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REVIEW PAPER

Survey on Data-Driven Decision Support Frameworks in Industrial IoT (IIoT)-Based Manufacturing

Dr. Manish Jain
Associate Professor
Department of Electronics and Communications
Mandsaur University
Mandsaur (M.P.)
manish.jain@meu.edu.in

***Abstract*— Industrial Internet of Things (IIoT) has become a revolution in the smart manufacturing paradigm as it provides pervasive connectivity, real-time data collection, and intelligent automation of industrial systems. In IIoT-enabled manufacturing, large volumes of heterogeneous data are constantly generated by sensors, machines, and enterprise systems, which must be used effectively to implement the data-driven decision support frameworks. This decision-making process relies on machine learning, artificial intelligence, edge-to-cloud computing, and optimization of processes, quality control, and real-time operational decisions. Using a manufacturing example, examine the following decision support system paradigms: data-driven, model-driven, knowledge-driven, document-driven, and communication-driven. Moreover, the key issues like data heterogeneity, complexity of integration, scalability, security, privacy, and interpretability of the model are also discussed, which can be used to consider creating robust, scalable, and intelligent IIoT-based data-driven decision support systems to be used in next-generation smart manufacturing systems**

Keywords*— *Industrial Internet of Things (IIoT), Data-Driven Decision Support Systems, Smart Manufacturing, Artificial Intelligence, Big Data Analytics, Edge Computing, Industry 4.0.

I. Introduction

The nature of industrial manufacturing is experiencing a paradigm change due to a rising complexity of the system, the dynamic nature of the market, and the necessity to raise productivity and quality [1][2]. The outdated method of decision-making, which is mainly experience-based and reactive, cannot be applied in the management of contemporary production set-ups [3][4][5]. With manufacturing systems becoming more automated and intelligent, timely and accurate decision-making based on sound data has become a very important requirement. This has made data-driven decision-making an essential part of the next-generation manufacturing systems.

The IIoT is at the center of facilitating this change through offering multi-layered connectivity and data collection across the manufacturing settings [6][7]. At the perception layer, sensors and embedded devices receive real-time data concerning machine conditions, process parameters and environmental parameters [8]. The network layer provides reliable data transmission and communication between physical resources and computing infrastructure as well as the application layer to process, analyze and visualize data in order to make operational and strategic decisions [9][10]. Collectively, these IIoT layers create a unified ecosystem that makes it possible to constantly monitor and exchange data during the manufacturing lifecycle.

The hierarchical IIoT architecture, data-driven decision-making mechanisms, systematically process raw sensor data into measurable knowledge that can be used to make smart and autonomous decisions [11]. information of the interconnected sensor, machine, and system to aid smart, quick, and correct decision-making throughout the manufacturing activities [12][13]. Through incorporating IoT, big data analytics. Information at the perception layer is initially preprocessed and filtered so as to provide accuracy and reliability before being sent to the network layer to edge or cloud-based platforms [14][15]. Advanced analytics and models of machine learning are implemented at the application layer to identify complicated links between process variables, equipment behavior, and production.

Data-driven decision support frameworks based on IIoT represent a formalized method that connects data capturing, communication, analytics, and decision implementation into a single system [16]. The frameworks create a closed-loop feedback, as application-layer insights form the basis of real-time action at the physical layer [17][18]. Such frameworks create a more responsive, reliable, and scalable industrial manufacturing by matching IIoT layers with information-based intelligence, and would facilitate the transition to autonomous and resilient smart manufacturing systems.

A. *Structure of the Paper*

This paper is organized in the following way: Section II: Enabling technologies for IIoT-based manufacturing. Section III Data-Driven Decision Support Systems (DSS), Section IV Architecture of IIoT-based decision support framework. Evaluation of Literature, Section V. Conclusion and future work are detailed in Section VI.

