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Review

Deep Learning-Assisted Smart Process Planning, Robotic Wireless Sensor Networks, and Geospatial Big Data Management Algorithms in the Internet of Manufacturing Things

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Abstract: The purpose of our systematic review is to examine the recently published literature on the Internet of Manufacturing Things (IoMT), and integrate the insights it configures on deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms by employing Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines. Throughout October 2021 and January 2022, a quantitative literature review of aggregators such as ProQuest, Scopus, and the Web of Science was carried out, with search terms including "deep learning-assisted smart process planning + IoMT", "robotic wireless sensor networks + IoMT", and "geospatial big data management algorithms + IoMT". As the analyzed research was published between 2018 and 2022, only 346 sources satisfied the eligibility criteria. A Shiny app was leveraged for the PRISMA flow diagram to comprise evidence-based collected and handled data. Major difficulties and challenges comprised identification of robust correlations among the inspected topics, but focusing on the most recent and relevant sources and deploying screening and quality assessment tools such as the Appraisal Tool for Cross-Sectional Studies, Dedoose, Distiller SR, the Mixed Method Appraisal Tool, and the Systematic Review Data Repository we integrated the core outcomes related to the IoMT. Future research should investigate dynamic scheduling and production execution systems advanced by deep learning-assisted smart process planning, data-driven decision making, and robotic wireless sensor networks.

Keywords: Internet of Manufacturing Things; deep learning-assisted smart process planning; robotic wireless sensor network; geospatial big data management; machine learning algorithm; Industry 4.0

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1. Introduction

The purpose of our systematic review is to examine the recently published literature on the Internet of Manufacturing Things (IoMT) and integrate the insights it configures on deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms. Real-time performance supervision, inspection, and control of IoMT-based industrial systems [1–9] necessitate smart sensors, devices, and actuators [10–18] in terms of manufacturing optimization through geospatial big data management algorithms. By inspecting the most recent (2018–2022) and relevant (Web of Science, Scopus, and ProQuest) sources, our paper has endeavored to prove that IoMT aims to improve shop floor operations, logistics, and production [19–28], decreasing machine downtime and system failure, and optimizing data acquisition and product quality [29–38] through geospatial big data management algorithms. The actuality and novelty of our study are configured by addressing the relationship between deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms. Our distinctive contribution is by showing how IoMT integrates real-time factory production scheduling and performance prediction, manufacturing big data, and sensor networks, leading to optimized regional connectivity. Similarities with previously published literature include analyses of IoMT-enabled production logistics systems and digital manufacturing shop floors by use of big data analytics and predictive maintenance processes, while differences encompass our integration of deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in IoMT-based real-time production logistics, planning, and scheduling in terms of system dynamics analysis, production system performance measurement, and product lifecycle management. IoMT-based sensing devices generate large-scale production data streams. The research problem is whether smart manufacturing systems require coherent streams in enterprise information systems [39–48], business processes [49–57], and big data-driven decision-making [58–67] accurately through robotic wireless sensor networks. Resource planning and execution systems require sensor data acquisition [68–77], support decision-making [78–86], and machine learning algorithms. In this review, previous findings have been integrated indicating that smart manufacturing plants harness big data analytics to deploy production data [87–96], optimizing the adjustability of operational processes. Shop floor operational performance can be supervised [97–108] by monitoring operational indicators and correcting system errors. The identified gaps advance how enterprise information systems in IoMT enable interoperability between manufacturing machines and resources [109–116] through real-time production management, scheduling, and data in terms of process planning, sensor networks, and management algorithms.

Our main objective is to indicate that IoMT integrates geospatial big data across product lifecycle management. Real-time manufacturing data of robotic wireless logistics resources and services can be accurately collected, shared, and integrated [117–125] through deep learning-assisted smart process planning. This systematic review contributes to the literature on IoMT by clarifying that advanced sensor technologies intensify data perceptibility and system controllability throughout shop floors [126–133] through deep learning-assisted smart process planning. This research endeavors to elucidate whether manufacturing tasks can be carried out in an on-demand fashion by real-time performance evaluation throughout management and supervision of production processes and logistics services. Our contribution is by cumulating research findings indicating that smart manufacturing facilitates big data-driven decision-making and coherent operations across the shop floor and supply chain traceability [134–149] developed on real-time information by use of robotic wireless sensor networks. The key implications of this systematic review are related to production logistics optimization of complex processes and decision support systems across IoMT-based shop floors through real-time data-driven smart manufacturing services, production scheduling, and performance analysis.

