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Research Article

Impact of IoT Technology Implementation in the Manufacturing Sector: A Systematic Literature Review

Rama Dani Eka Putra [1,*], Tessa Zulenia Fitri [2], Helmizar [1], Khotso Shai [3], Nia Arfina Foci [2], M. Arif Yunanda [1], Muhamad Yasin [1], Handi Wilujeng Nugroho [4], Fuad Dwi Hanggara [5]

[1] Department of Mechanical Engineering, Universitas Bengkulu, Bengkulu, Indonesia
[2] Department of Industrial Engineering, Universitas Bengkulu, Bengkulu, Indonesia
[3] Department of Mechanical and Mechatronics Engineering, Lerotholi Polytechnic, Maseru, Lesotho
[4] Logistic Engineering Programme, Universitas Sains dan Teknologi Indonesia, Pekanbaru, Indonesia
[5] Mechanical Engineering, UIN Maulana Malik Ibrahim Malang, Malang, Indonesia

*Corresponding Author: rdputra@unib.ac.id

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ABSTRACT

The rapid development of IoT research in various fields has promoted the evolution of manufacturing in the Industry 4.0 context. However, the growing and dispersed literature makes it difficult to see the dominant trends and open challenges. The aim of the study is to synthesize the existing IoT research in the manufacturing, by analyzing the sectoral adoption, enabling technologies and implementation objectives. The review develops a systematic understanding of the links between manufacturing sectors, IoT technologies and operational priorities to identify dominant research directions and gaps for future research. A systematic literature review was conducted according to the PRISMA guidelines, screening and analysing peer-reviewed studies along three analytical dimensions: distribution by manufacturing sector, typologies of IoT technologies and strategic objectives of implementation. The analysis identified shared adoption patterns in some manufacturing sectors, common use of sensor-based and cloud-enabled technologies, and a high emphasis on productivity, monitoring and efficiency of operations. The results reveal a significant concentration of IoT research in discrete manufacturing, as well as noticeable attention in process manufacturing, healthcare and general manufacturing, while other sectors remain less explored, indicating an uneven research focus across industries. In terms of technology, Industrial IoT and smart manufacturing solutions are the most common, followed by IoT-enabled digital twin technologies, while the combination of IoT with artificial intelligence, machine learning, and computer vision indicates a growing shift towards more adaptive and intelligent systems. A smaller portion of IoT implementations are related to sensors and monitoring applications, blockchain enabled IoT solutions and distributed architectures, while middleware and system integration appear least often. Regarding implementation objectives, efficiency enhancement is the main driver, followed by predictive maintenance, quality control and productivity enhancement, and real-time monitoring, showing a strong orientation toward improving operational performance. In summary, the synthesis implies that the IoT research in manufacturing is mainly focused on discrete manufacturing applications, operational efficiency objectives, and intelligent automation technologies. The concentration indicates a continued research focus on production optimisation, while broader contexts of industrial integration are relatively underexplored.

Keywords: Internet of Things (IoT), smart manufacturing, digital twin, enabling technologies, Industry 4.0, systematic literature review

INTRODUCTION

As Industry 4.0 drives the digitalization of manufacturing and production becomes ever more reliant on interconnected and data intensive systems, efficiency and security resilience are paramount. The manufacturing industry is under increasing pressure to improve operational efficiency and manufacturing integration through digital technologies and automated manufacturing systems [1], [2], [3], [4], [5]. Efficiency is not just related to the reduction of cost and time, but also to the optimal use of resources and improving the overall productivity [6]. Security also has a major role to play in ensuring the continuity of operations and at the same time reducing the risks of technical failures and cyber threats [7]. In Industry 4.0, the automation with IoT improves the data transparency and closed-loop control, altering the nature of the response of manufacturing systems to the operational challenges [8], [9].

The rapid advancement of IoT in the manufacturing environments has brought innovative solutions boosting the efficiency and security at once. IoT allows to collect data in real time, to analyse it by AI, and to automate processes, all of which leads to more lean operations and improved safety at the workplace [10], [11], [12]. Its practical uses include real-time monitoring of machine conditions, automation of production processes and increased transparency in supply chain management [13], [14]. For instance, it has been demonstrated that the IoT-enabled analytics can enhance operational efficiency up to 30%, primarily through reducing the downtime of equipment and energy usage [6]. These results are consistent with findings from high impact manufacturing and IoT studies, showing that the real-time data acquisition and predictive analytics enabled by IoT architectures lead to a significant enhancement of asset utilisation and energy efficiency in smart manufacturing settings [7]. In addition, IoT based sensors have been a foundation for predictive maintenance to reduce unplanned downtime and extend equipment lifespan [11].

Although the use of IoT in manufacturing systems is growing, its implementation is still struggling with the interconnected problems of system integration, operational reliability, and cyber-security. Seamless integration, cybersecurity vulnerabilities and the costly retrofitting of legacy systems together with high technical debt are driving capital investment. The increasing complexity of such systems only raises the demand for skilled personnel able to cope with heterogeneous cyber–physical infrastructures. These interdependent constraints limit the scalability and sustainability of the IoT-enabled manufacturing systems [9], [10]. The problem of cybersecurity is still here, as IoT infrastructures are more and more exposed to the risks of data breaches and hardware sabotages [7]. Recent studies have explored the application of blockchain-based security schemes and AI-based intrusion detection systems for improving security and resiliency of industrial IoT environments especially in manufacturing automation systems [15], [16]. These approaches have shown promise for improving data integrity, anomaly detection and real-time mitigation of threats within interconnected production networks. However, current studies are more fragmented in terms of the individual technologies or individual case applications. However, there is no comprehensive synthesis and comparison of these security approaches for manufacturing-oriented industrial IoT. This review intends to fill this gap by systematically reviewing and assessing the available literature evidence. Manufacturers still struggle to optimise the use of equipment, minimise downtime and meet sustainability imperatives from an efficiency perspective [17].

The internet of things has become a major technological enabler for digital transformation initiatives in manufacturing environments by providing real-time data acquisition, predictive maintenance, process monitoring and interconnected production systems [18], [19]. These capabilities not only reduce the machine downtimes but also improve the work place safety by detecting anomalies and mitigating hazards [14], [20]. Additionally, the IoT-based automation offers dynamic process control and smart asset management. Blockchain-based cybersecurity models ensure data integrity and protection from unauthorized access [21].

The urgency of this study therefore resides in the limited knowledge about the association between the enhancements in operational efficiency enabled by IoT in manufacturing on the one hand, and the adoption of security mechanisms and integration strategies in the different implementation contexts on the other hand. In this study, a systematic literature review is conducted to gather the results of studies on operational efficiency, security approaches, and system integration challenges of IoT-enabled automation in manufacturing. The goal of the review is to structure

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and evaluate the existing findings critically, not to suggest a new framework. This will help to clarify the directions that the current research is taking and what gaps remain in the studies of industrial IoT implementation. The findings provide practical insights for industrial stakeholders by highlighting commonly adopted IoT approaches, operational objectives and security considerations that may assist future implementation planning and research development [8], [9], [10].

METHODS

Protocol

The systematic literature review (SLR) was performed based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, which provide a structured approach to identification, screening, eligibility and reporting of systematic reviews [22]. This a priori protocol was developed to ensure methodological rigour and transparency. The protocol indicated the aims of the review, the research questions, the criteria for the inclusion of studies, the search strategy used in a number of scholarly databases, and the process of selection, extraction and synthesis of the studies. The review protocol and search strategy were explicitly defined based on the Scopus database, following the recommended practices for systematic reviews in engineering and computer science [23]. This also improved transparency, accountability and reproducibility. The review protocol was prospectively registered with the Open Science Framework (OSF) and is available at https://osf.io/d6mnf. All changes from the original plan were documented and justified to preserve the integrity of the research process.

Eligibility Criteria

A Studies are only eligible for inclusion if they meet the following criteria: only articles published in peer-reviewed journals and conference proceedings are eligible, and conference papers are accepted as they are a common way to disseminate novel and peer-reviewed research in the areas of engineering and IoT; moreover, a full manuscript in English should be available for rigorous critical assessment, although this criterion is necessary for practical and methodological reasons, it can cause language bias and might result in the exclusion of relevant studies in other languages; in addition, studies must explicitly investigate automation, production, or assembly lines involving IoT technologies, and these may be empirical studies, simulation-based approaches, conceptual frameworks or applied case studies; furthermore, IoT's role needs to be clearly discussed in the context of automation lines e.g. enabling machine-to-machine communication, sensor and RFID integration, cloud/edge connectivity, predictive maintenance, real-time monitoring or smart manufacturing systems; finally, to be consistent with the review scope, interdisciplinary studies were included only if their IoT-enabled automation or integration mechanisms can be directly related to manufacturing systems, industrial operations or production-oriented environments.

Studies will be excluded if they meet any of the following criteria: excluded are publications like book chapters, dissertations, reports, white papers or trade magazines, as these are not peer-reviewed research outputs; furthermore, studies where the full text is not accessible in English will be excluded; in addition, articles that address IoT in non-related domains (i.e., smart homes, general IoT frameworks) or articles that discuss automation lines without IoT integration will be excluded; moreover, papers that are solely related to software engineering, computer science or networking architectures without direct relevance to industrial or manufacturing automation lines will be excluded; finally, preprints, works in progress, and other unreviewed documents will be excluded as the results and methods have not yet been verified by peer review.

The research questions for this SLR are as follows: RQ1. What are the main cybersecurity challenges reported in Industrial IoT-based manufacturing environments? and RQ2. What security solutions have been proposed to address these challenges? and RQ3. What research gaps remain in the current literature?

Information Sources

A number of scholarly databases were employed to ensure that the relevant literature was fully covered. The main sources were Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink and ACM Digital Library, as these repositories are known for their large indexing of engineering, industrial automation and computer science research [24]. An additional search on Google Scholar was performed according to PRISMA, using a structured keyword string that mirrored the primary database strategy. We screened retrieved records against pre-defined inclusion and exclusion criteria and excluded duplicate entries. Eligible studies were then added to the primary pool of studies for full-text assessment of eligibility, to maintain transparency and methodological consistency. In addition, backward and forward citation tracking was conducted on the reference lists of included studies to identify other relevant publications. This multi-pronged approach guaranteed a larger retrieval of evidence and reduced the risk of missing relevant contributions in the field of IoT-enabled automation lines.

Search

A comprehensive search strategy was developed to maximize retrieval sensitivity and specificity Boolean operators and controlled vocabulary terms were modified to the syntax of each database. The main concepts were “automation industry” and “Internet of Things (IoT)”, and their synonyms, such as “production line”, “assembly line”, “manufacturing line” and “Industrial IoT (IIoT)”. For example, the search string used in Scopus was developed based on pilot searches and a review of the most commonly used terms in the industrial IoT literature to increase sensitivity.

The final search string was developed in the following way:

("manufacturing" OR "manufacturing system*" OR "production system*" OR "production line*" OR "assembly line*" OR "automation system*" OR "industrial automation" OR "smart manufacturing" OR "smart factory") AND ("Internet of Things" OR IoT OR "Industrial Internet of Things" OR IIoT OR "cyber-physical system*" OR "industrial IoT")

Results were limited to peer-reviewed journal articles and conference proceedings in English. The literature search was performed between January 2015 and December 2025. All search queries, database names and retrieval procedures were documented to ensure transparency and reproducibility of the systematic review process [25].