II. Enabling Technologies for IIoT-Based Manufacturing

The term "Internet of Things" (IoT) refers to a broad technical notion that defines pervasive Internet connectivity, turning commonplace items into networked gadgets. connected digital and physical realms, a phenomenon called a CPS. By addressing critical industrial concerns, the IIoT seeks to improve security, privacy, and networking standards without disrupting real production processes. The IoT layer is depicted in Figure 1.

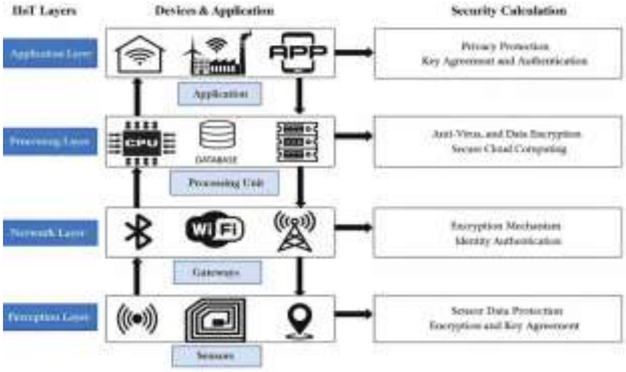

Fig. 1. IIoT layer architecture

A. Perception Layer

The sensor layer is another name for the perception layer. It is a combination of RFID, 2-dimensional barcodes, global positioning system (GPS) modules, and CCTV cameras, among other physical and sensor devices. Transportation of raw materials, surveillance of production areas, and collection of sensory data are all responsibilities of equipment in an industrial setting [19]. Systems for transport, automated guided vehicles, and industrial robots are all part of this category of gadgets. Prospective security flaws affecting the perception layer include node injection, manipulation, eavesdropping, reply attacks, timing attacks, RF interference, and node capture.

B. Network Layer

The data transmission or network layer is responsible for receiving and sending data between servers, smart objects, devices, sensors, networks, and other physical objects via wired or wireless connections. It allows traffic to flow between the network and the perception (or sensor) layer, which is susceptible to various attacks, through the use of protocols like as IPv4, IPv6, Wi-Fi, ZigBee, and others. Dangerous and widely known attacks on the network layer include MITM, Sybil, spoofing, DoS, and sinkhole threats.

C. Application Layer

Applications for the IIoT are passed down from connected devices to users by means of the application layer. To put it simply, it connects the end nodes to the IIoT network. Some well-known IIoT applications include smart homes, smart factories, and smart robotics. Smart home apps are vulnerable to security breaches because to their inherent insecurity, which can be found both within and externally. Application layer security concerns include hazardous code, side-channel attacks, cross-site scripting, and Trojan horses.

D. Processing Layer

Numerous security concerns in the multiple IIoT layers are the primary driver behind the creation of the fourth processor (or support layer). Due to security concerns, data cannot be transmitted directly to the network tiers in the three-tiered design; this layer mitigates several risks [20]. A solution to the security problems in IIoT was suggested by the fourth-level architecture. Before transmitting data acquired to the network levels, authentication is given precedence utilizing keys, pre-shared secrets, and passwords. A variety of functions, including decision-making, data storage, and algorithm execution, are housed in its databases and servers.

E. Industrial IoT-based Enabling Technologies

Industrial IoT (IIoT)-based manufacturing uses advanced communication technologies, smart sensors, and connected machines to collect and analyze data in real time across production systems. In order to showcase adaptable, networked procedures, digital and physical technologies are utilized. Businesses are making quick decisions all the way through the supply chain and smart factory by using the internet and related technologies. IIoT [21]. The openness, socialization, interoperability, and globalization of the internet provide a solid foundation for the idea of the IoT. Data mining and AI are two of the most efficient ways to handle and store enormous data sets. The applications shown in Figure 2 make use of neural networks and fuzzy logic. These applications include data analytics/modeling, machine learning, edge and fog computing, blockchain, and so on. The IIoT improves operational visibility, automation, and data-driven decision-making in contemporary manufacturing settings by integrating edge computing, cloud computing, and data analytics.