The manuscript is organized as following: a theoretical overview of the main concepts (Section 2), methodology (Section 3), deep learning-assisted smart process planning in IoMT (Section 4), robotic wireless sensor networks in IoMT (Section 5), geospatial big data management algorithms in IoMT (Section 6), discussion (Section 7), synopsis of the main research outcomes (Section 8), conclusions (Section 9), and limitations, implications, and further directions of research (Section 10).

2. Theoretical Overview of the Main Concepts

Industry 4.0-based manufacturing equipment and processes require smart technologies. Networked machines are deployed to perform manufacturing operations [1–12] by use of geospatial big data management algorithms. Big data acquisition, sensing, processing, storage, analysis, and integration [13–22] improve the production process and performance. Data-driven smart manufacturing services can optimize resource utilization and enhance productivity. Dynamic scheduling and production execution systems, leveraging real-time data and tools for performance enhancement [23–34] in a manufacturing big data setting, increase process complexity, carrying out integrated process planning, data-driven decision making, and operational scheduling [35–47] in a flexible shop floor. Smart manufacturing and automation systems are correlated with manufacturing digitization [48–59], optimizing the volume of data available to increase output by the use of data-driven decision-making across robotic wireless sensor networks. Smart manufacturing systems necessitate data production process analysis across life cycle management [60–73] by use of predictive maintenance. Smart manufacturing operations integrate production process enhancement [74–88] and geospatial big data management algorithms, performance evaluation, and distribution and configuration of production resources. Smart sensors assist production planning and scheduling developed on deep learning and robotic wireless sensor networks with manufacturing big data [89–97] with regard to dynamic production status and predictive modeling. Sensing devices can transfer real-time manufacturing data throughout the shop floor [98–109], assisting in identifying operational deficiencies by use of decision support systems. Enterprise decision-making [110–122] requires data mining tools and decision support systems. The architecture and performance of cyber-physical production systems (CPPSs) can reinforce production system enhancement through context modeling and data [123–136], in addition to sensors, smart devices, and factory assets. The manufacturing data is gathered, stored, handled, and inspected through big data technologies [137–149] and deep learning-assisted smart process planning.

3. Methodology

A systematic review of recently published literature was performed on the Internet of Manufacturing Things developed on deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms by employing Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines. Only original research and review articles published in scholarly outlets indexed in aggregators such as ProQuest, Scopus, and the Web of Science between 2018 and 2022 were analyzed. Conference proceedings, books, and editorial materials, in addition to content written in other languages than English, were not considered. No institutional ethics approval was needed as only publicly available scientific articles were extracted and analyzed. A Shiny app was leveraged for the PRISMA flow diagram to comprise evidence-based collected and handled data in terms of identification, screening, eligibility, and inclusion. Major difficulties and challenges comprised identification of robust correlations among the inspected topics, but focusing on the most recent and relevant sources and deploying screening and quality assessment tools such as the Appraisal Tool for Cross-Sectional Studies (to assess the quality of cross-sectional research), Dedoose (for inspecting qualitative and mixed methods research), Distiller SR (for data screening and extraction), the Mixed Method Appraisal Tool (for establishing the quality of the selected scholarly articles), and the Systematic Review Data Repository (for data acquisition, processing, and analysis), we integrated the core outcomes related to IoMT (Figure 1).

Throughout October 2021 and January 2022, a quantitative literature review of aggregators such as ProQuest, Scopus, and the Web of Science was carried out, with search terms including "deep learning-assisted smart process planning + IoMT", "robotic wireless sensor networks + IoMT", and "geospatial big data management algorithms + IoMT". As the analyzed research was published between 2018 and 2022, only 346 sources satisfied the eligibility criteria. Imprecise findings, results unsubstantiated by replication, and content having quite similar titles or being too general were removed and thus 140 articles, predominantly empirical, were selected (Tables 1 and 2).

