analyze customer behaviour and needs. RFID tags can assist in providing precise and real-time data to manufacturers without the need for the involvement of merchants, allowing better judgments to be made when producing goods and offering services to end consumers. AI can improve the transparency, availability, and reliability of data because there is a vast amount of data to be gathered for the lifespan assessment of the items [129]. However, the lack of data availability has made it difficult for decisions to be made within the manufacturing process on the basis of such data. Therefore, AIoT-based applications

Table 8: Smart manufacturing solutions, vendors and their objectives

Vendor	Solution Name	Objectives
Advantech [6]	iFactory smart manufacturing suite	Allows users to monitor machine availability, production status, power consumption, and energy efficiency to increase productivity, decrease loss, and boost profits
Oracle [7]	Smart Manufacturing	Detect, analyze, and respond to IoT signals in factory settings. Enable real-time visibility of asset health, location, and utilization
GE [8]	Proficy Smart Factory (MES) and Brilliant Manufacturing Suite	Intelligent factory management, predictive analytics, improve productivity, execution, and optimization through advanced analytics
Siemens [9]	MindSphere	Predictive maintenance and machine monitoring
Google (partner: ClearObject, Quantiphi, etc.) [10]	Google Cloud Platform, Google Cloud, and Professional Services Organization	Predictive maintenance, remote monitoring, and streaming data analytics, asset tracking
Microsoft [11]	Azure IoT Edge	Predictive maintenance, remotely monitor devices, end-to-end threat protection and security posture management
IBM [12]	IBM Edge Computing Solutions	Infrastructure for data and AI at the edge, deliver edge-enabled industry solutions, automate operations, improve the experience and enhance safety measures
Amazon [13]	AWS IoT Greengrass	Remote monitoring, anomaly detection in precision agriculture, optimized analytics
PTC [14]	ThingWorx	Asset monitoring, digital performance management, scalability, improved quality, and productivity

[6] www.advantech.com
[7] www.oracle.com
[8] www.ge.com
[9] www.plm.automation.siemens.com
[10] cloud.google.com/iot-core
[11] azure.microsoft.com
[12] www.ibm.com/au-en/edge-computing
[13] www.amazonaws.cn/en/greengrass
[14] www.ptc.com/en/products/thingworx

may be the best solution to assist sustainable T&A manufacturing.

4.3. AIoT-based Industrial Toolkits

Data analysis and automated production are two fundamental applications of AIoT technology in manufacturing. Industrial manufacturing benefits from data-analysis-based forecasting, including demand forecasting and predictive maintenance [130]. Therefore, data gathered from industrial contexts has been analyzed using AI technology, including conventional machine learning and deep learning techniques. Existing IoT-based solution providers are now transforming their solutions into AIoT to provide intelligent service for different industrial purposes. Some smart manufacturing tool kits are listed in Table 8.

Siemens developed and launched **MindSphere**[9], an open cloud-based operating system for the Internet of Things (IoT), in 2016. This powerful system allows for the monitoring of machines and facilitates predictive maintenance by integrating data from various sources. MindSphere utilizes artificial intelligence and the Internet of Things (AIoT) technology, enabling the analysis of extensive data and measurements during machine operation. Deep learning techniques and neural networks are employed to optimize systems. Additionally, Siemens collaborated with IBM to enhance MindSphere by incorporating IBM Watson Analytics and additional tools, enhancing its intelligence and capabilities.

To assist sustainable manufacturing objectives, GE has launched the **Brilliant Manufacturing Suite** [8] to improve productivity, execution, and optimization through advanced analytics and the realization of the digital thread. It utilizes big data analytics across the whole product life cycle to improve efficiency in a closed loop from design to production, operations, and maintenance to service—a new breed of data-driven tool. Digital industrial businesses will benefit from intelligent software that can analyze a multitude of data and measurements during operation and combine manufacturing analytics; production losses are reduced, quality is increased, resources are used effectively, and production execution is managed for adaptability, consistency, and repeatability.