Evidence based Sources Selection

Evidence selection was performed according to the PRISMA 2020 workflow (Figure 1). All records retrieved from the databases were first imported into a reference management software and duplicate entries were removed. The screening was carried out in two phases; (i) title and abstract screening to exclude not relevant studies and (ii) full text assessment to define eligibility criteria. Screening was performed independently by two reviewers to avoid bias and disagreement was resolved by discussion or arbitration by a third reviewer. Reasons for exclusion in the full-text screening phase were explicitly documented using standardized categories such as no explicit focus on the Internet of Things, non-manufacturing application contexts, and no primary empirical or technical contributions. These reasons were reported as appropriate in the PRISMA flow diagram and summarized in an accompanying table to improve transparency and reproducibility. We used the PRISMA 2020 flow diagram to report study selection. Records identified from bibliographic databases and other sources were clearly separated. The processes of removing duplicates, screening, assessing eligibility and the final inclusion were clearly reported. This modified structure guarantees transparency and adherence to the PRISMA 2020 reporting guidelines of systematic and reviews in engineering research [22] (Fig. 1).

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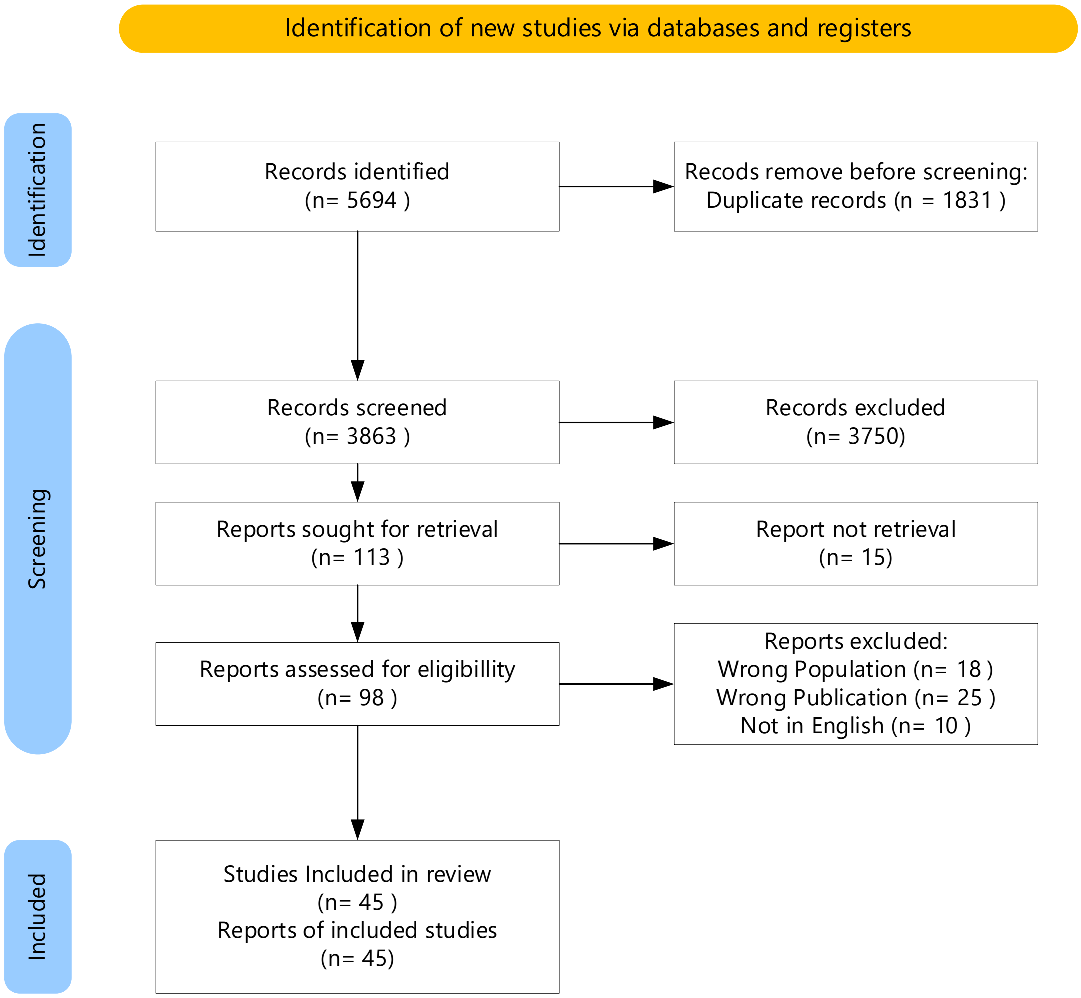

Figure 1. PRISMA Flow Diagram

Data Extraction Process

To ensure consistency and reliability, a structured data extraction form was developed and piloted. Data from each of the included studies were extracted independently by two reviewers and included bibliographic, methodological and technical details and reported outcomes. Consensus was used to resolve disagreements to minimize bias in extraction. The extracted data were tabulated in a standard spreadsheet to allow for comparison across studies and thematic synthesis. This approach ensured that relevant information was systematically captured as suggested by systematic review practices in engineering research [26].

Data Items

The data were collapsed into four broad areas. The bibliographic data included: first of all, the names of the authors, the year of publication, the country of origin and the type of publication. Secondly, the review protocol data consisted of the study design and methodological approach, study objectives. Third, search data included details on search terms used, databases searched, search dates and filtering strategies. Fourth, the source data provided specific technical data on the implementation of IoT in automation lines such as system architecture (e.g., edge, cloud, or hybrid computing), communication protocols (e.g., MQTT, OPC-UA, or Modbus), application areas (e.g., predictive maintenance, quality control, monitoring, and energy optimization), implementation environment (e.g., laboratory prototype, pilot study, or industrial deployment) and reported performance results (e.g., downtime reduction, throughput improvement, latency, and scalability). Furthermore, a light-touch quality appraisal was carried out during the data extraction to evaluate the rigour of the studies based on the criteria of the clarity of the description of the system, the validity of the performance metrics, the reproducibility of the experimental setup and relevance to real-world manufacturing contexts. Systematic documentation of challenges and limitations such as interoperability, cybersecurity, and integration costs was also conducted. The data collection at such a comprehensive level allowed for robust synthesis and identification of research trends.

Synthesis of Results

A narrative thematic synthesis was used due to heterogeneity of study design, outcome measures and context. An initial coding framework was developed inductively from a subset of studies included in the review and refined iteratively with ongoing review of additional evidence. The framework was then applied systematically to all studies and the themes were consolidated by discussion between reviewers to reach consensus and ensure consistent interpretation. The studies analyzed in the review were classified according to the following thematic categories: (1) system architectures, (2) technological components, (3) application domains, (4) performance outcomes and (5) challenges and limitations. The thematic synthesis found hybrid edge-cloud architectures common, MQTT and OPC-UA as the most used communication protocols and the widespread application of IoT in predictive maintenance and real-time monitoring. Reported results included reduced downtime, improved overall equipment efficiency (OEE) and enhanced process transparency. However, a series of studies kept highlighting the ongoing issues such as cybersecurity threats, interoperability between legacy systems and IoT platforms and costly integration. This synthesis provides a comprehensive knowledge base and identifies key research gaps such as lack of standardized metrics to evaluate performance, limited number of longitudinal studies on industrial scale deployments and need for more cost-benefit analysis. The findings can be of great help to future research and industry practice of IoT enabled automation lines.

RESULTS AND DISCUSSION

RQ1: What are the main cybersecurity challenges reported in Industrial IoT-based manufacturing environments?

The internet of things (IoT) has revolutionized the manufacturing industries by enabling real-time data collection, predictive analytics and adaptive control of processes in automation lines (see Appendix). IoT solutions link machines, sensors and enterprise platforms to create a seamless cyber-physical production system that supports the principles of Industry 4.0. The rate of adoption varies from one industrial domain to another. However, empirical evidence shows a generic trend of moving towards IoT-enabled automation lines, triggered by the need of cost efficiency, sustainability and operational excellence [14],[27].

Analysis of the 45 reviewed studies shows that IoT adoption in manufacturing automation is mainly oriented towards discrete manufacturing systems (51%), followed by healthcare manufacturing (9%) and general manufacturing (9%). The findings suggest that IoT applications are not uniformly distributed across manufacturing sectors, and that the operational characteristics and complexity of each production system strongly affect adoption patterns. The studies reviewed were grouped into eight manufacturing-related categories, according to the industrial setting and the IoT application context presented in each article, to organize the evidence base (Figure 2). These include discrete manufacturing, healthcare manufacturing, general manufacturing, process manufacturing, agriculture manufacturing, energy and environmental manufacturing, advanced manufacturing and construction manufacturing. The distribution of the studies proportionally indicates that discrete manufacturing represents 51%

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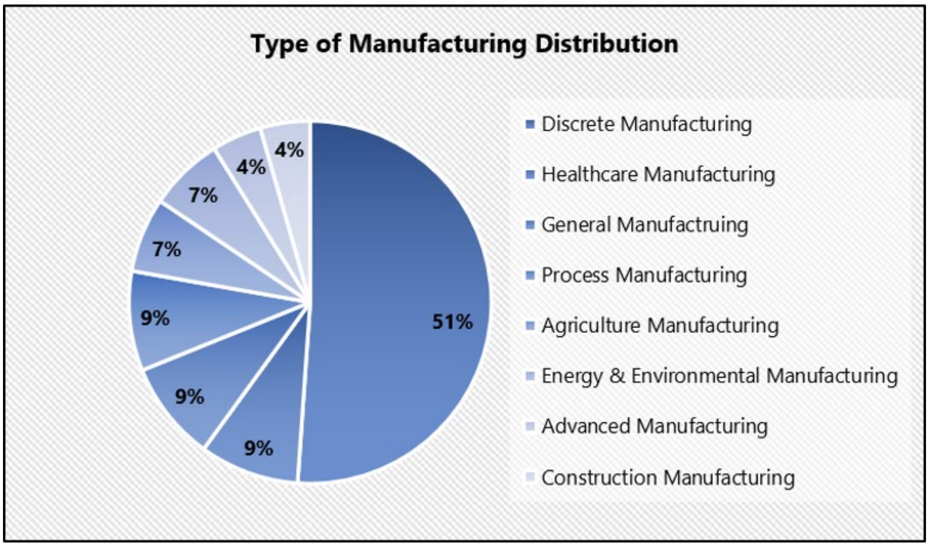

Figure 2. Type of Manufacturing Distribution

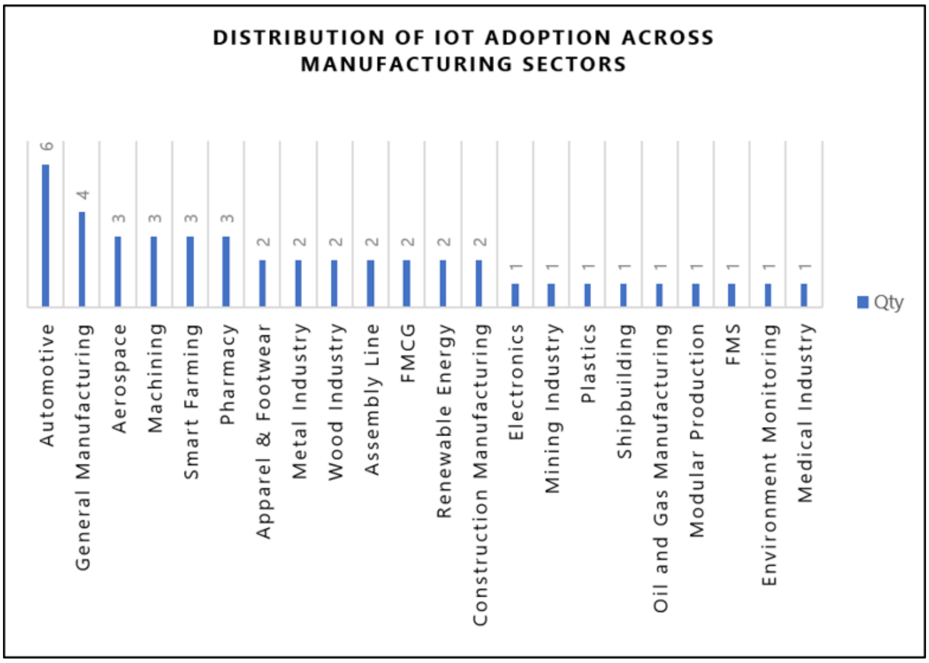

Figure 3. Distribution of IoT Adoption Across Manufacturing Sectors

(23 articles), healthcare manufacturing 9% (4 articles), general manufacturing 9% (4 articles), process manufacturing 9% (4 articles), agriculture manufacturing 7% (3 articles), energy and environmental manufacturing 7% (3 articles), advanced manufacturing 4% (2 articles) and construction manufacturing 4% (2 articles) (Figure 3).