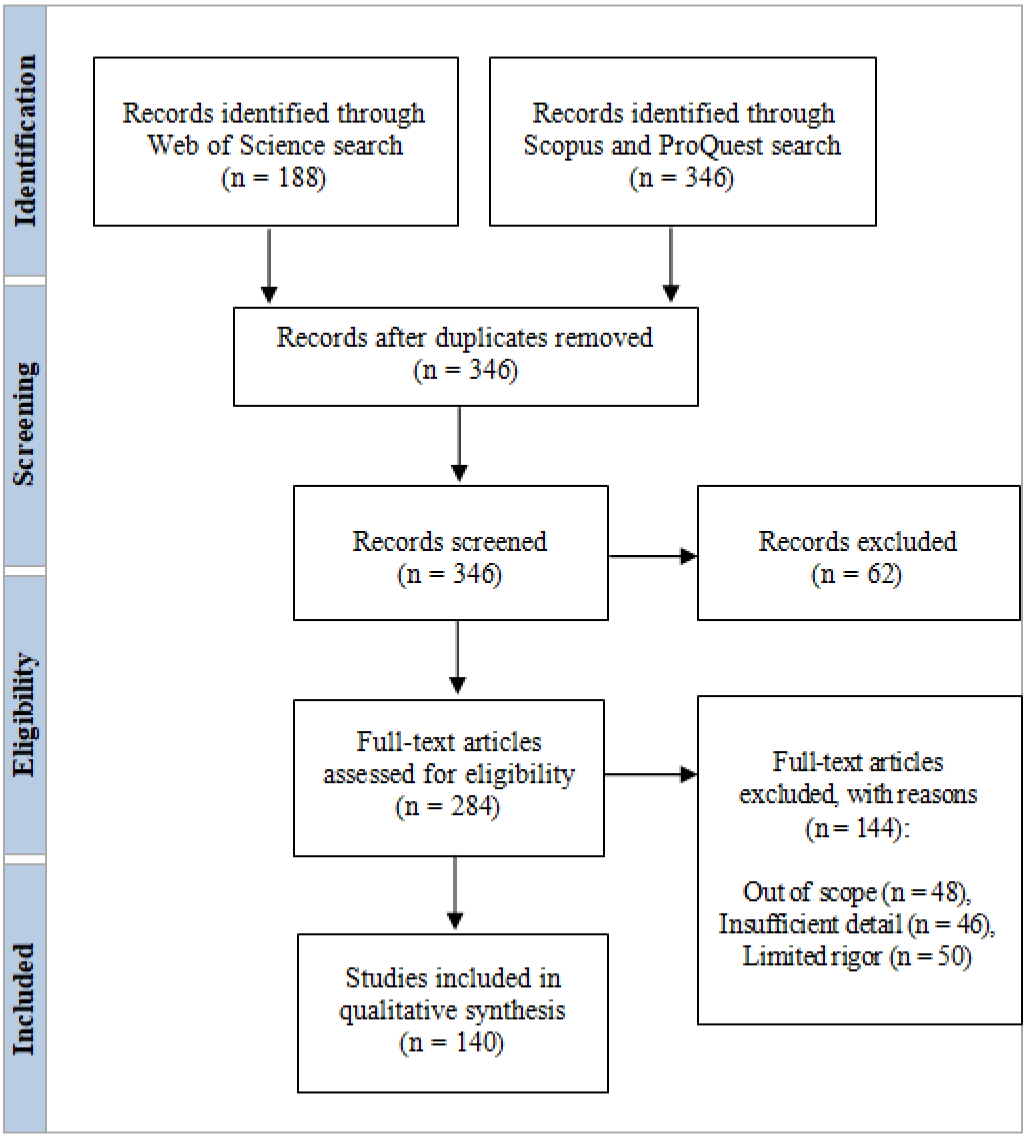

Figure 1. PRISMA flow diagram describing the search results and screening.

Table 1. Topics and types of paper identified and selected.

Topic	Identified	Selected
deep learning-assisted smart process planning + IoMT	121	48
robotic wireless sensor networks + IoMT	111	45
geospatial big data management algorithms + IoMT	114	47
Type of Paper		
original research	238	136
review	27	4
conference proceedings	44	0
book	16	0
editorial	21	0

Source: Processed by the authors. Some topics overlap.

Table 2. Synopsis of evidence regarding analyzed topics and descriptive outcomes (research findings).