Advantech is one of the leading IoT intelligent system brands boosting industry digital transformation. Advantech's **iFactory** [6] smart manufacturing suite offers a WISE-PaaS private server with several integrated applications

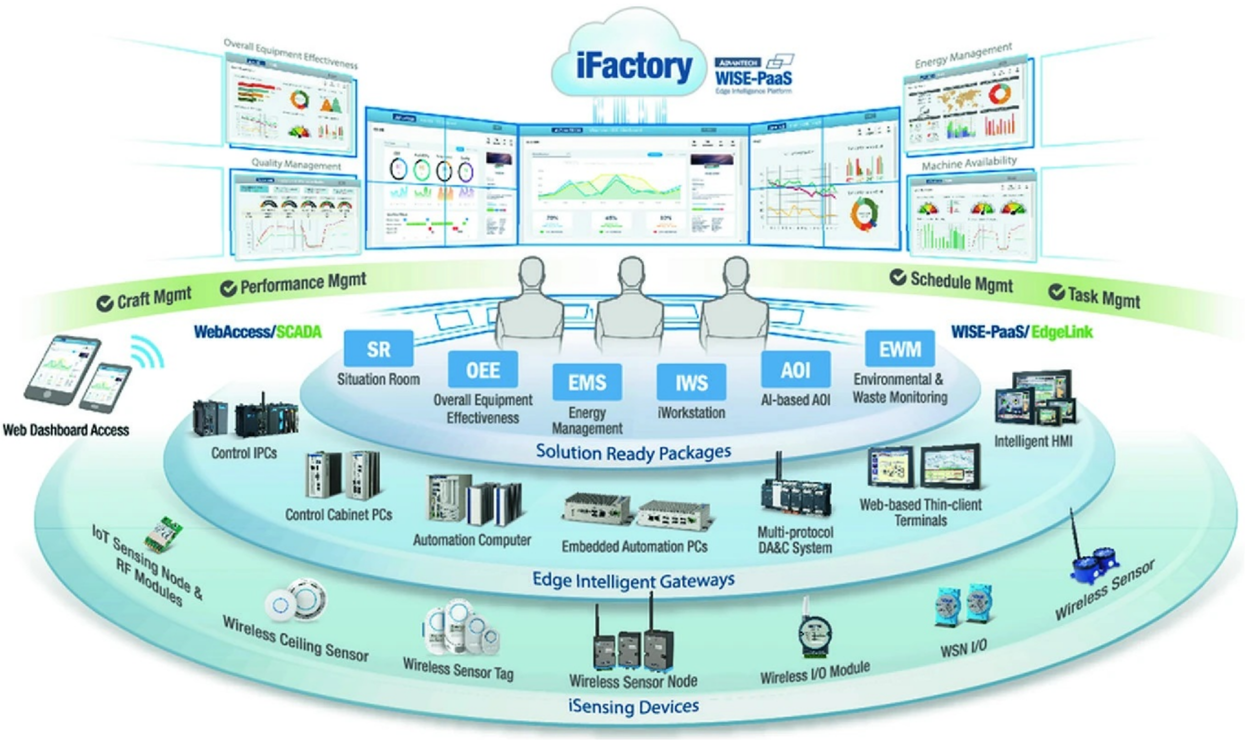

Figure 15: Architecture of Advantech iFactory [131]

designed specifically for industrial users. This remote server includes OEE (Overall Equipment Effectiveness), EHS (Environmental Health and Safety), and EAN (Event, Alarm and Notification) applications, allowing users to monitor machine availability, production status, power consumption, and energy efficiency to increase productivity, decrease loss, and boost profits. The Advantech system also offers immediate event alarms and notifications to inform users of abnormal circumstances in production and enable quick action. The overall architecture of iFactory is shown in Figure 15. Advantech has some long-term and short-term goals to primarily focus on incorporating AIoT technology and fostering the AIoT ecosystem [131].

Alibaba Cloud Intelligence formally introduced **Hardware as a Service (HaaS)** [132], a platform-building tool to assist small and medium-sized business industries in upgrading their AIoT more quickly. This tool was created to assist small and medium-sized AIoT developers to concentrate on their businesses while swiftly putting the pieces of software and hardware together. They can safely move devices to the cloud by doing this.