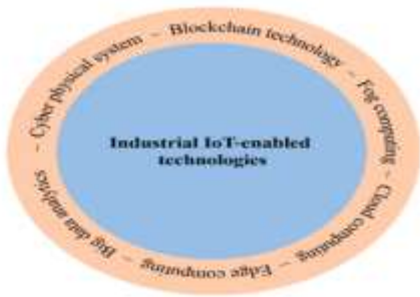

Fig. 2. Industrial IoT-enabled technologies

1) Cyber-physical System

Industry 4.0's CPS is one of its main technologies. It uses smart systems built into production equipment to link the manufacturing sector to the real world (figure 3).

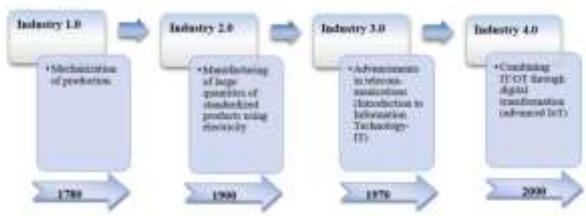

Fig. 3. History of industrial revolutions

IoT makes it possible to connect the real world of production to the virtual world. Computational power systems (CPS) enable an interactive industrial environment through networking, processing, and storage, resulting in smart factories [22]. Looking at it from this angle, smart products are becoming to be more and more recognized and traceable. In order to achieve Industry 4.0's goals of providing optimal security support across all levels of the CPS network and protecting sensitive data while guaranteeing data anonymity, the system must meet certain standards in terms of its functionality, maintainability, extensibility, adaptability, and variability.

2) Blockchain Technology

The unique properties of blockchain technology, such as distributed qualities, durability, certainty, tamper resistance, dependability, and built-in data origin, make it an ideal fit for

IIoT [23]. One data structure, the blockchain, leverages Bitcoin's distributed ledger and public key cryptography to facilitate safe peer-to-peer network transactions [24]. A hash value for the preceding link in the chain is referenced by each subsequent link.

3) Fog Computing

Fog computing is regarded as an augmentation of cloud computing, facilitating the interaction of the majority of commercial applications and operations with the Internet of Things (IoT) systems. In fog computing, no third parties are involved in the execution of necessary processes in industrial applications by means of a network of wireless and decentralized devices [25]. In fog computing, information technology infrastructure is used to provide online services.

4) Cloud Computing

The huge amount of data produced by IIoT needs to be processed, analyzed, and stored on many high-speed computers that are spread out in many places. All of the parts of an IIoT system can benefit from the computational, networking, and storage capacities offered by cloud computing technologies. There is a direct connection between backend clouds and all of the associated software and hardware [26]. There is a steady merging of IIoT with AI, and 5G and other forthcoming technologies, such as VR, AR, and MR, are finding more and more applications in business, academia, and healthcare.

5) Edge Computing

The term "edge computing" describes a new way of thinking about data processing that uses local nodes rather than a centralized cloud [27]. Outline features of edge computing include:

- **Proximity:** Resources for computation are situated in close proximity to devices that generate data.
- **Low latency:** Processing and answers can now take place in real-time, thanks to data transit distance reduction.
- **Bandwidth efficiency:** Minimizing network strain, only pertinent data is sent to the cloud.
- Enhanced privacy and security: Reducing exposure, sensitive data can be processed locally.
- **Autonomy:** Edge devices have the capability to function without being connected to the cloud.
- **Context awareness:** Improved use of context is made possible by local processing [28].

6) Big Data Analytics

The utilization of very complicated, high-performance computing platforms is essential for big data analysis due to the massive amounts of data generated by IIoT systems and devices. The use of conventional data processing methods was hindered by the considerably higher data volumes caused by the IoT [29]. Because there are so many SThs and EoIs linked to the cloud, the IoT centers on big data and AI to derive inferences and make judgements from sensory input. In contrast to the usual big data challenges, IoT big data presents its own set of challenges in terms of analysis and the integration of various big data analytics processes.