Discrete Manufacturing (51%, 23 articles)

Discrete manufacturing is the production of discrete items that can be counted individually, assembled or disassembled, such as cars, airplanes, electronics, machinery. This is the most explored category of IoT adoption and it requires high flexibility, precision and traceability. Examples include real-time monitoring, predictive maintenance and digital twin integration and smart factory automation [33], [55], [66].

Healthcare Manufacturing (9%, 4 articles)

Healthcare manufacturing includes design, production and validation of medical devices, equipment and pharmaceutical instruments. This is an area subject to stringent regulatory requirements, high safety standards and the need for sterilisation monitoring and traceability. IoT applications are concerned with smart production integration, real-time quality validation and compliance with international medical standards [19], [50].

General Manufacturing (9%, 4 articles)

General manufacturing covers a wide range of industrial activity that is not narrowly defined by a specific sector. It normally contains assembly line system and generalized production process. The IoT adoption in this domain enables lean digitalization, waste reduction and energy optimization. Assembly line utilises robotics, computer vision and sensor technologies to increase throughput and efficiency [32], [72].

Process Manufacturing (9%, 4 articles)

Process manufacturing is the manufacture of goods by use of a continuous or batch process. Process manufacturing often involves chemical, thermal or biological transformations. Industries represented include pharmaceuticals, oil and gas, mining and fast moving consumer goods (FMCG). IoT integration in this sector enables continuous monitoring of processes, ensures GxP compliance and predictive analytics to improve product consistency and visibility across the supply chain [36], [52].

Agriculture Manufacturing (7%, 3 articles)

Agro-manufacturing, or agriculture manufacturing, is the use of machinery and technology to transform agricultural inputs into food and bio-based products. IoT applications, for example, are focused on precision farming with soil monitoring, automated irrigation and pest detection, all of which support sustainable production and efficient resource utilization [49], [54].

Energy and Environmental Manufacturing (7%, 3 articles)

This involves industries for renewable energy systems production (e.g., wind turbines, solar panels) and environmental monitoring technologies. It is characterized by the integration of IoT with predictive maintenance, smart grids, and sustainability monitoring. Applications such as air quality assessment, water management and carbon emission reduction are provided to ensure industrial production complies with environmental regulations [64], [70].

Advanced Manufacturing (4%, 2 articles)

Advanced manufacturing is a production system that employs emerging technologies such as robotics, cyber-physical systems, and cloud-based platforms to achieve adaptability, flexibility, and high customization. As a backbone technology for modular production systems and flexible manufacturing systems (FMS), IoT provides real-time data exchange, system reconfigurability and adaptive decision-making [67].

Construction Manufacturing (4%, 2 articles)

Construction manufacturing is the industrial production of building materials, prefabricated elements and structural assemblies. IoT applications in this area are typically large scale projects with long life cycles, such as process monitoring, quality assurance or adoption of digital twin for construction site integration [31], [71].

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The findings reveal that previous IoT research in manufacturing is mainly focused on discrete manufacturing systems, followed by process and hybrid manufacturing environments. However, the number of studies related to IoT applications in the manufacturing sectors of healthcare, agriculture and construction is very low. Process, energy and advanced manufacturing are promising areas for future research which include integration of IoT with artificial intelligence and digital twin framework. Together, these results confirm the transformative role of IoT in multiple manufacturing sectors, but also highlight the need for more balanced exploration across underrepresented sectors.

RQ2: What security solutions have been proposed to address these challenges?

Internet of Things (IoT) technologies have been extensively used in the context of industrial transformation to smart manufacturing as a major driver for operational efficiency, production flexibility and real-time data-driven decision making. In manufacturing, different IoT solutions are used to link the physical and digital worlds, track the condition of machines, optimize workflows, predict failures, and improve product quality. As the need for automation and complex connectivity increases, IoT deployment is moving beyond data collection from simple sensors to include integration with artificial intelligence, digital twins, edge computing and blockchain-based security solutions. For instance, CNN based IoT machine vision systems have been proposed for real-time inspection and decision making on the production floor [28], and other works have suggested computer vision based IoT systems to improve the automated monitoring and quality control in manufacturing environments [32]. This highlights the broad and complementary set of IoT technologies used in manufacturing, and their strategic importance in building a smarter, adaptive and competitive industrial ecosystem.

Figure 4 shows the distribution of the Internet of Things (IoT) technologies applied in the manufacturing processes based on a literature-based analysis. The results show that Industrial IoT (IIoT) and Smart Manufacturing have the highest share of ~30% (14 studies) indicating that automation, machine integration and real-time production management are the major areas of interest for IoT implementation in industrial settings. The IoT-enabled Digital Twin, with about 22% (10 studies), is the next one, which points to the increasing importance of virtual modeling of systems and real-time simulation in optimizing production processes. Similarly, 20% (9 studies) of IoT + AI/ML + Computer Vision is used highlighting the importance of intelligent analytics and visual recognition to improve

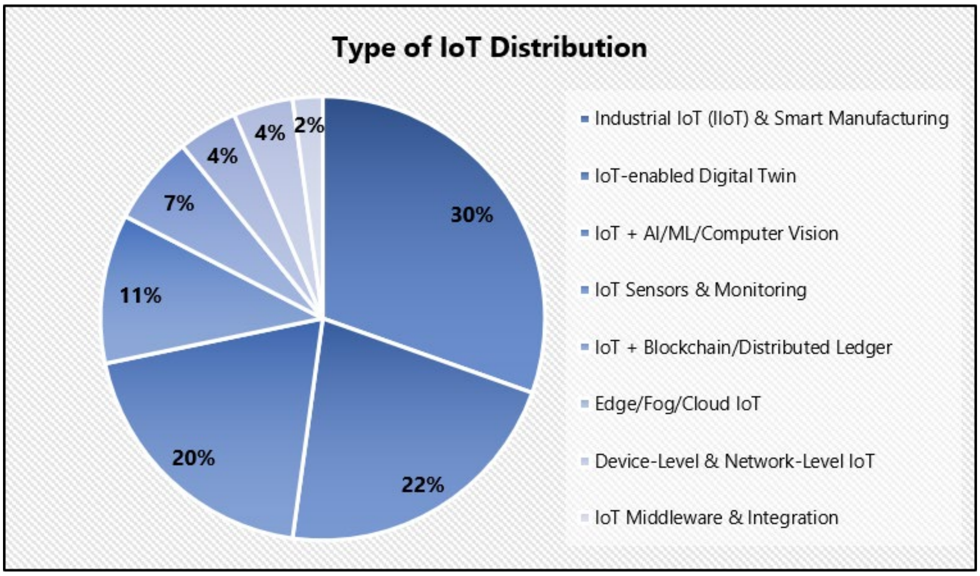

Figure 4. Distribution of IoT Types in Manufacturing Automation

Table 1. Type Industrial IoT (IoT+ AI/ML/Computer Vision)

Author	Implemented IoT	Classification
[28]	IoT-enabled machine vision with CNN	IoT + Computer Vision (AI/ML)
[32]	Computer vision system	IoT + Computer Vision
[33]	Machine learning algorithms	IoT + AI/ML
[34]	Machine learning / data mining	IoT + AI/ML
[39]	Machine learning, Data mining techniques	IoT + AI/ML
[62]	IoT-enabled computer vision (STEP-NC, MQTT, Raspberry Pi, OpenCV)	IoT + Edge AI + CV
[63]	IoT-enabled AI object detection & image processing	IoT + AI/ML + CV
[68]	IoT-enabled deep learning with computer vision (Mask R-CNN, CLAHE, Kalman filtering)	IoT + Deep Learning + CV
[64]	IoT-based PV monitoring with AI fault detection	IoT + AI for Energy Systems

accuracy, decision making and operational efficiency. 11% (5 studies) Research on IoT Sensors and Monitoring It shows the importance of sensor networks for data collection and monitoring of the status of the manufacturing systems.

Other categories such as IoT integrated with Blockchain/Distributed Ledger (7%), Edge/Fog/Cloud IoT (4%), Device-Level and Network-Level IoT (4%), IoT Middleware and Integration (2%) had lower adoption rate but still important for data security, system scalability, network interoperability and seamless integration. The results give a comprehensive view of the heterogeneity and complementarity of IoT adoption in manufacturing with a strong emphasis on automation, digitalization and intelligent data management to improve industrial performance, resilience and competitiveness.

Type of Industrial IoT: IoT + AI/ML/Computer Vision

Figure 1 displays the types of IoT technology identified in the reviewed studies. The results suggest that the largest share of implemented systems reported are the ones integrated with artificial intelligence (AI), machine learning (ML) and computer vision (CV) within the IIoT systems, followed by traditional IIoT architectures without advanced analytics and a smaller share of sensor-based IoT systems for basic monitoring functions. Table 1 summarizes that AI and ML enabled IIoT applications are mainly used for predictive maintenance, anomaly detection and production optimization using real-time and historical data streams. Computer Vision is mainly used for automated quality inspection and defect detection in discrete manufacturing environments. The other hand, the IIoT implementations without advanced AI components (shown in Table 6) are mainly supporting condition monitoring, asset tracking and energy management. Basic sensor-based IoT systems are often deployed at pilot-scale or laboratory settings with limited integration to enterprise-level decision support systems. These distributions indicate that the convergence of AI, ML, and CV with IoT has become a dominant trajectory in the evolution of IIoT driven by the need for autonomous decision-making and scalable data-driven optimization in manufacturing automation.

This hybrid approach utilizes real-time sensor data acquisition, edge or cloud computing and intelligent algorithms to facilitate predictive, adaptive and autonomous decision-making in manufacturing systems. AI/ML + IoT. The studies reviewed in Table 1 reveals three major patterns. Several works [33], [34], [39] are devoted to the integration of machine learning and data mining algorithms into the IoT ecosystems. These implementations allow sustainable production and better resilience of the system, improving pattern recognition, anomaly detection and predictive maintenance. CV + Io T Other studies [28], [32] focus on the integration of IoT with vision-based inspection and

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monitoring systems. IoT-enabled computer vision based on the convolutional neural network (CNN) and real-time imaging improves defect detection, quality assurance and automation in assembly line and discrete manufacturing processes.