5. Obstacles and Future Directions

The emergence of AIoT technology is significantly altering the manufacturing landscape. However, the progress of AIoT adaptation in manufacturing sectors is still in the initial stage because of its limitations. In this section, we explore some existing challenges of AIOT-enabled manufacturing and future research directions.

5.1. Open Challenges

Based on the SLR methodology and the comprehensive analysis of the state-of-the-art AIoT-based research, we identified the following challenges of AIOT-based manufacturing that require additional investigation.

5.1.1. Heterogeneous Data Acquisition, Processing, and Information Integration

Smart manufacturing industries use different types of sensors, IoT devices, and other data-acquisition systems to collect real-time data. Other incalculable data are extracted from raw data through complicated production processes, such as industrial activity records, machine logs, performance, the history of the working environment, and so forth.

The manufacturing steps, such as conceptual design, validation, product design, prototyping, testing, and system design, are all interconnected in the process sector, along with storage, usage, transportation, and waste management. Every process has different functionalities. They produce heterogeneous information types in different types of data formats. However, they are interlinked through a network. From the AIoT perspective, the interconnected network system collects data from heterogeneous host devices and sends it to the cloud storage facility, and decisions and forecasting information are returned to the host machines. The information must also be exchanged from agent to agent, system to system, and organization to organization in a manufacturing facility. In the real world, a manufacturing factory's enormous output capability results in the collection of vast amounts of data. As a result, there is a significant need for information processing and storage capability. Additionally, information isolation and integration problems arise in interconnected multiple-process fields. In studying multiple process fields, data is hampered by improper information transmission between various processes. AIoT adoption in the process sector should start with the complex tasks of integrating a wealth of information and creating knowledge bases. However, this data comes from various systems that are hard to connect or integrate, not to mention variations in data formats, sample rates, and data collection techniques. These problems also hamper the integration of safety-related information into the process life cycle. Additionally, the data gathered across multiple life-cycle activities is supported by various disciplines, and combining knowledge and factual data into a coherent system is not easy. Several AI methods such as knowledge graphs [133, 134], deep learning [135, 136], and Bayesian networks [137, 138] have been used to resolve heterogeneous data isolation and integration problems.

5.1.2. Resource Connectivity and Management

Numerous applications, including smart healthcare and smart homes, have been made possible by AIoT advancements. Various sensors and IoT devices are dynamically interconnected through a network used in AIoT systems for collecting data, communicating, and decision driving. It is challenging to carry out latency-sensitive operations on their limited computing resources and power-constrained storage capabilities. The complexity of heterogeneous resources and service environments makes it difficult to predict what will happen. Robust network connectivity with high bandwidth is essential for continuous heterogeneous device connectivity that boosts cost and energy consumption. Therefore, to handle significant AIoT tasks and ensure constant resource connectivity on IoT devices, it is necessary to utilize edge resource orchestration and provisioning, which is also a complex procedure. A joint caching and computing policy was proposed in [139] to reduce bandwidth and energy consumption. Systematic resource coordination methods should be developed to maintain heterogeneous end-device connectivity following various task requirements.

5.1.3. Information Security and Privacy

The provision of information security is one of the main challenges for digitizing manufacturing businesses through AIoT applications. For AIoT-based industrial automation, a variety of physical and digital systems are interconnected to generate and maintain data communication using IoT technology and artificial intelligence for analysis, enabling real-time decision making. However, there is a high risk of increasing the attack level [140]. Vulnerabilities in any of these devices can expose the system to assaults when several machines and devices are linked to single or multiple networks in intelligent processes [141]. AIoT systems need to generate and process large volumes of data. To collect real-time data from different manufacturing units to implement intelligent manufacturing systems, a range of physical IoT devices and digital strategies need to work together, which makes them appealing attack targets [140]. These device vulnerabilities make systems vulnerable to attack when large numbers of machines and devices are connected to single or multiple networks and are intelligently operated [142]. Due to the low cost, IoT devices are typically unsecured and open to cyber attacks, so security assurance becomes a complex problem. The following criteria must be met by an adequate security and privacy assurance method for AIoT: data confidentiality and integrity, user authentication and authorization, service availability, data freshness, forwards and backward secrecy assurance [143]. AIoT system developers must prepare for operational data vulnerabilities at the machine level and organizational system weaknesses. Therefore, manufacturing industries usually rely on intelligent systems to address these security issues. Blockchain technology and federated learning have the potential to be used to create distributed, lightweight algorithms that guarantee security and privacy in the AIoT and assist front-end devices in carrying out the intricate tasks required by security services [143, 144].