III. Taxonomy of Data-Driven Decision Support Frameworks

Smart manufacturing's use of IoT and DSS technology, providing an in-depth analysis of existing implementation approaches. With the rise of Industry 4.0, the IoT has enormous potential to improve data-driven decision-making and hence transform production processes [30]

A. Types of Decision Support Systems

Decision Support systems are the computerized tools provided to the decision-making process, analyzing data, modelling scenarios, collaboration, managing documents, or making intelligent recommendations. They are classified into five types

- **Data-driven decision support system:** Accessing and modifying structured data, both internal and external, is the focus of a data-driven DSS, which may also possess time series capabilities. They include the very basic query tools, file systems, and more complex systems such as EIS, BI systems, and OLAP. The main focus is to facilitate decision-making by enabling the retrieval, analysis, and presentation of large amounts of high-quality data.
- **Model-driven decision support system:** A model-driven DSS aids in decision-making by utilizing a variety of models, such as simulation, optimization, and financial models. It is a special type of design customized to analyze. Such DSS can be especially effective at modelling real-life scenarios and are widely applied to such objects as supply chain management in terms of manufacturing, planning, and logistics.
- **Communication-driven decision support system:** A Communication-based DSS is based on the exploitation of network and electronic solutions to support the cooperation between decision-makers[31]. It places them in one environment to share data, information, and resources to enhance decision-making. This architecture can also be referred to as a GDSS or a Collaborative DSS (CDSS).
- **Document-driven decision support system:** Document-driven DSS. This type of DSS can be used to manage and retrieve different electronic documents, such as texts, photos, images, and audio/video files. With the growth of Internet technologies. key components, helping organizations to efficiently locate, structure, and retrieve relevant documents for decision-making.
- **Knowledge-driven decision support system:** A knowledge-based DSS or intelligent DSS is a system that delivers information, understanding and propositions to assist users. It began its formation in the context of artificial intelligence, and is constructed on expert systems, working on rules, fuzzy logic, genetic algorithms or neural networks. develop effective solutions, and support decision-making effectively, particularly in areas such as manufacturing and scheduling.

B. Key Data-driven decision support system in manufacturing

The main idea behind a DSS and the main groups of DSSs that work together to help people make good decisions are shown in Figure 4. The five types of DSSs—data-driven, model-driven, knowledge-driven, document-driven, and communication-driven—each have their own benefits for looking at these parts and working together to make smart decisions.

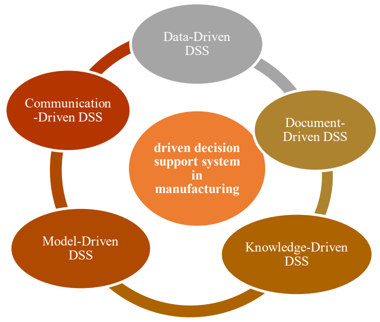

Fig. 4. Data-Driven Decision Support Systems (DSS)

1) Data-Driven DSS

Data distribution and management for "machine-generated data" and "human-generated data" can be enhanced with cloud-based big data management. Monitoring data from sensors should be optimized for usage in real-time automated fault identification, categorization, and root-cause detection.

2) Document-Driven DSS

Managing, retrieving, and analyzing unstructured or semi-structured documents such as reports, manuals, emails, and logs to support decision-making. In manufacturing, they help extract useful information from maintenance records, inspection reports, and technical documents. Techniques like text mining and natural language processing enable faster access to relevant knowledge, improving operational decisions and problem resolution.

3) Knowledge-Driven DSS

The exchange of expert subject information between operators and machines, as well as between managers, is crucial in smart manufacturing. Live, data-driven DM can be bolstered by recommendation engines and opinion mining. Clustering and machine-user relationship mining can make production systems more self-aware, learn better, and maintain themselves.

4) Model-Driven DSS

The future of manufacturing depends on supply chain management that is both integrated and technologically advanced. Better demand forecasting and integrated technology are also essential components of this process. Costs can be reduced and supply network defects like sensor failure and degradation can be identified with the use of quantitative models and sensors.