IoT + Hybrid AI/ML + Computer Vision, Many contributions are based on a hybrid approach where IoT is the backbone for data acquisition and AI/ML and CV are the analytical engines [63], [68]. These works show advanced implementations (e.g. deep learning for object detection (Mask R-CNN, Kalman filtering)) and AI-based fault detection in renewable energy systems [64]. Further, architectures such as edge-based architectures [62] show the trend towards decentralized intelligence where IoT devices with ML algorithms embedded on them, perform near real-time decision making on the shop floor. The case is being made that IoT with AI/ML and Computer Vision is one of the most transformational paradigms in industrial digitalization. This convergence opens up possibilities for real time process monitoring, autonomous fault detection and adaptive production control in different manufacturing environments. The IoT provides the infrastructure for ubiquitous sensing and connectivity while AI/ML and CV extend its capability towards intelligent perception, predictive and decision making. Overall, these investigations demonstrated the importance of IoT + AI/ML + CV to the achievement of smart factories and Industry 4.0, notably in areas where accuracy, quality assurance and operational resilience are pertinent.

The Internet-of-Things (IoT) enabled Digital Twin (DT) has emerged as an important pillar of Industrial IoT (IIoT) applications, providing a dynamic virtual representation of physical assets, systems and processes through continuous synchronization between real-time sensor data and digital simulation models. This integration dramatically improves situational awareness, predictive power and decision-making accuracy in the industrial sectors. Recent studies (see Table 2) show that IoT-enabled DT architectures are the underlying framework for real-time synchronization, predictive maintenance and operational optimization [48], [53]. In particular, IoT-enabled DT has been used in agriculture for smart farming with sensor integration and predictive analytics [49] and in healthcare for real-time validation of patient data and compliance with regulatory standards [50]. The DT is used in automotive for vehicle performance simulation and safety monitoring [51] and in industrial processes for sensor-based monitoring and advanced analytics to improve operational efficiency [52]. Environmental monitoring has also benefited from DT enabled by IoT through the integration of sensor networks with predictive modeling [54].

Table 2. Type Industrial IoT (IoT-enabled Digital Twin (DT))

Author	Implemented IoT	Classification
[43]	IoT-enabled digital twin with augmented reality integration	IoT + DT + AR
[48]	IoT-enabled digital twin systems integrating sensor data and simulation	IoT + DT
[49]	IoT-enabled digital twins integrating sensors, farm data, predictive analytics	IoT + DT (Agriculture)
[50]	IoT-enabled digital twins integrating patient data, medical devices, predictive analytics	IoT + DT (Healthcare)
[51]	IoT-enabled digital twin systems integrating sensors, vehicle data, simulation	IoT + DT (Automotive)
[52]	IoT-enabled digital twin systems integrated with sensors, process monitoring, analytics	IoT + DT (Industrial Process)
[53]	IoT-enabled digital twin systems integrating sensors, simulation, operational data	IoT + DT (Manufacturing Ops)
[54]	IoT-enabled digital twin systems integrating sensors, environmental monitoring, predictive analytics	IoT + DT (Environment)
[66]	IoT-enabled DT with KPI monitoring & DES	IoT + DT + Simulation (DES)
[67]	IoT-integrated DT platform with OPC-UA, edge computing, cloud connectivity	IoT + DT + Edge/Cloud

Table 3. Type of Industrial IoT (Sensors & Monitoring)

Author	Implemented IoT	Classification
[44]	IoT sensors for vibration, surface monitoring, tool condition tracking	Device-Level IoT
[45]	IoT sensors and hybrid monitoring architecture for production data collection	Network-Level IoT
[46]	IoT sensors and image processing systems for real-time waste monitoring	IoT + CV + Environmental Monitoring
[56]	IoT sensors integrated into the manufacturing process for real-time data collection & defect detection	IIoT + CV + QC
[60]	Industrial IoT (sensors, monitoring systems, digital platforms)	IoT for Digital Mining (Monitoring & Collaboration)

Besides these sectoral implementations, recent developments show convergence with complementary technologies. Augmented reality has been combined with IoT-enabled digital twin to enhance operator interaction with digital replicas [43], while discrete event simulation (DES) is employed to improve key performance indicator (KPI) monitoring and system-level optimization [66]. Moreover, the integration of edge and cloud computing enhances the scalability, interoperability and data driven intelligence of the DT platforms [67]. In general, results indicate that IoT-enabled DT is not only a technology enabler for cyber-physical production systems, but also a strategic driver for resilient, adaptive, and sustainable industrial ecosystems in the context of Industry 4.0.

Sensors and monitoring are among the most fundamental and common uses of Industrial IoT (IIoT) (Table 3). For a wide range of industrial sectors, they are the backbone of real-time data acquisition, condition monitoring and process optimization. Device-level IoT is based on sensor-based systems and therefore provides accurate vibration, surface and tool condition monitoring. This enables early fault detection and tool life management as demonstrated by Chen & Pan [44]. More generally, network-level IoT architectures offer hybrid monitoring frameworks for data collection in production systems thus enabling scalable and interconnected operations [45]. IoT and computer vision together extend the monitoring ability beyond traditional sensing. For example, Jagtap et al. [46] mention the use of IoT enabled image processing for real time monitoring of the waste which adds towards sustainability and environmental performance. Similarly, Intalar et al. [56] employ IoT sensors in the manufacturing process for applications such as defect detection and quality control, thereby emphasizing the advantages of IIoT and computer vision to improve accuracy in production environments. The IoT has allowed the development of digital collaboration and monitoring platforms for the mining industry that allow real-time process monitoring and decision making in complex operational environments [60]. IoT based sensors and monitoring systems are enabling smart and data driven industrial ecosystems through predictive maintenance, environmental sustainability and process efficiency.

Application of Industrial Internet of Things (IIoT) into smart manufacturing (Table 4) is a considerable step towards the realization of Industry 4.0, which facilitates intelligent production system with real time data collection, adaptive control and interconnected operations. Digital manufacturing systems [30] and IoT-enabled lean manufacturing frameworks [38] are basic examples for improving efficiency and streamlining processes in smart factories. More mature applications are IIoT-enabled warehouse management and logistics integration [35], and smart process monitoring and data-driven production optimization [40].

The successful adoption of Industry 4.0 technologies such as IIoT has been demonstrated in domain-specific sectors such as aerospace manufacturing, where the integration of cyber-physical systems (CPS), smart sensors and data

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Table 4. Type Industrial IoT (IIoT & Smart Manufacturing)

Author	Implemented IoT	Classification
[30]	Digital Manufacturing System (DMS)	IIoT + Smart Factory
[31]	IoT integration	General IIoT Integration
[35]	Smart production system, IoT-enabled warehouse management, digital integration	IIoT + Smart Factory + Logistics
[38]	IoT-enabled lean manufacturing systems	IIoT + Smart Manufacturing
[40]	IoT-enabled smart process monitoring and data collection	IIoT + Smart Monitoring
[41]	IoT-enabled aerospace production systems (CPS, smart sensors, data integration)	IIoT + Aerospace CPS
[42]	Digital manufacturing technologies, flexible automation, CPS, smart assembly (aerospace)	IIoT + Aerospace
[61]	IoT in smart factory framework	IIoT + Smart Factory
[65]	IoT-integrated cyber–physical robotic system (AR/VR, SCADA, OPC-UA)	IIoT + Robotics + CPS
[55]	Industrial IoT (IIoT) with smart sensors, edge devices, cloud connectivity	IIoT + Edge/Cloud
[58]	IIoT (SCADA, vibration, temp, current, pressure sensors)	IIoT (Sensor Network + SCADA)
[59]	IIoT devices + LoRaWAN sensors (temp, vibration, sound), AI/ML	IIoT + Edge AI + LoRaWAN
[71]	Industrial IoT (IIoT) for building automation (HVAC, BMS)	IIoT + Smart Building
[72]	Industrial IoT (IIoT) / Edge-Oriented System (Arduino, vibration sensor, LabVIEW)	Edge IIoT Prototype

analytics supports flexible automation and intelligent assembly processes [41], [42]. Similarly, the robotics-enabled smart manufacturing systems also depict the convergence of IIoT with cyber-physical robotics and advanced control platform with AR/VR, SCADA and OPC-UA for the improved accuracy and flexibility of the system [65]. The implementation of IIoT in smart buildings, e.g. in HVAC and building management system [71], also demonstrates the versatility of IoT-led automation beyond production environments. Recent trends point to the value of connectivity and distributed intelligence. The scalable architectures of edge- and cloud-enabled IIoT platforms [55], [72] allow for smart sensor integration and low-latency processing. LoRaWAN and AI/ML algorithms in IoT devices provide intelligent monitoring and local decision making at the network edge [59]. In addition, the use of sensor networks in SCADA systems [58] points to the importance of supervisory control for interoperability and operational visibility. IIoT is bringing smart factories, robotics, logistics and aerospace systems together into a single digital ecosystem and that's a testament to its transformational power for smart manufacturing.

The integration of edge, fog and cloud computing in Industrial IoT (IIoT) (Table 5) architectures is a key paradigm to achieve scalable, low latency and intelligent industrial ecosystems. Hybrid architectures combining different layers of edge, fog and cloud can distribute computational resources across the different layers, thereby reducing latency in decision making, improving the efficiency of data management and enabling real-time responsiveness. Such a hybrid IoT architecture is reported in [57] where edge devices perform instant local processing, fog nodes are in charge of intermediate aggregation and analytics and cloud platforms are managing large-scale storage, advanced analytics and global coordination. This hierarchical integration allows to optimize the performance of the industrial networks in terms of computational loads and enhance the network resilience to network failures.

Table 5. Type Industrial IoT (Edge, Fog, and Cloud IoT)

Author	Implemented IoT	Classification
[57]	Edge IoT + Fog Computing + Cloud IoT	Hybrid IoT Architecture (Edge- Fog-Cloud)
[67]	IoT-integrated DT platform with OPC-UA, edge computing, cloud connectivity	IoT + Edge/Cloud + DT

Table 6. Type Industrial IoT (Middleware & Integration)

Author	Implemented IoT	Classification
[29]	Middleware for CPP	IoT Middleware (Cyber-Physical Production)

Recent advances also suggest the convergence of edge and cloud with digital twin (DT) technologies. Liubčuk et al. [67] propose an OPC-UA-based DT platform for IoT integration, edge computing and cloud connectivity. It guarantees interoperability, scalability and constant synchronization between physical assets and their digital twins. This hybrid architecture enables local decision making at the edge and strategic analytics in the cloud for improved predictive and operational intelligence. The results highlight that the edge-fog-cloud integration in IIoT is not only a technical enabler for real-time monitoring and adaptive control but also a strategic basis for cyber-physical production systems.

Middleware and integration (Table 6) frameworks are important in the deployment of Industrial IoT (IIoT) as they allow seamless interaction between heterogeneous devices, networks and enterprise level applications. Middleware differs from device level or network level IoT, as it provides an abstraction layer between the cyber–physical production systems (CPPs) and the higher-level decision-making architectures to enable scalability, interoperability and standard communication protocols. Stock et al. [29] focus on the implementation of middleware designed for the CPP environments. This middleware solution is a unifying platform that manages distributed IoT components, synchronizes real-time data exchange and integrates production processes with digital services. The IoT middleware reduces system complexity, decreases latency in information flows, and improves system reliability by allowing interoperability between different industrial systems. Furthermore, middleware solutions usually incorporate service-oriented architectures (SOA), data orchestration and semantic interoperability mechanisms that enable adaptive reconfiguration of manufacturing operations to meet dynamic production needs.