IoMT technologies harness processes and data, production performance indicators and planning systems, and machine status, management, and operation to determine production abnormalities across management infrastructure.	Wang et al., 2018a; Wang et al., 2018b; Zhang, 2018a
IIoT decreases manufacturing time and enhance production and logistics across the shop floor through machine learning algorithms and deep learning-assisted smart process planning.	Zvarikova et al., 2021; Konecny et al., 2021; Popescu Ljungholm and Olah, 2020; Bal-Domańska et al., 2020
IoMT can enhance system-level diagnostics accuracy, maintenance scheduling, and operational robustness in industrial environments by condition data analysis.	Li et al., 2018; Müller et al., 2018; Ng et al., 2018; Majeed et al., 2019; Feng et al., 2020
IoMT-enabled real-time shop floor management and production scheduling shape sustainable development and manufacturing.	Zhang et al., 2018b; Wang et al., 2018c; Shoaib-ul-Hasan et al., 2018; Gaustad et al., 2018
Sensing is instrumental in gathering real-time and accurate data throughout smart manufacturing operations and environments, bringing about adaptive decisions when disturbances occur by use of planned operating parameters and resulting in improved production performance.	Grant, 2021; Welch, 2021; Turner and Pera, 2021
Data-driven smart manufacturing assists shop floors considerably, furthering relevant optimizations in production efficiency and in manufactured item performance.	Tao et al., 2018; Yang et al., 2019
Big data supply coherent technical support for supervising production processes through predictive maintenance.	Lawrence and Durana, 2021; Wells et al., 2021; Mircică, 2020; Bal-Domańska et al., 2020
With the swift development and broad applications of data-driven technologies on the shop floor, a massive volume of real-time input is produced, monitoring unpredictable exceptions.	Wang et al., 2019a; Zuo et al., 2018; Alexopoulos et al., 2018
Manufacturing enterprises can optimize the coherence of real-time scheduling, reducing the impact of exceptional events.	Nica and Stehel, 2021; Mitchell and Krulicky, 2021; Ionescu, 2021; Skvarciany et al., 2021
Throughout the production process, IoMT devices are leveraged for the sustainable development of manufacturing resources and enterprises.	Zhang et al., 2018c; Wang and Wang, 2019; Huang et al., 2019a; Liu et al., 2019; Zhang et al., 2019; Lee, 2019; Huang et al., 2019b
IoMT-based real-time data manufacturing and big data-driven dynamic optimization integrate sustainable and green logistics, together with data sensing, processing, visualization, and operational resources and services.	Wade and Vochozka, 2021; Lăzăroiu and Harrison, 2021; Harrower, 2019; Matuszewska-Pierzynka, 2021
Smart sensors assist IoMT-driven smart manufacturing in the performance of production and logistics operations, and of machining processes, by use of massive volumes of data generated by interconnected devices.	Zhong et al., 2021; Ismail et al., 2019; Park et al., 2019; Rossit et al., 2019; Qu et al., 2019; Hohmann and Posselt, 2019
CPPSs integrate groundbreaking computational tools, facilitating a real-time networking between shop floors and decision support systems in terms of scheduling procedures and production planning.	Brown, 2021; Evans and Horak, 2021; Pera, 2019; Androniceanu et al., 2021
Performance of IoMT systems requires harnessing edge analytics, smart connected devices, and shared computational resources to provide real-time decision-making.	Bui and Jung, 2019; Guo et al., 2020; Jung, 2019; Li et al., 2020; Munín-Doce et al., 2020; Tian et al., 2020
Predictive production planning deploying big data enhance resource performance in manufacturing, assisting enterprises in configuring competitive advantages.	Hu et al., 2020; Ma et al., 2020; Zhang et al., 2020a; Zhang et al., 2020b
Decentralized and real-time operational processes assist dynamic production decision-making and market prediction, furthering big data-driven business networking across the shop floor.	Bacalu, F. 2021; Nica et al., 2021