5) Communication-Driven DSS

The increased availability of decision-making capabilities between computers and humans can pave the way for machine sharing in a variety of contexts and tasks. Better training of operators and decision-makers, as well as the ability to foresee and respond to potential issues, can result from the development of simulation technologies [32].

IV. Architecture of IIoT-Based Decision Support Frameworks

A decision-support framework called the FASTEN Suite Tool is part of the IIoT design for decision support in the manufacturing system shown in Figure 1. It is supported by an open IIoT platform that makes sure all the system's parts can talk to each other in both directions [33]. Factors including manufacturing resources, business systems, and the FASTEN Suite Tool's integration are taken into account. As seen in Figure 5, the IIoT Platform enables connectivity between various systems and software modules through the provision of an Application Programming Interface (API) for broker subscriptions.

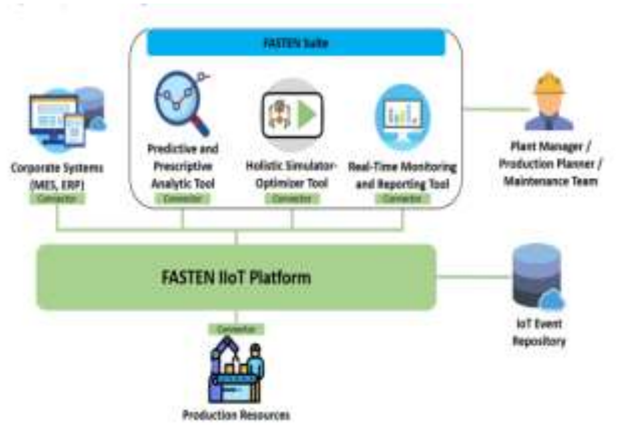

Fig. 5. Architecture of IIoT-based decision support in manufacturing system

- Decision support framework: Visualization, optimization, simulation, and real-time monitoring capabilities.
- One for real-time monitoring and another for predictive and prescriptive analytics. These tools can be used either in conjunction with one another or alone, depending on the particular application.
- The Real-Time Monitoring Tool generates reports and dashboards using data visualized by a suite of tools. The user interface also allows for interaction with the tools.
- The data input for the FASTEN Suite Tool is sourced from various sensors and corporate systems, including but not limited to the MES and the MMS. Before being transferred to the IIoT platform, the sensory data collected from the industrial processes undergoes local conditioning and pre-processing, such as sampling, filtering, compressing, and more.

A. Challenges of IIoT-based manufacturing in data driven decision

Industry 4.0 implementations of AI-based DSS do encounter certain challenges. Factors such as data quality, integration complexity, and the need for robust cybersecurity measures should be carefully considered. a number of obstacles must be overcome:

1) Integration and Interoperability

The lack of appropriate standards in communication networks has a significant influence on the integration of IoT devices. With the multitude of languages used in IoT hardware development and the numerous moving components, achieving communication interoperability has proven to be even more challenging than the already formidable task of implementing traditional communication interoperability.

2) Privacy

Hackers now have a multitude of new ways to take advantage of security holes in computer systems, thanks to the widespread use of Internet-enabled devices. Just as the number of Internet of Things (IoT) devices connected to a network increases, so does the attack surface [34]. This is because there are more devices for an attacker to compromise, making the network as a whole more vulnerable.

3) Sensor Networks

Sensor networks are a remarkable technical development that enables the Internet of Things. The world can be shaped by their abilities to assess, infer, and understand environmental indicators [35]. Efficiency and cost-effectiveness in large-scale remote sensing.

4) Data-Related Challenges

Poor data quality, inconsistency, incompleteness, and limited accessibility, which reduce the reliability of analysis and decision-making. Additionally, ensuring data privacy, security, and proper integration from multiple sources remains a major challenge. Data Quality and Accessibility, Data Privacy and Security, Data Governance and Compliance.