The device and network level IoT (Table 7) are the base layers of the Industrial IoT (IIoT), providing the foundation for data acquisition, communication and integration at the system level. The device layer is concerned with local sensing, logging and immediate data exchange in constrained environments, enabled by IoT technologies. Gadhave et al. [69] demonstrates the use of Bluetooth-enabled device-level IoT with local logging capability . It provides low-power, short-range communication and efficient data storage on-site. These implementations are important for condition monitoring, localized control, and when low latency feedback is needed without network dependence. Device level IoT increases operational autonomy and reliability of industrial processes with the possibility of decentralized data handling at machine or component level.

In contrast network-level IoT extends the communication infrastructure to connect beyond the local boundaries to create interconnected monitoring systems. This is illustrated by Staude et al. [70] with the integration of GSM-based

Table 7. Type Industrial IoT (Device-Level & Network-Level IoT)

Author	Implemented IoT	Classification
[69]	Device-Level IoT (Bluetooth, local logging)	Device-Level IoT
[70]	Network-Level IoT (GSM, cloud, monitoring network)	Network-Level IoT

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Table 8. Type Industrial IoT (Blockchain/Distributed Ledger)

Author	Implemented IoT	Classification
[36]	dApp + IoT (real-time data capture)	IoT + Blockchain/dApp
[37]	Smart labels (RFID, QR, NFC) + IoT logistics	IoT + Smart Logistics
[47]	IoT-enabled blockchain / NFT integration (supply chain monitoring)	IoT + Blockchain/NFT + Supply Chain

connectivity with cloud-enabled monitoring networks. This enables large data movement, central processing and real-time visibility across distributed assets. By using cloud platforms, network-level IoT can provide advanced analytics, predictive monitoring, and global access to industrial data, which are essential for scaling IIoT solutions across geographically dispersed production sites.

Blockchain and distributed ledger technologies (DLT) are increasingly perceived as transformational enablers of trust, transparency and decentralization in Industrial IoT (IIoT) ecosystems (Table 8). Such systems exploit immutable data structures and IoT-enabled sensing and monitoring to improve data integrity, traceability and security in complex industrial networks.

Chiacchio et al. [36] discusses the use of IoT-enabled dApps for real-time data collection, and the use of blockchain-enabled dApps for immutable recording of sensor data and secure peer-to-peer interactions in manufacturing processes. This approach reduces the risk of data manipulation and enables decentralized decision making in the production environment. Also, Mueller & Vogelsang [37] show the use of smart labels, e.g. RFID, QR codes and NFC in combination with IoT based logistics. Here, distributed ledger integration is used to provide end-to-end traceability and verification of authenticity of supply chains, thereby enhancing product provenance and operational efficiency. Later, Chiacchio et al. [47] present the integration of blockchain and non-fungible tokens (NFTs) in the monitoring of IoT supply chains. This innovation not only enables traditional traceability with digital ownership, certification and secure lifecycle management of assets but also new paradigms for industrial transparency and accountability. The studies show that the combination of blockchain / DLT and IoT enhances data trustworthiness and the resilience of the supply chain, creating new opportunities for digital asset management and decentralized industrial governance.

RQ3: What research gaps remain in the current literature?

The adoption of Internet of Things (IoT) technologies in manufacturing has transitioned from a supportive tool to a strategic enabler for operational excellence in the context of Industry 4.0. In addition to connectivity, IoT is a critical enabler for several key industrial goals such as production efficiency, overall productivity, real-time monitoring of assets and processes, predictive maintenance and quality control. For example, the integration of IoT with AI/ML and computer vision has been shown to improve efficiency and quality control. Specifically, previous studies have demonstrated that the IoT-enabled deep learning-based vision systems can significantly reduce the inspection time and errors in defect detection and thus improve the product quality and the efficiency of the production workflow [28]. Similarly, the use of IoT middleware and integration platforms has been shown to greatly improve the efficiency and productivity by enabling the flow of data, improving interoperability and enabling seamless coordination across manufacturing systems [29]. The results emphasise the strategic role of IoT as a disruptive technology that allows manufacturers to evolve from reactive operations to intelligent data-driven ecosystems for ongoing performance optimization.

The review included a total of 45 articles and the most reported impact objective was efficiency enhancement (38% of total distribution) (Figure 6). The distribution of the reviewed studies is shown in the figure. Individual

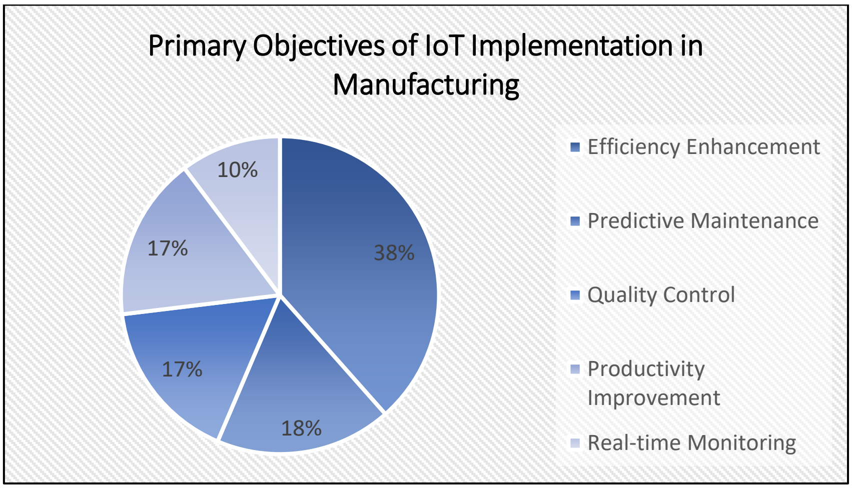

Figure 6. Percentage Distribution of Primary Objectives for IoT Implementation in Manufacturing

publications cover several dimensions of the IoT implementation and therefore contribute to several impact categories. For example, Shahin et al. [28] reported two impacts, Efficiency Enhancement and Quality Control, enabled through integration of IoT with advanced technologies such as Artificial Intelligence, Machine Learning and Computer Vision. Likewise, Stock et al. [29] improved Efficiency and Productivity simultaneously by IoT Middleware and System Integration. The frequency distribution of reported objectives shows that the most reported objectives were Efficiency Enhancement (30) among all the objectives, indicating the high amount of attention paid to operational efficiency in the literature analysed. This finding is consistent with the global trend in smart manufacturing where the efficiency gains are given priority to reduce operational costs, optimise resource utilisation and maintain competitiveness in volatile markets.

The second most frequent category was Predictive Maintenance (14 instances) indicating the strategic significance of asset reliability and minimising downtime. IoT-powered condition monitoring and predictive analytics are propelling manufacturers' shift from reactive to proactive maintenance paradigms. Quality Control and Productivity Improvement (13 each) balance the concern for product conformance to standards and throughput improvement. These two objectives are representative of the trade-offs in manufacturing systems where IoT technologies are employed to enable real-time defect detection, process optimisation and workflow synchronisation.

Finally, Real-time Monitoring (8 hits) is still a significant impact, but is mentioned less frequently. This is no less important for being less common. Real-time visibility is the basic building block from which higher order impacts such as predictive analytics and quality assurance are built.

The literature reviewed reflects that efficiency enhancement, quality control, productivity improvement, predictive maintenance, and real-time monitoring are not separate goals but interconnected results of IoT-enabled manufacturing systems. The core capability is real-time monitoring with dense sensor networks, edge–cloud architecture, and IIoT platforms for continuous visibility of process conditions, equipment state, and production flows [36], [45], [46], [47], [56], [57]. This real-time streaming data is the basis for other higher level functions for several goals.

Real-time monitoring can be converted into efficiency and productivity gains in a big way in predictive maintenance. The health of the asset is monitored on a rolling basis using the IoT-assisted digital twins and sensor-based analytics, which enables early detection of faults, optimal scheduling of maintenance and minimisation of unplanned downtime [43], [44], [49], [52], [53], [60]. These capabilities enhance operational efficiency both directly by

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minimizing disruptions and indirectly by productivity improvements due to stable production throughput [38], [55], [72]. This link is further reinforced by the studies that include AI and ML to enhance the accuracy of failure predictions and to automate decisions [48], [58], [71].

Objectives of quality control are also closely coupled with real-time monitoring and advanced analytics. IoT integration with AI/ML and computer vision enables continuous inspection and defect detection in production lines, reducing variability and inspection delays [28], [32], [33], [62], [63], [64]. Blockchain based solutions go one step further by providing data integrity and traceability, and thus reinforcing closed-loop quality assurance systems [36], [37], [47]. So, quality control improvements are usually "coupled" with efficiency gains from lower rework and scrap rates.

These objectives are interrelated and the sum of these objectives is productivity improvements. IIoT middleware, edge computing and distributed architectures enable seamless coordination of manufacturing assets providing faster response time and scalable automation [29], [30], [31], [40], [41], [42], [57], [61]. Together with predictive maintenance and real-time quality feedback, these systems enable increased equipment availability, reduced cycle times and more agile production environments [34], [35], [38], [39].

Overall, the literature indicates that the IoT impact objectives in manufacturing represent a tightly integrated ecosystem instead of individual performance goals. Real-time monitoring is the enabling layer, predictive maintenance is the key efficiency and reliability mechanism, and advanced analytics bridges quality control and productivity improvement. This integrative perspective underscores the importance of a holistic evaluation of IoT implementations since an improvement in one objective usually cascades across multiple dimensions of manufacturing performance.

Discussion

The present research directions in IoT-enabled manufacturing are obtained from a systematic synthesis of 45 articles that satisfy the inclusion criteria. The thematic analysis of the studies led to three overall findings on IoT adoption in manufacturing which are summarised in Figure 7. First, research on IoT is still largely focused on discrete manufacturing systems whereas the healthcare, agriculture and construction contexts related to manufacturing have been relatively neglected. Second, the literature reveals a distinct tendency for converged IIoT architectures, fusing IoT with artificial intelligence, machine learning and computer vision, notably for predictive maintenance and real-time quality control. Third, impact objectives such as efficiency enhancement, productivity improvement and quality assurance are rarely pursued in isolation, but rather become interdependent outcomes enabled by real-time monitoring and data-driven automation.

A major finding is the dominance of discrete manufacturing as the main area for IoT adoption, with more than half of the studies reviewed. The high level of the studies in discrete manufacturing shows that the research activities are mainly directed to the production environments with high system complexity and tight real time monitoring. However, the limited representation of the healthcare, agriculture and construction manufacturing sectors highlights potential research gaps despite their growing strategic importance. This is mainly due to the high operational flexibility, accurate control and strict requirements for real-time monitoring. However, the healthcare, construction and agriculture industries still have the potential of substantial gains through IoT-based automation and are still unexplored. This mismatch stresses the importance of targeted research and technology transfer towards sectors with potential for emerging digitization.