Table 2. *Cont.*

Manufacturing requirements and equipment operations can be reconfigured swiftly throughout a flexible production system, and thus monitoring and assessment tools have to adapt and perform concertedly across the shop floor.	Saez et al., 2018; Tao et al., 2018
IIoT can supervise operations on the shop floor and harmonize the real and virtual settings.	Androniceanu, 2020; Nica, 2021; Popescu et al., 2021
Intelligent algorithms and predictive models improve manufacturing operations through big data analytics that facilitates smart material assignment, product tracking, predictive maintenance, and performance management.	Andronie et al., 2021; Blake and Frajtova Michalikova, 2021; Clayton and Kral, 2021
Cyber-physical integration of digital twin and data-driven manufacturing service in digital factory optimize smart production and data fusion.	Chen et al., 2020; Cheng et al., 2018; Park et al., 2020; Qi et al., 2018
Digital twin can attain data distribution and integration between heterogeneous stages of the product lifecycle, increasing the extent of deployment of manufacturing data, and preventing repetition and waste.	Durica et al., 2019; Johnson and Nica, 2021; Peters, 2022
CPPSs gather real-time manufacturing data and network with computation modules in smart factory production operations by use of digital twin and virtual mapping.	Androniceanu, 2019; Bekken, 2019; Gray and Kovacova, 2021; Tucker, 2021
Production planning and scheduling developed on real-time manufacturing data can enhance task distribution, operational resources and processes, and IoMT-enabled shop floor management, through sensing machines.	Fang et al., 2020; Osterrieder et al., 2020; Pinzone et al., 2020; Wang et al., 2020a
Performance-optimizing functionalities are instrumental in managing, planning, and monitoring operations throughout the production plant lifecycle in collaborative manufacturing environments.	Ionescu, 2021; Vrbka, 2020; Woodward and Kliestik, 2021
IoMT can swiftly and dynamically adapt scheduling to satisfy fluid demands throughout production execution.	Matsumoto et al., 2020; Wang et al., 2020c; Wang et al., 2022; Zhang et al., 2022
IoMT is decisive in monitoring robust manufacturing operations and collecting real-time data in production logistics planning.	Ben-Daya et al., 2019; Feng et al., 2020; Huang et al., 2019c; Tian et al., 2019
Sustainable manufacturing shop floor integrates distributed and smart production equipment in the IoMT environment by use of scheduling and processing data, optimization algorithm, and operational resources.	Lăzăroiu et al., 2021; Lewis, 2021; Meyers et al., 2019; Pelau et al., 2021
IoMT facilitates remote management of production scheduling and planning, of supply chain operations, of data-collecting storage, and of predictive maintenance.	Hashemkhani Zolfani et al., 2021; Rogers and Zvarikova, 2021; Wallace and Lăzăroiu, 2021
IoMT environment can collect real-time data on shop floor production through scheduling algorithms and process monitoring to detect abnormal events so as to achieve optimal production efficiency.	Bao et al., 2019; Gulati and Kaur, 2019; Qian et al., 2019; Wu et al., 2019
Predictable, manageable, and adjustable production operations require robust resource allocation, coherent task execution, and continuous decision-making support.	Barbu et al., 2021; Gibson, 2021; Hopkins and Siekelova, 2021; Noack, 2019
The assimilation and enhancement of business processes, machine tools, information systems, and plant resources can carry out synergy during product design, maintenance and fault data, manufacturing, dynamic machining process control, and service.	Goodman and Frajtova Michalikova, 2021; Ionescu, 2020; Janovská et al., 2021

Table 2. *Cont.*

Shop floor logistics networks with smart manufacturing planning and control during the production process to attain conjoinedly integrated operations.	Guo et al., 2021; Jwo et al., 2021; Yao et al., 2019; Zhang et al., 2021a; Zhang et al., 2021b; Zhang et al., 2021c
The management of CPPS-based smart manufacturing plants and decision-making in IoMT are developed on data acquisition and on distributed smart devices and systems across the product value chain.	Barnes and Zvarikova, 2021; Konhäusner et al., 2021; Lowe, 2021; Rogers and Kalinova, 2021
CPPSs technologies enable plants to maintain manufacturing traceability and monitoring for increased quality and output, while production disturbances can be detected and fixed swiftly.	Hopkins, 2021; Wang et al., 2021a; Wang et al., 2020b;
To handle constant alterations and disturbances, plants can harness cutting-edge CPPS technologies across production management to maintain first-rate production traceability and monitoring on shop-floor through optimized manufacturing machine data and operations.	Bailey, 2021; Kovacova and Lăzăroiu, 2021; Stanley and Kucera, 2021
IoMT technologies carry out large-scale integration of physical operations and production data on a shop floor through the real-time collection of information and smooth equipment networking, boosting plant productivity.	Dai et al., 2020; Dall'Ora et al., 2021; Lv et al., 2021; Qian et al., 2021; Wang et al., 2021b
Digital transformation and computation across industrial plants requires that components of the production line are networked with enterprise applications, to collect and analyze real-time production line data across manufacturing phases.	Cohen and Macek, 2021; Ford, 2021; Phillips, 2021
As a result of the difficulties in handling large volumes of gathered data, heterogeneity environment, and instantaneous alterations across IoMT, a data-driven production-oriented platform can supply manufacturing services and process monitoring, articulating the continuous configuration of services.	Dong et al., 2018; Yang et al., 2019; Yao et al., 2018
Sensing data can be harnessed from large-scale IoMT networked machines to advance cutting-edge tools for diagnostics, prognostics, and upgrading of smart manufacturing systems through machine information processing, adaptive equipment control, real-time data acquisition, network modeling, predictive maintenance systems, and condition monitoring.	Hurley and Popescu, 2021; Mihăilă and Braniște, 2021; Novak et al., 2021
Articulating CPPSs, IoMT data include significant information to be extracted and processed from interconnected machines by use of networked operations and manufactured item lifecycles across supply chains.	Tao et al., 2018; Yang et al., 2019
IoMT and big data result in the configuration of cyber-physical connected networks of production systems by use of processing, modeling, and simulation.	Costea, 2020; Holmes and Cug, 2021; Małkowska et al., 2021
IoMT sensing networks can be deployed and assimilated to further data-driven manufacturing.	Dawson, 2021; Morrison, 2021; Woods and Miklencicova, 2021