5) Reliability

Include difficulties in integrating AI systems with existing infrastructure, lack of interoperability among technologies, and high system complexity. Limited scalability, reliability issues, and the need for skilled technical expertise further hinder effective implementation. Scalability and Performance, Interoperability and Integration, Model Interpretability and Transparency.

6) Model interpretability and Adaptibility

High-order data-driven models, specifically machine learning ones, are not always transparent and may not be effective in adapting to the dynamics of operation[36]. which restricts trust and effectiveness in the long term in industrial decision-making.

V. LITERATURE REVIEW

The reviewed literature highlights recent of IIoT based manufacturing in data driven decision framework. The summary Table I systematically organizes key research studies, key findings, methodologies, challenges, and future work studies are discussed below:

Tang et al. (2025) IIoT systems are inherently dynamic, deeply embedded in physical environments, and often embodied in autonomous agents. These characteristics demand an AI paradigm that can continuously adapt and generalize across heterogeneous data and tasks. IIoT infrastructure supports data collection or distributed training, large pre-trained foundation models (FMs) can be leveraged as a service to empower general industrial intelligence in IIoT. a four-dimensional SCCE framework (Sensing–Computing–Connectivity–Evolution) that systematically examines the deployment of FMs in IIoT along the data processing pipeline and system lifecycle [37].

S et al. (2025), proposed the IIoT has changed the game for smart applications entirely. Despite the problem of efficient service placement and data analytics, resource allocation and meeting the stringent Quality of Service (QoS) standards remain challenging in Fog-Cloud systems. Cloud and mission-critical IIoT services move closer to the edge to reduce latency. A QoS-aware optimization approach simplifies service placement and resource management. Real time decisions are possible with the use of latest day in data analytics [38].

Lv and Li (2025), IIoT devices and the need for real-time processing in medical device production and pharmaceutical manufacturing. a distributed healthcare-aware deep learning resource orchestration (DH-DLRO) algorithm for edge computing-enabled healthcare IIoT flexible manufacturing systems. a joint optimization problem for task offloading decisions and resource allocation, specifically tailored to healthcare manufacturing requirements. DH-DLRO maintains consistent Quality of Service levels above 0.95 for medical device assembly tasks while achieving optimal CPU utilization effectiveness in balancing computational efficiency with healthcare manufacturing quality [39].

Ojha et al. (2024) proposed a novel framework for the adoption of DDDM in AMS to enhance its decision-making capabilities. This framework consists of six stages: manufacturing stage, sensing stage, data stage, knowledge stage, decision stage, and application stage leverages big data analytics to extract actionable, integrates CPS to create a seamless interaction between physical and digital systems, and employs IoT technologies for real-time data acquisition and monitoring, decision accuracy, and response time detailed data collection steps, preprocessing, and analysis, practical implementation and effectiveness [26].

Gandhi (2023) A novel framework called Hybrid-sense can optimize maintenance schedules, detect future problems, and cut down on operational expenses and downtime. It uses state-of-the-art machine learning and data analytics approaches. In order to improve the accuracy of predictions, developed a hybrid architecture that incorporates data from multiple sources, such as operating logs, environmental conditions, and sensor readings. This design combines classic statistical methods with deep learning algorithms [40].

Rosati et al. (2023) DSS consists of the following fundamental components: data gathering, feature extraction, drawing on relevant literature, innovative method relies on a feature extraction approach and ML prediction model. The integration of ML into cloud-based architecture paves the way for data analysis, cloud storage, and predictive models. to optimize maintenance schedules and receive real-time alerts regarding operational risks; this allows manufacturers to decrease service costs by increasing uptime and productivity [41].

Sergeeva, Voskobovich and Kukharenko (2022) Optimization of processes, predictive maintenance, and real-time decision-making in IIoT-based manufacturing are all substantially improved by IIoT decision support frameworks. the incorporation of sensor-driven architectures, big data analytics, and machine learning; recognizing difficulties associated with data heterogeneity, scalability, and security in smart processing systems. The usage of natural language processing is associated with AI and mathematical linguistics; synthesis refers to the process of producing text that is literate. This study examines processing methods for making structured data accessible to AI systems by transforming unstructured data [42].