The review also discusses the transition of IoT from a simple sensing and connectivity platform to a full-fledged cyber-physical infrastructure. The combination of the Internet of Things (IoT) with the artificial intelligence (AI),

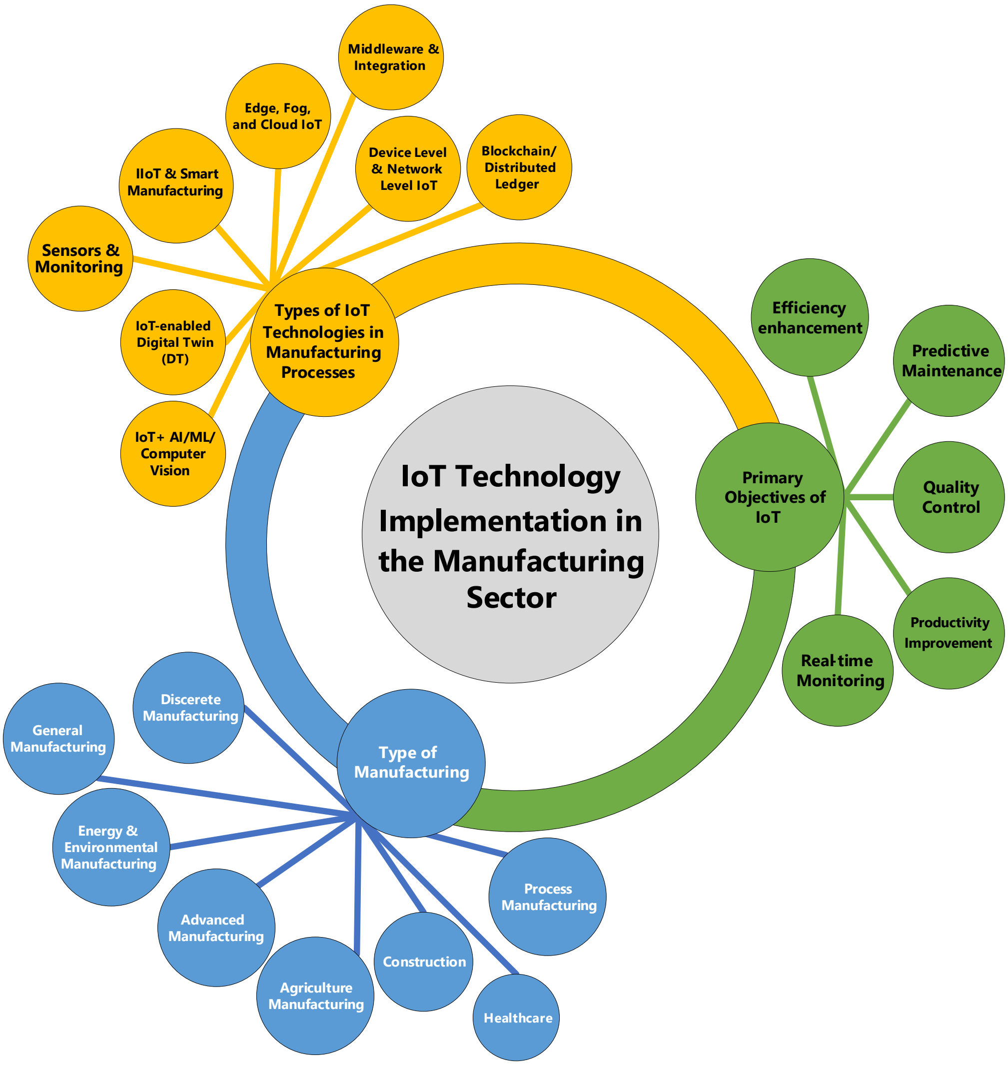

Figure 7. IoT Technology Implementation in the Manufacturing Sector

machine learning (ML) and computer vision (CV) has allowed to change the functioning of the manufacturing systems from reactive to predictive and prescriptive. Such integration enables autonomous decision making, real-time defect detection and adaptive control strategies which lead to a significant enhancement in production agility and throughput. Moreover, the emergence of digital twins driven by IoT signals a paradigm shift towards data-driven simulation and optimization, enabling real-time synchronisation between physical assets and their virtual twins. These capabilities are vital for predictive maintenance, risk assessment and operational optimization in complex manufacturing environments.

The widespread adoption of Industrial IoT (IIoT) and smart manufacturing platforms reflects a strategic focus on interoperability, scalability and system integration. The growing deployment of hybrid architectures of edge, fog and cloud computing is enabling distributed intelligence and low-latency decision making along with large-scale data analytics and system-level coordination. Likewise, the deployment of blockchain and distributed ledger technologies tackles persistent problems of cybersecurity, data integrity, and traceability, which remain major barriers to the broader adoption of IoT in industrial environments.

However, the synthesis of the reviewed literature indicates that several challenges still hinder large-scale IoT adoption in manufacturing. The most common barriers reported on the studies reviewed are cybersecurity risks and

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interoperability issues with legacy systems, especially on works that deal with industrial-scale and brownfield deployments [36], [37], [40], [41], [47]. Also, the high integration and maintenance costs are recurring issues especially in studies involving complex IIoT architectures and digital twin implementations [29], [43], [49]. Moreover, research on small and medium-sized manufacturing enterprises (SMEs) always points out the lack of skilled personnel, where limited expertise hinders the effective deployment of IoT and the long-term management of the system [30], [31], [42]. Moreover, the lack of standardized performance metrics and the limited number of longitudinal studies on industrial-scale deployments make it difficult to evaluate long-term return on investment and operational impacts.

Future research should build on the gaps identified in this review and should prioritize a few targeted directions. First, longitudinal and empirically grounded case studies are needed in the under-represented manufacturing sectors such as agriculture-related manufacturing and construction to assess the long-term operational and sustainability impacts of IoT adoption. Second, there is a clear need for lightweight and cost-effective integration frameworks tailored to small and medium-sized enterprises, as the current literature is mostly focused on large-scale and resource-intensive IIoT deployments. Third, future studies should develop standardized evaluation frameworks that can jointly assess efficiency, security, and organizational readiness, in addition to scalable cybersecurity models that take into account legacy system constraints and workforce skill limitations.

The review also identifies a number of unmet needs that signal concrete opportunities for advancing IoT-enabled manufacturing. A common limitation of various studies is the communication latency and reliability as well as the scalability limitations especially in real-time monitoring, predictive maintenance and distributed control applications. In this respect, the use of next-generation communications technologies, including 5G and the emerging 6G architectures, is a natural continuation of the current research efforts, as these can directly address the bandwidth, latency and reliability limitations reported in the current IIoT deployments and allow more advanced real-time control and remote operation capabilities. Energy-efficient IoT devices and self-powered sensor networks are innovations that allow deployment at scale in a sustainable and cost-effective manner. Furthermore, the combination of IoT with emerging paradigms like augmented reality (AR), digital thread, and human-machine collaboration can facilitate adaptive production environments and more natural human-system interfaces. The continued deployment of IoT across cross-sectoral ecosystems such as supply chain logistics, circular economy applications and smart infrastructure may further amplify its transformative impact beyond the boundaries of factories. These opportunities show the huge potential of IoT technologies to power the next wave of industrial innovation, resilience and sustainability.

CONCLUSION

The results of the review reveal a clear presence of sectoral imbalance in the IoT manufacturing literature with a predominant focus on discrete manufacturing sectors. However, the evidence collected from the studies reviewed in this paper suggests that this focus has been accomplished at the cost of other manufacturing areas, such as process, construction and advanced manufacturing, where the adoption of IoT is still limited, although it has the potential to address complex operational and sustainability challenges. This review maps the distribution of studies across manufacturing categories, thus providing a clearer overview of the distribution of IoT research at present and identifying areas that are comparatively less represented in the existing literature. From the technology perspective, the results indicate that the research on industrial IoT has entered into a more mature stage with the convergence of enabling technologies instead of their isolated use, and illustrates how these components are now being aligned to deliver system-level capabilities. The limited number of studies found for middleware and system integration shows that these topics are less prominent in the literature reviewed than higher-level IoT architectures and application-oriented research, and this pattern might indicate that interoperability and integration issues are not so explicitly investigated, even though they remain critical in the context of real-world implementation These technological advances belie a continued orientation towards short-term operational gains as the primary implementation objective, and predictive maintenance, quality control, productivity improvement, and real-time monitoring are objectives often mentioned, but the distribution shows that they are mainly treated as means to improve efficiency rather than as independent strategic goals. This hierarchy of objectives shows that the current IoT research in manufacturing is still based on incremental performance improvement and cost-driven logic, and as a result, the body of literature reviewed tends to pay less attention to broader implementation outcomes than operational performance. Together these patterns suggest that the current state of IoT research in manufacturing is closely related to operational improvement goals, especially in the context of discrete manufacturing, and integrated and efficiency-driven approaches enhance operational resilience and adaptive capacity; however, the distribution of sectors is uneven and the focus on efficiency is narrow, which indicates that the transformative potential of IoT under the Industry 4.0 paradigm is not yet fully realised.

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CONFLICT OF INTEREST

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

[1] H. Yang, S. Kumara, S. T. S. Bukkapatnam, and F. Tsung, “The internet of things for smart manufacturing: A review,” IISE Trans., vol. 51, no. 11, pp. 1190–1216, 2019, doi: 10.1080/24725854.2018.1555383.
[2] M. Asif, L. Yang, and M. Hashim, “The Role of Digital Transformation, Corporate Culture, and Leadership in Enhancing Corporate Sustainable Performance in the Manufacturing Sector of China,” 2024.
[3] E. Alfaqiyah, A. Alzubi, and H. Y. Aljuhmani, “How Industry 4.0 Technologies Enhance Supply Chain Resilience: The Interplay of Agility, Adaptability, and Customer Integration in Manufacturing Firms,” 2025.
[4] M. A. Munir, M. Mujtaba, A. Qamar, and M. Farooq, “Managing volatile markets: A dynamic capability approach to analytics-driven performance in fast-moving supply chains for sustainable development,” Sustain. Futur., vol. 10, no. December 2024, p. 101338, 2025, doi: 10.1016/j.sftr.2025.101338.
[5] M. Alquraish, “Digital Transformation, Supply Chain Resilience, and Sustainability: A Comprehensive Review with Implications for Saudi Arabian Manufacturing,” 2025.
[6] U. N. Chinedu and E. Brendan, “The Impact of Internet of Things in Manufacturing Management,” Engineering, vol. 15, no. 09, pp. 533–560, 2023, doi: 10.4236/eng.2023.159039.

 DOI:10.25077/josi.v25.n1.p94-119.2026

[7] P. Malhotra, Y. Singh, P. Anand, D. Bangotra, P. Singh, and W. Hong, "Internet of Things: Evolution, Concerns and Security Challenges," 2021.

[8] K. Wójcicki, M. Biegańska, B. Paliwoda, and J. Górna, "Challenges and Opportunities — A Review," MDPI, vol. 15, no. 1806, 2022.

[9] M. Soori, B. Arezoo, and R. Dastres, "Internet of things for smart factories in industry 4.0, a review," Internet Things Cyber-Physical Syst., vol. 3, no. April, pp. 192–204, 2023, doi: 10.1016/j.iotcps.2023.04.006.

[10] G. Aggarwal, H. Chaukse, and A. Sualeh, "IoT Implementation in Manufacturing using Data Analysis and Data Management," vol. 3075, no. 1, pp. 371–375, 2019, doi: 10.35940/ijitee.A4137.119119.

[11] Y. M. Al-Naggar, N. Jamil, M. F. Hassan, and A. R. Yusoff, "Condition monitoring based on IoT for predictive maintenance of CNC machines," Procedia CIRP, vol. 102, no. March, pp. 314–318, 2021, doi: 10.1016/j.procir.2021.09.054.

[12] L. Dhirani, E. Armstrong, and T. Newe, "Industrial IoT, Cyber Threats, and Standards Landscape: Evaluation and Roadmap," vol. 21, no. 11, pp. 1–30, 2021.

[13] M. Saqlain, M. Piao, Y. Shim, and J. Y. Lee, "Framework of an IoT-based Industrial Data Management for Smart Manufacturing," J. Sens. Actuator Networks, vol. 8, no. 2, 2019, doi: 10.3390/jsan8020025.

[14] T. Kalsoom et al., "Impact of IoT on manufacturing industry 4.0: A new triangular systematic review," Sustain., vol. 13, no. 22, pp. 1–22, 2021, doi: 10.3390/su132212506.