4. Deep Learning-Assisted Smart Process Planning on the Internet of Manufacturing Things

IoMT technologies harness processes and data, configuring production performance indicators and planning systems, and machine status and operations [16–18] to determine production abnormalities across management infrastructure. Thus, enterprise information systems enable interoperability between manufacturing machines and resources through real-time production management, scheduling, and data. Smart machines integrate sensor networks and data management to monitor production disturbances and logistics capability by determining real-time manufacturing status through deep learning-assisted smart process planning. Sensing devices can transfer real-time manufacturing data throughout the shop floor, assisting in identifying operational deficiencies by the use of decision support systems. Manufacturing control systems necessitate management and planning, robust processes, and suitable equipment that are decisive in production scheduling, quality control, and assessment. Manufacturing tasks can be carried out in an on-demand fashion by real-time performance evaluation throughout management and supervision of production processes and logistics services. Industrial Internet of Things (IIoT) decreases manufacturing time and enhances production and logistics across the shop floor [1–4] through machine learning algorithms and deep learning-assisted smart process planning. Smart production systems require manufacturing status and resources to determine equipment failures, computational resources, and production schedules. Data-driven smart manufacturing services can optimize resource utilization and enhance productivity.

Industry 4.0 comprises process digitization, big data-driven manufacturing, and operational networking, configuring value creation. IoMT integrates data across product lifecycle management and can enhance system-level diagnostics accuracy, maintenance scheduling, and operational robustness in industrial environments [19–23] by condition data analysis. Real-time manufacturing data can shape production decision-making across smart factories, optimizing quality management. Predictive maintenance and deep learning-assisted smart process planning assist distributed decision-making systems in machinery fault diagnostics and dynamic production scheduling. Big data acquisition, sensing, processing, storage, analysis, and integration improve the production process and performance. IoMT-enabled real-time shop floor management and production scheduling [24–27] shape sustainable development and manufacturing. A circular economy can ensure the long-term sustainability of big data-driven industrial systems, as supply disruptions can lead to commodity price volatility, uncontrollable price escalations, and production bottlenecks. CPPSs can be deployed in smart manufacturing as regards customized products and services by use of deep learning-assisted smart process planning. Sensing is instrumental in gathering real-time and accurate data throughout smart manufacturing operations and environments [28–30], bringing about adaptive decisions when disturbances occur by use of planned operating parameters, and resulting in improved production performance.

Data-driven smart manufacturing assists shop floors considerably [31,32], furthering relevant optimizations in production efficiency and in manufactured item performance. Data analytics can supply preliminary warnings concerning quality defects and swift diagnosis of main causes. Operational data designed for manufacturing quality supervision and item defect traceability are acquired during production through big data analytics. Smart manufacturing plants harness big data analytics to deploy production data, optimizing the adjustability of operational processes. The manufacturing data is gathered, stored, handled, and inspected through big data technologies and deep learning-assisted smart process planning. Big data-driven applications facilitate smart design and planning, stuff sharing and tracking, production process supervision, quality monitoring, and smart machine maintenance. Big data supply coherent technical support for supervising production processes [4–7] through predictive maintenance, and thus virtual machine networks can aim for large-scale manufacturing optimization and management. IoMT and cloud computing can configure virtual machine networks, enhancing production decision-making performance by use of the cyber-physical integration of shop floors. Advanced sensing transfers relevant data streams across IoMT that connects equipment in the CPPSs and produces big data, leveraging heterogeneous sensors to incessantly supervise machine conditions, enhancing the administration and planning of production operations. Advanced sensor technologies intensify data perceptibility and system controllability throughout shop floors through deep learning-assisted smart process planning.