5.1.4. Energy Requirements for AIoT Application

AIoT technology is an essential technology in planning mass production, quality control, process control, predictive maintenance, and logistics optimization for smart industries. However, an AIoT infrastructure comprises diverse subsystems based on various industrial manufacturing applications. Each subsystem consists of enormous IoT devices that generate massive amounts of data. A robust network links all the subsystems to maintain continuous communication and interaction by exchanging data among heterogeneous subsystems and cloud data centers. Overall, running the entire AIoT workflow—from storing massive data in the cloud data center to processing complex data using AI techniques for wise decision-making—requires a considerable amount of energy. The exponential rise of cloud computing facilities is similar to the exponential growth of AIoT applications. Therefore, additional efforts are needed to overcome the aforementioned issues by developing lightweight AIoT mechanisms for IoT device connectivity, network data transmission, and processing. Energy use in data centers should be an area of concern.

5.1.5. Inadequate Capabilities/Limitations of Industries

Automation powered by AIoT for sustainable manufacturing is emerging. The future of manufacturing industries is inextricably linked to AI and IoT. Some intelligent applications have already been incorporated in process industries [145], which are insufficient to achieve sustainable manufacturing objectives. It is a complex phenomenon to modernize all manufacturing industries due to their limitations. Some industries can adopt AIoT technology and transform it into smart manufacturing. However, a large proportion of the manufacturing sector is not able to transition to the new trend due to technical limitations [34]. Usually, installed conventional systems are not replaced until they have lost all their value. Investments in infrastructure are typically made with extremely long-term horizons in mind. Decision makers can delay the implementation of AI systems even though they provide new capabilities and increased productivity [25]. To resolve this issue, the AI transformation playbook [146] outlines five steps: execute pilot projects to gain momentum, build an in-house AI team, provide comprehensive AI training, develop an AI strategy, and finally, develop internal and external communications.

5.2. Future Directions

The IoT is a technology that supports people in rethinking their daily lives. However, the underlying driving force behind IoT's full potential is AI. The growing partnership between AI and the IoT suggests that a more innovative future may be closer than first envisioned, from the most basic manufacturing applications to its vast potential through industrial and urban development. The results of our study show that it is essential that manufacturing industries incorporate AIoT solutions to improve production processes, product quality, machine control and efficiency, supply chain management, and predictive maintenance. We also discovered that AIoT assists industries in implementing Industry 4.0 practices. Future research might explore the effects of AIoT approaches in Industry 4.0 from a sustainable manufacturing perspective, which would be of greater interest. It would also assist in providing detailed instructions on how AIoT technology might be advantageous for sustainable manufacturing. Additionally, the following directions can help to understand the research improvements needed for future AIoT solutions in manufacturing industries.

5.2.1. Real-time AIoT-based Manufacturing Datasets for Domain-specific Research

Deriving accurate decisions requires having access to enough correct information. Massive manufacturing data is generated from low-cost IoT devices, which can assist intelligent systems in understanding the current manufacturing progress and machine conditions and making better judgments. However, IoT applications can be restricted by the absence of efficient data analysis. Before constructing an intelligent AIoT-based framework, a problem-specific data production plan is crucial from the perspective of system analysis. Since AI is a vital component of AIoT frameworks, none of the AIoT solutions will perform one hundred percent accurately. Still, some error or biasing opportunities must be considered (i.e., wrong prediction or biased decisions). AI-based systems frequently fall victim due to insufficient training data. If the algorithms are flawed, AIoT applications will provide incorrect forecasts. It could also have unjust outcomes and hinder the manufacturing process. Therefore, real-time AIoT-based task-specific manufacturing datasets are essential for testing and training the AIoT framework to measure system feasibility. Then, more research will be possible on manufacturing datasets to develop accurate decision-driven algorithms for task-specific AIoT-based manufacturing applications.