TABLE I. SUMMARY OF LITERATURE REVIEW ON IIOT BASED MANUFACTURING IN DATA DECISION FRAMEWORK

Author	Study On	Key Findings	Application	Challenges	Future Work
Tang et al. (2025)	Foundation Models (FMs) in IIoT using SCCE (Sensing	SCCE enables adaptive, generalizable AI across IIoT lifecycles	General industrial intelligence,	Data heterogeneity, deployment cost,	Lightweight FMs, continual learning, edge–FM co-design

	Computing Connectivity Evolution) framework		autonomous IIoT systems	system evolution complexity	
S et al. (2025)	QoS-aware service placement and resource allocation in Fog Cloud IIoT	QoS-aware optimization improves latency and reliability	Mission-critical smart industrial applications	Dynamic workloads, strict QoS constraints, scalability	AI-driven real-time orchestration, predictive QoS models
Lv & Li (2025)	Edge-enabled healthcare IIoT manufacturing with DH-DLRO	Maintains QoS > 0.95 with optimal CPU utilization	Medical device and pharmaceutical manufacturing	Real-time constraints, healthcare compliance	Multi-objective optimization, cross-factory deployment
Ojha et al. (2024)	Data-Driven Decision Making (DDDM) framework for AMS	The six-stage framework improves decision accuracy and response time	Advanced Manufacturing Systems (AMS)	Data pre-processing complexity, CPS integration	Automated data pipelines, AI-enhanced decision layers
Gandhi (2023)	Hybrid-sense predictive maintenance framework	Hybrid ML + DL improves failure prediction accuracy	Predictive maintenance in smart manufacturing	Multi-modal data fusion, model interpretability	Explainable AI, adaptive maintenance scheduling
Rosati et al. (2023)	Cloud-based ML Decision Support System for maintenance	ML-based DSS reduces downtime and service costs	Industrial maintenance optimization	Cloud latency, data security, real-time alerts	Edge–cloud hybrid DSS, real-time anomaly detection
Sergeeva et al. (2022)	Data-driven DSS in IIoT manufacturing with NLP integration	ML and NLP enhance decision support from heterogeneous data	Smart manufacturing and process optimization	Data heterogeneity, scalability, security	Secure AI frameworks, advanced NLP for IIoT data

VI. Conclusion with Future Work

The increasing role of data-driven decision support systems as an underlying component of smart manufacturing systems based on Industrial IoT (IIoT). It is confirmed in the reviewed literature that the combination of layered IIoT structures with advanced analytics, machine learning, artificial intelligence, and edge-cloud computing can be used to support more effective real-time monitoring, predictive maintenance, quality assurance, and process optimization in an industrial setting. Decision support systems (DSSs) that are data-driven, model-driven, knowledge-driven, document-driven, or communication-driven provide a comprehensive decision-making ecosystem that can address the strategic and operational demands of manufacturing in all its facets. Although these developments are positive, some significant issues like heterogeneity of data, inability to interoperate between heterogeneous devices and platforms, vulnerability to cybersecurity and privacy, inability to operate at scale, and insufficient interpretability and adaptability of the complex analytical models have still not been addressed. The integrity of intelligent decision support systems, their perceived transparency, and their overall popularity with industry. Future research must be on designing standardized and interoperable IIoT systems, data analytics that are secure and do not compromise privacy, and explainable and reliable AI that is suited to industrial decision-making. High-level edge intelligence, digital twins, and adaptive learning algorithms can further minimize the latency and improve the system responsiveness. Enhancing human-machine cooperation and integrating the knowledge of the domain into the circle of decision making will be critical to the success of resilient, autonomous and sustainable follow-up generation smart manufacturing ecosystems.

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