The IoMT-based real-time plant environment integrates the status of machines, flexible manufacturing systems, and processing performance to handle operational scheduling and enhance production tasks in conformity with machine status, improving factory planning, execution, and monitoring. Manufacturing enterprises can optimize the coherence of real-time scheduling [8–11], reducing the impact of exceptional events. IoMT technologies integrate green and sustainable manufacturing processes across the product's entire life cycle. With the swift development and broad applications of data-driven technologies across shop floors [33–35], a massive volume of real-time input is produced, monitoring unpredictable exceptions. Thus, dynamic scheduling and production execution systems, leveraging real-time data and tools for performance enhancement in a manufacturing big data setting, increase process complexity, carrying out integrated process planning, data-driven decision-making, and operational scheduling in a flexible shop floor. Resource planning and execution systems require sensor data acquisition, support decision-making, and machine learning algorithms. The architecture and performance of CPPSs can reinforce production system enhancement through context modeling and data, in addition to sensors, smart devices, and factory assets. Context-aware systems of big data-driven manufacturing integrate production tasks, shop floor data handling, sharing, storage, and decision-making. Context-aware intelligent service systems can be harnessed to supply data and decision support in IIoT through deep learning-assisted smart process planning.

Throughout the production process, IoMT devices are leveraged [36–42] for the sustainable development of manufacturing resources and enterprises. In the IoMT-enabled shop floor, historical manufacturing data and real-time condition input can improve low-prediction faultlessness and unsatisfactory generalization operations. IoMT-based real-time data manufacturing and big data-driven dynamic optimization integrate sustainable and green logistics [12–15], together with data sensing, processing, visualization, and operational resources and services. Cutting-edge automatic production systems are adopted on shop floors to upgrade smart manufacturing. In make-to-order plants, precise manufacturing progress prediction assists in dynamic production process enhancement and prompt order delivery. The optimal management, scheduling, and distribution of logistics resources and services require real-time data acquisition in terms of feedback, control, and processing. Real-time production data are leveraged in smart manufacturing enterprises to detect unexpected shop floor anomalies, and thus resources are trackable. Real-time manufacturing data of logistics resources and services can be accurately collected, shared, and integrated through deep learning-assisted smart process planning. Augmented reality technologies are essential in determining production performance indicators (e.g., cycle time, performance, and work-in-process) in wide-reaching manufacturing environments (Table 3).

Table 3. Synopsis of evidence regarding analyzed topics and descriptive outcomes (research findings).

IoMT technologies harness processes and data, production performance indicators and planning systems, and machine status, management, and operation to determine production abnormalities across management infrastructure.	Wang et al., 2018a; Wang et al., 2018b; Zhang, 2018a
IIoT decreases manufacturing time and enhance production and logistics across the shop floor through machine learning algorithms and deep learning-assisted smart process planning.	Zvarikova et al., 2021; Konecny et al., 2021; Popescu Ljungholm and Olah, 2020, Bal-Domańska et al., 2020
IoMT can enhance system-level diagnostics accuracy, maintenance scheduling, and operational robustness in industrial environments by condition data analysis.	Li et al., 2018; Müller et al., 2018; Ng et al., 2018; Majeed et al., 2019; Feng et al., 2020
IoMT-enabled real-time shop floor management and production scheduling shape sustainable development and manufacturing.	Zhang et al., 2018b; Wang et al., 2018c; Shoaib-ul-Hasan et al., 2018; Gaustad et al., 2018
Sensing is instrumental in gathering real-time and accurate data throughout smart manufacturing operations and environments, bringing about adaptive decisions when disturbances occur by use of planned operating parameters and resulting in improved production performance.	Grant, 2021; Welch, 2021; Turner and Pera, 2021