5.2.2. Decentralized AIoT Architecture for Private and Secure Computing

A decentralized AIoT architecture transfers data and services from network nodes to edge nodes for processing and decision making. Edge nodes process data faster and share it more efficiently since they are closer to the client terminal device. Due to the attributes of IoT sensors, such as cost, size, and power, sensor systems are attractive for various applications, even though they frequently lack quantifiable functionality. So, to compare and assess how sensor systems and reference data interact, standard data transfer protocols need to be designed to handle data transmission from the edge node to the cloud and vice-versa. The issues of protecting data privacy and secure computing are difficult to handle given the rapid growth of AI and IoT technologies. Intelligent IoT devices must exchange data using the finest encryption techniques to prevent manufacturing data leakage. Additionally, authentication protocols are required to achieve mutual authentication between communication entities (i.e., IoT devices, cloud servers, and manufacturers). To prevent unauthorized parties from accessing the system, future research should focus on implementing blockchain architecture for access control measures to ensure data privacy. Integrating blockchain technology with AIoT can be viewed as a naturally beneficial and promising area of research. Therefore, everything must be made apparent to the system's programmer. As a result, research projects should be conducted to enhance the privacy of the AIoT framework.

5.2.3. Lightweight AI Algorithms for Edge or Resource-restrained Devices

Edge computing plays a crucial role in enabling the widespread adoption of AI services, particularly in resource-constrained AI devices used for manufacturing. The limited availability of resources in most IoT devices poses a challenge when it comes to handling complex AI activities in AIoT applications. In order to efficiently manage decision-driven processes in AIoT operations, it becomes essential to offload them to cloud and edge computing platforms that offer abundant resources. However, further research is needed to develop lightweight AI algorithms tailored for edge and resource-restrained devices. These algorithms would not only promote energy-efficient operations in machining processes but also minimize energy consumption at the intelligent service end, specifically in addressing big data analysis within the industrial domain.

5.2.4. Systematic Evaluation of AIOT Systems

In the future, researchers can compare the effectiveness of different AI techniques in solving specific manufacturing problems. In addition, it is essential to systematically evaluate the trustworthiness and ethical implications of AIoT systems, which are a rapidly growing field. The systematic evaluation of AIoT systems should consider the accuracy of the data used to train the system, the transparency of the algorithms used in the system, the security of the system, the privacy of the data collected by the system, the potential for bias in the system, the fairness of the system, and the accountability of the system. As a result, systematic evaluation ensures that the AIoT systems are safe, reliable, fair, and ethical. This will help to build trust in AIoT systems and promote their responsible development and deployment. Moreover, it is essential to assess what changes and actions are needed to align the objectives of Industry 4.0 with sustainable manufacturing by changing existing manufacturing patterns with AIoT applications.

6. Conclusion

As digitalizing manufacturing industries are becoming increasingly significant to achieve sustainable manufacturing goals, the intelligence of IoT devices, known as AIoT, integrates AI methodologies into IoT devices to improve IoT operations and data analysis. Until now, AIoT has been implemented in manufacturing industries for multiple purposes, from promoting productivity, machine efficiency, and product quality to decreasing total energy consumption and enhancing knowledge-based maintenance and predictions. These AIoT-based solutions eventually cut off production and labor costs, reduce environmental pollution, and make manufacturing industries more intelligent overall. In this work, we thoroughly analyzed the important contributions and prospects of state-of-the-art efforts on AIoT-based applications. As more productive and efficient AIoT-based manufacturing solutions are to appear and attract the increasing interest of researchers and businesses, this survey provides a comprehensive overview of the area. It pinpoints the remaining pain points and future directions for future researchers.

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