[15] H. Alrashede, F. Eassa, A. M. Ali, F. Albalwy, and H. Aljihani, "A Blockchain-Based Security Framework for East-West Interface of SDN," 2024.

[16] Y. Sanjalawe, S. Fraihat, S. Al-e, and S. N. Makhadmeh, "A review of artificial intelligence-based intrusion detection in industrial internet of things," 2026.

[17] R. J. Raimundo and A. T. Rosário, "Cybersecurity in the Internet of Things in Industrial Management," Appl. Sci., 2022.

[18] M. Sujatha et al., "IoT and Machine Learning-Based Smart Automation System for Industry 4.0 Using Robotics and Sensors," J. Nanomater., vol. 2022, 2022, doi: 10.1155/2022/6807585.

[19] S. Afrin et al., "Computers in Industry Industrial Internet of Things: Implementations, challenges, and potential solutions across various industries," Comput. Ind., vol. 170, no. July 2024, p. 104317, 2025, doi: 10.1016/j.compind.2025.104317.

[20] R. Y. Zhong, L. Wang, and X. Xu, "An IoT-enabled Real-time Machine Status Monitoring Approach for Cloud Manufacturing," Procedia CIRP, vol. 63, pp. 709–714, 2017, doi: 10.1016/j.procir.2017.03.349.

[21] M. S. Al-Rakhami and M. Al-Mashari, "ProChain: Provenance-Aware Traceability Framework for IoT-Based Supply Chain Systems," IEEE Access, vol. 10, pp. 3631–3642, 2022, doi: 10.1109/ACCESS.2021.3135371.

[22] M. J. Page et al., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," Syst. Rev., vol. 10, no. 1, pp. 1–11, 2021, doi: 10.1186/s13643-021-01626-4.

[23] N. R. Haddaway et al., "A suggested data structure for transparent and repeatable reporting of bibliographic searching," Campbell Syst. Rev., vol. 18, no. 4, pp. 1–12, 2022, doi: 10.1002/cl2.1288.

[24] B. Maqbool and S. Herold, "Potential effectiveness and efficiency issues in usability evaluation within digital health: A systematic literature review," J. Syst. Softw., vol. 208, no. September 2022, 2024, doi: 10.1016/j.jss.2023.111881.

[25] K. Gregory, P. Groth, H. Cousijn, A. Scharnhorst, and S. Wyatt, "Searching Data: A Review of Observational Data Retrieval Practices in Selected Disciplines," J. Assoc. Inf. Sci. Technol., vol. 70, no. 5, pp. 419–432, 2019, doi: 10.1002/asi.24165.

[26] L. Schmidt, B. K. Olorisade, L. A. McGuinness, J. Thomas, and J. P. T. Higgins, "Data extraction methods for systematic review (semi)automation: A living systematic review," F1000Research, vol. 10, p. 401, 2021, doi: 10.12688/f1000research.51117.1.

[27] M. Javaid, Abid Haleem, R. Pratap Singh, S. Rab, and R. Suman, "Upgrading the manufacturing sector via applications of Industrial Internet of Things (IIoT)," Sensors Int., vol. 2, no. August, p. 100129, 2021, doi: 10.1016/j.sintl.2021.100129.

[28] M. Shahin, F. Frank Chen, H. Bouzary, and A. Hosseinzadeh, "Deploying Convolutional Neural Network to reduce waste in production system," Manuf. Lett., vol. 35, pp. 1187–1195, 2023, doi: 10.1016/j.mfglet.2023.08.127.

[29] D. Stock, D. Schel, and T. Bauernhansl, "Middleware-based cyber-physical production system modeling for operators," Procedia Manuf., vol. 42, no. 2019, pp. 111–118, 2020, doi: 10.1016/j.promfg.2020.02.031.

[30] F. Piedade, M. Baptista, and P. Chaves, "In2DIG - Implementation of a digital manufacturing system in a production cell of the metal mold industry: From planning to action," Procedia Manuf., vol. 42, no. 2019, pp. 104–110, 2020, doi: 10.1016/j.promfg.2020.02.030.

[31] F. Henriksson and K. Johansen, "Integrated Product and Production Research on Introducing Internet of Things in Swedish Wood Industry Products," Procedia Manuf., vol. 25, pp. 10–16, 2018, doi: 10.1016/j.promfg.2018.06.051.

[32] C. A. P. Rocha, E. Rauch, T. Vaimel, M. A. R. Garcia, and R. Vidoni, "Implementation of a Vision-Based Worker Assistance System in Assembly: A Case Study," Procedia CIRP, vol. 96, no. March, pp. 295–300, 2021, doi: 10.1016/j.procir.2021.01.090.

[33] N. Chuenmee, N. Phothi, K. Chamniprasart, S. Khaengkarn, and J. Srisertpol, "Machine learning for predicting resistance spot weld quality in automotive manufacturing," Results Eng., vol. 25, no. December 2024, p. 103570, 2025, doi: 10.1016/j.rineng.2024.103570.

[34] P. Dobra and J. Jósvai, "Enhance of OEE by hybrid analysis at the automotive semi-automatic assembly lines," Procedia Manuf., vol. 54, pp. 184–190, 2021, doi: 10.1016/j.promfg.2021.07.028.

[35] B. Puniani and S. Abdoli, "Development of Capability for Integrated Smart Production-Spare Part Warehouse System for SMEs in Fast-Moving Consumer Goods sector," Procedia CIRP, vol. 136, pp. 159–164, 2025, doi: 10.1016/j.procir.2025.08.029.

[36] F. Chiacchio, L. Compagno, D. D'Urso, L. Velardita, and P. Sandner, "A decentralized application for the traceability process in the pharma industry," Procedia Manuf., vol. 42, no. 2019, pp. 362–369, 2020, doi: 10.1016/j.promfg.2020.02.063.

[37] D. Mueller and F. Vogelsang, "Towards smart manufacturing logistics: A case study of potentials of smart label data in electronics manufacturing," Procedia CIRP, vol. 104, no. March, pp. 1741–1746, 2021, doi: 10.1016/j.procir.2021.11.293.

[38] K. Jackson, K. Efthymiou, and J. Borton, "Digital Manufacturing and Flexible Assembly Technologies for Reconfigurable Aerospace Production Systems," Procedia CIRP, vol. 52, pp. 274–279, 2016, doi: 10.1016/j.procir.2016.07.054.

[39] G. Koulinas, P. Paraschos, and D. Koulouriotis, "A machine learning-based framework for data mining and optimization of a production system," Procedia Manuf., vol. 55, no. C, pp. 431–438, 2021, doi: 10.1016/j.promfg.2021.10.059.

[40] S. Salman, S. M. Morshed, M. R. Karim, R. Rahman, S. Hasanat, and A. Ahsan, "Exploring lean manufacturing drivers for enhancing circular economy performance in the pharmaceutical industry: a Bayesian best–worst approach," Int. J. Ind. Eng. Oper. Manag., vol. 7, no. 1, pp. 68–96, 2025, doi: 10.1108/IJIEOM-10-2023-0074.

[41] M. R. Hoque, S. R. Tushar, M. A. S. Shafil, M. M. Bappy, and M. G. S. Rayhan, "An integrated VSM 4.0 and interval-valued q-Rung orthopair fuzzy approach to sustainable process development in the apparel manufacturing industry," Int. J. Ind. Eng. Oper. Manag., no. September, 2025, doi: 10.1108/IJIEOM-12-2024-0094.

[42] S. Gupta et al., “From failure to success: a framework for successful deployment of Industry 4.0 principles in the aerospace industry,” Int. J. Ind. Eng. Oper. Manag., vol. 6, no. 4, pp. 277–298, 2024, doi: 10.1108/IJIEOM-04-2023-0042.

[43] R. F. Pitzalis, A. Giordano, A. Di Spigno, A. Cowell, O. Niculita, and G. Berselli, “Application of augmented reality-based digital twin approaches: a case study to industrial equipment,” Int. J. Adv. Manuf. Technol., vol. 138, no. 7, pp. 3747–3763, 2025, doi: 10.1007/s00170-025-15755-w.

[44] C. S. Chen and P. Y. Pan, “Applied Internet of Things to Analyze Vibration, Workpiece Roughness, and Tool Wear: Case Study of Successive Milling,” Processes, vol. 13, no. 4, pp. 1–20, 2025, doi: 10.3390/pr13040978.

[45] G. Luisi, V. Di Pasquale, M. C. Pietronudo, S. Riemma, and M. Ferretti, “A Hybrid Architectural Model for Monitoring Production Performance in the Plastic Injection Molding Process,” Appl. Sci., vol. 13, no. 22, 2023, doi: 10.3390/app132212145.

[46] S. Jagtap, C. Bhatt, J. Thik, and S. Rahimifard, “Monitoring potato waste in food manufacturing using image processing and internet of things approach,” Sustain., vol. 11, no. 11, 2019, doi: 10.3390/su11113173.

[47] F. Chiacchio, D. D’Urso, L. M. Oliveri, A. Spitaleri, C. Spampinato, and D. Giordano, “A Non-Fungible Token Solution for the Track and Trace of Pharmaceutical Supply Chain,” Appl. Sci., vol. 12, no. 8, 2022, doi: 10.3390/app12084019.

[48] Z. Lv, H. Lv, and M. Fridenfalk, “Digital Twins in the Marine Industry,” Electron., vol. 12, no. 9, pp. 1–26, 2023, doi: 10.3390/electronics12092025.

[49] C. Verdouw and J. W. Kruize, “Digital twins in farm management: illustrations from the FIWARE accelerators SmartAgriFood and Fractals,” 7th Asian-Australasian Conf. Precis. Agric., pp. 1–5, 2017, doi: 10.5281/zenodo.893662.

[50] T. Erol, A. F. Mendi, and D. Dogan, “The Digital Twin Revolution in Healthcare,” 4th Int. Symp. Multidiscip. Stud. Innov. Technol. ISMSIT 2020 - Proc., no. October, 2020, doi: 10.1109/ISMSIT50672.2020.9255249.

[51] D. Piromalis and A. Kantaros, “Digital Twins in the Automotive Industry: The Road toward Physical-Digital Convergence,” Appl. Syst. Innov., vol. 5, no. 4, pp. 1–12, 2022, doi: 10.3390/asi5040065.

[52] T. R. Wanasinghe et al., “Digital Twin for the Oil and Gas Industry: Overview, Research Trends, Opportunities, and Challenges,” IEEE Access, vol. 8, pp. 104175–104197, 2020, doi: 10.1109/ACCESS.2020.2998723.

[53] L. Li, S. Aslam, A. Wileman, and S. Perinpanayagam, “Digital Twin in Aerospace Industry: A Gentle Introduction,” IEEE Access, vol. 10, pp. 9543–9562, 2022, doi: 10.1109/ACCESS.2021.3136458.

[54] J. Monteiro, J. Barata, M. Veloso, L. Veloso, and J. Nunes, “Towards sustainable digital twins for vertical farming,” 2018 13th Int. Conf. Digit. Inf. Manag. ICDIM 2018, no. Icdim, pp. 234–239, 2018, doi: 10.1109/ICDIM.2018.8847169.

[55] C. Cronin, A. Conway, and J. Walsh, “Flexible manufacturing systems using IIoT in the automotive sector,” Procedia Manuf., vol. 38, no. 2019, pp. 1652–1659, 2019, doi: 10.1016/j.promfg.2020.01.119.

[56] N. Intalar, K. Chumnumporn, C. Jeenanunta, and A. Tunpan, “Towards Industry 4.0: Digital transformation of traditional safety shoes manufacturer in Thailand with a development of production tracking system,” Eng. Manag. Prod. Serv., vol. 13, no. 4, pp. 79–94, 2021, doi: 10.2478/emj-2021-0033.

[57] Orive, A. Agirre, H.-L. Truong, I. Sarachaga, and M. Marcos, “Quality of Service Aware Orchestration for Cloud–Edge Continuum Applications,” 2022.

[58] E. Jovicic, D. Primorac, M. Cupic, and A. Jovic, “Publicly Available Datasets for Predictive Maintenance in the Energy Sector: A Review,” IEEE Access, vol. 11, no. June, pp. 73505–73520, 2023, doi: 10.1109/ACCESS.2023.3295113.

[59] P. Tanuska, L. Spendla, M. Kebisek, D. Rastislav, and M. Stremy, “Maintenance in Compliance with Industry 4.0,” Sensors 2021, vol. 21, p. 2376, 2021.

[60] J. Wang, L. Bi, L. Wang, M. Jia, and D. Mao, "A Mining Technology Collaboration Platform Theory and Its Product Development and Application to Support China's Digital Mine Construction," Appl. Sci., vol. 9, no. 24, pp. 1–33, 2019, doi: 10.3390/app9245373.

[61] T. Tanizaki and R. Yamashita, "Application of Metaheuristics to Packing Formation Support Systems of Pre-Cut Lumber Factory," Int. J. Autom. Technol., vol. 16, no. 3, pp. 269–279, 2022, doi: 10.20965/ijat.2022.p0269.

[62] Y. Saif et al., "Advancements in Roundness Measurement Parts for Industrial Automation Using Internet of Things Architecture-Based Computer Vision and Image Processing Techniques," Appl. Sci., vol. 13, no. 20, 2023, doi: 10.3390/app132011419.

[63] Y. J. Chen, Y. H. Yeh, and J. F. Yang, "A System for the Real-Time Detection of the U-Shaped Steel Bar Straightness on a Production Line," Sensors, vol. 25, no. 13, pp. 1–21, 2025, doi: 10.3390/s25133972.

[64] Nedaei, A. Eskandari, and M. Aghaei, "Photovoltaic fault detection and classification: Reconsideration of classic machine learning and dataset shrinkage techniques for simplification," Results Eng., vol. 27, no. May, p. 106356, 2025, doi: 10.1016/j.rineng.2025.106356.

[65] G. Simion, A. Filipescu, D. Ionescu, and A. Filipescu, "Cloud/VPN-Based Remote Control of a Modular Production System Assisted by a Mobile Cyber–Physical Robotic System—Digital Twin Approach," Sensors, vol. 25, no. 2, pp. 1–36, 2025, doi: 10.3390/s25020591.

[66] Kampa, "Modeling and Simulation of a Digital Twin of a Production System for Industry 4.0 with Work-in-Process Synchronization," Appl. Sci., vol. 13, no. 22, 2023, doi: 10.3390/app132212261.

[67] V. Liubčuk, V. Radziukynas, G. Kairaitis, and D. Naujokaitis, "Power Quality Impact and Its Assessment: A Review and a Survey of Lithuanian Industrial Companies," Inventions, vol. 10, no. 2, 2025, doi: 10.3390/inventions10020030.

[68] C. O'Donovan, I. Popov, G. Todeschini, and C. Giannetti, "Ladle pouring process parameter and quality estimation using Mask R-CNN and contrast-limited adaptive histogram equalisation," Int. J. Adv. Manuf. Technol., vol. 126, no. 3–4, pp. 1397–1416, 2023, doi: 10.1007/s00170-023-11151-4.

[69] S. Gadhave et al., "Enhancing agricultural efficiency in India with IoT based smart boats," Sigma J. Eng. Nat. Sci., vol. 43, no. 2, pp. 570–581, 2025, doi: 10.14744/sigma.2025.00045.

[70] M. Staude, P. Brożek, E. Kostecka, D. Tarnapowicz, and J. Wysocki, "Remote Water Quality Monitoring System for Use in Fairway Applications," Appl. Sci., vol. 14, no. 23, 2024, doi: 10.3390/app142311406.

[71] H. H. Hosamo, H. K. Nielsen, D. Kraniotis, P. R. Svennevig, and K. Svidt, "Improving building occupant comfort through a digital twin approach: A Bayesian network model and predictive maintenance method," Energy Build., vol. 288, p. 112992, 2023, doi: 10.1016/j.enbuild.2023.112992.

[72] H. Hashim et al., "Development of Machine Down-Time Monitoring System for Production Line Efficiency Evaluation," J. Adv. Res. Appl. Mech., vol. 133, no. 1, pp. 1–11, 2025, doi: 10.37934/aram.133.1.111.

APPENDIX

Classification of Manufacturing Industries Adopting IoT

No	Author	Type of Manufacturing	Type of IoT
1	[28]	General Manufacturing	IoT + AI/ML/Computer Vision
2	[29]	General Manufacturing	IoT Middleware & Integration
3	[30]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
4	[31]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
5	[32]	Discrete Manufacturing	IoT + AI/ML/Computer Vision
6	[33]	Discrete Manufacturing	IoT + AI/ML/Computer Vision

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Classification of Manufacturing …. (Cont.)

No	Author	Type of Manufacturing	Type of IoT
7	[34]	Discrete Manufacturing	IoT + AI/ML/Computer Vision
8	[35]	Process Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
9	[36]	Healthcare	IoT + Blockchain/Distributed Ledger
10	[37]	Discrete Manufacturing	IoT + Blockchain/Distributed Ledger
11	[38]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
12	[39]	General Manufacturing	IoT + AI/ML/Computer Vision
13	[40]	Healthcare	Industrial IoT (IIoT) & Smart Manufacturing
14	[41]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
15	[42]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
16	[43]	Discrete Manufacturing	IoT-enabled Digital Twin
17	[44]	Discrete Manufacturing	IoT Sensors & Monitoring
18	[45]	Discrete Manufacturing	IoT Sensors & Monitoring
19	[46]	Process Manufacturing	IoT Sensors & Monitoring
20	[47]	Healthcare	IoT + Blockchain/Distributed Ledger
21	[48]	Construction	IoT-enabled Digital Twin
22	[49]	Agriculture Manufacturing	IoT-enabled Digital Twin
23	[50]	Healthcare	IoT-enabled Digital Twin
24	[51]	Discrete Manufacturing	IoT-enabled Digital Twin
25	[52]	Process Manufacturing	IoT-enabled Digital Twin
26	[53]	Discrete Manufacturing	IoT-enabled Digital Twin
27	[54]	Agriculture Manufacturing	IoT-enabled Digital Twin
28	[55]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
29	[56]	Discrete Manufacturing	IoT Sensors & Monitoring
30	[57]	General Manufacturing	Edge/Fog/Cloud IoT
31	[58]	Energy & Environmental Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
32	[59]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
33	[60]	Process Manufacturing	IoT Sensors & Monitoring
34	[61]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing
35	[62]	Discrete Manufacturing	IoT + AI/ML/Computer Vision
36	[63]	Discrete Manufacturing	IoT + AI/ML/Computer Vision
37	[64]	Energy & Environmental Manufacturing	IoT + AI/ML/Computer Vision
38	[65]	Advanced Manufaturing	Industrial IoT (IIoT) & Smart Manufacturing
39	[66]	Discrete Manufacturing	IoT-enabled Digital Twin
40	[67]	Advanced Manufaturing	IoT-enabled Digital Twin & Edge/Fog/Cloud IoT
41	[68]	Discrete Manufacturing	IoT + AI/ML/Computer Vision
42	[69]	Agriculture Manufacturing	Device-Level & Network-Level IoT
43	[70]	Energy & Environmental Manufacturing	Device-Level & Network-Level IoT
44	[71]	Construction	Industrial IoT (IIoT) & Smart Manufacturing
45	[72]	Discrete Manufacturing	Industrial IoT (IIoT) & Smart Manufacturing

AUTHORS BIOGRAPHY

Rama Dani Eka Putra is a full-time lecturer at the Faculty of Engineering, Department of Industrial Engineering, Universitas Bengkulu. The author earned Bachelor's degrees in Law and Industrial Engineering and subsequently completed a Master's degree in Industrial Engineering. Prior to joining academia, the author worked as an engineer in the manufacturing industry. The author's research interests include industrial engineering, quality management, and continuous improvement, and the author has obtained several national and international professional certifications in these fields.

Tessa Zulenia Fitri is currently working as a lecturer in the Department of Industrial Engineering, Faculty of Engineering, Universitas Bengkulu. She earned both her Bachelor’s and Master’s degrees in Industrial Engineering from the Faculty of Engineering, Universitas Andalas. Her research interests focus on risk management and quality management.

Helmizar is a lecturer in the Department of Mechanical Engineering, Faculty of Engineering, Universitas Bengkulu. He earned his bachelor's and master's degrees in Mechanical Engineering from Institut Teknologi Sepuluh Nopember (ITS) and completed his doctoral degree in Mechanical Engineering at the University of Southampton. His research interests include energy conversion, renewable energy systems, hydropower technology, and sustainable mechanical engineering applications.

Khotso Shai is a Lecturer at the School of Engineering & Technology, Department of Mechanical Engineering and Mechatronics Engineering, at Lerotholi Polytechnic in Maseru, Lesotho. Obtained Bachelor's Degree from the Central University of Technology (CUT), Free State, South Africa, and Masters Degree in Mechanical Engieering from Institut Teķnologi Sepuluh Nopember (ITS), Surabaya, Indonesia. Research interests focus in Energy Conversin, with particular emphasis on Sustainable Energy Technologies and Energy Coversion Systems.

Nia Arfina Foci is an academic and practitioner in the field of Industrial Engineering who currently serves as a Permanent Lecturer at the University of Bengkulu. She holds a bachelor's and master's degree in industrial engineering from Andalas University and is actively involved in industrial HR system management. She is currently interested in research related to industrial engineering management, human resource development (HRD), MSME sustainability, and logistics.

M. Arif Munanda is a lecturer in the Department of Industrial Engineering, Universitas Bengkulu, Indonesia. He holds a Master's degree in Industrial Engineering from Syiah Kuala University. His research interests primarily focus on ergonomics, occupational health and safety, biomechanical analysis, and physiological workload assessment. He is dedicated to advancing engineering education and applying ergonomic principles to create safer, more inclusive, and highly efficient work environments.

Muhamad Yasin is a Lecturer in the Department of Industrial Engineering, Faculty of Engineering, Universitas Bengkulu, Indonesia. Before joining academia, he gained professional experience as a Quality Control specialist in the manufacturing industry. He received his Master Degree in Industrial Engineering from Adhi Tama Institute of Technology Surabaya, Indonesia, in 2023. His research interests include Manufacturing and Production Management, Production Systems, Supply Chain Management, and Industrial Engineering applications.

Handi Wilujeng Nugroho is an Industrial Engineering lecturer with expertise in manufacturing systems, occupational safety and health, engineering design, and scientific publication management. He holds a Master's degree in Industrial Engineering from Andalas University and has experience in higher education, logistics, and engineering consultancy. Active as an Editor-in-Chief and journal editorial member, he is committed to advancing research quality, innovative Challenge-Based Learning, and industry-oriented engineering education through interdisciplinary collaboration and continuous professional development.

Fuad Dwi Hanggara is a full-time lecturer at the Faculty of Engineering, Department of Mechanical Engineering. The author earned Bachelor's degrees in Industrial Engineering and subsequently completed a Master's degree in Industrial Engineering. The author's research interests include industrial and mechanical engineering, supply management, modelling system, and manufacturing processes.

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