Table 3. *Cont.*

Data-driven smart manufacturing assists shop floors considerably, furthering relevant optimizations in production efficiency and in manufactured item performance.	Tao et al., 2018; Yang et al., 2019
Big data supply coherent technical support for supervising production processes through predictive maintenance.	Lawrence and Durana, 2021; Wells et al., 2021; Mircică, 2020; Bal-Domańska et al., 2020
With the swift development and broad applications of data-driven technologies on the shop floor, a massive volume of real-time input is produced, monitoring unpredictable exceptions.	Wang et al., 2019a; Zuo et al., 2018; Alexopoulos et al., 2018
Manufacturing enterprises can optimize the coherence of real-time scheduling, reducing the impact of exceptional events.	Nica and Stehel, 2021; Mitchell and Krulicky, 2021; Ionescu, 2021; Skvarciany et al., 2021
Throughout the production process, IoMT devices are leveraged for the sustainable development of manufacturing resources and enterprises.	Zhang et al., 2018c; Wang and Wang, 2019; Huang et al., 2019a; Liu et al., 2019; Zhang et al., 2019; Lee, 2019; Huang et al., 2019b
IoMT-based real-time data manufacturing and big data-driven dynamic optimization integrate sustainable and green logistics, together with data sensing, processing, visualization, and operational resources and services.	Wade and Vochozka, 2021; Lăzăroiu and Harrison, 2021; Harrower, 2019; Matuszewska-Pierzynka, 2021

5. Robotic Wireless Sensor Networks on the Internet of Manufacturing Things

Smart sensors assist IoMT-driven smart manufacturing in the performance of production and logistics operations, and machining processes [43–48] by use of massive volumes of data generated by interconnected devices. Smart manufacturing and automation systems are correlated with manufacturing digitization, optimizing the volume of data available to increase output by the use of data-driven decision-making across robotic wireless sensor networks. Smart manufacturing systems require coherent streams in enterprise information systems, business processes, and big data-driven decision-making accurately through robotic wireless sensor networks. Enterprise data systems are pivotal in smart manufacturing in terms of knowledge sharing and innovation, autonomous operations, seamless integration, dynamic optimization, business intelligence, value creation, and sustainable values. Manufacturing process data and execution systems integrate digitization of production services and equipment, enterprise data management and resource planning, supervising and inspecting process input for quality control. Process and efficiency optimization reconfigure operational performance as regards productivity and sustainable growth. CPPS-based service systems integrate the design and management of data flow across industrial manufacturing and logistics. CPPSs integrate groundbreaking computational tools [49–52], facilitating real-time networking between shop floors and decision support systems in terms of scheduling procedures and production planning.

Performance of IoMT systems requires harnessing edge analytics, smart connected devices, and shared computational resources [53–57] to provide real-time decision-making. Decentralized and real-time operational processes assist dynamic production decision-making and market prediction [62,63], furthering big data-driven business networking across the shop floor. Enterprise decision-making requires data mining tools and decision support systems. IoMT-based production information management systems can optimize shop floor scheduling. IoMT enables the integration of physical devices and virtual systems in smart factories, configuring connected manufacturing in digital environments and robotic wireless sensor networks. Monitoring and scheduling services are pivotal in machining systems and sustainable manufacturing by the use of robotic wireless sensor networks. IoMT-based sensor networks integrate production and quality control throughout the manufacturing chain, processing massive datasets. Smart manufacturing is instrumental in regards to sustainability, flexibility, and networking: service identification and distribution can supply on-demand manufacturing performance for satisfying personalized production demands. Predictive production planning deploying big data enhance resource performance in manufacturing [58–61], assisting enterprises in configuring competitive advantages. Process monitoring of product lifecycle phases enables optimal configuration and self-organizing aggregation of multi-level resources for manufacturing tasks, networks, and services.

Intelligent algorithms and predictive models improve manufacturing operations through big data analytics [68–70] that facilitates smart material assignment, product tracking, predictive maintenance, and performance management. Manufacturing requirements and equipment operations can be reconfigured swiftly throughout a flexible production system [31,64], and thus monitoring and assessment tools have to adapt and perform concertedly across the shop floor. Production abnormities can be predicted through mining the characteristic patterns and the tendency of unusual situations in time series. The operations of manufacturing systems and robotic wireless sensor networks are shaped by both the behavior of equipment and by networked devices. Sensors are integrated on manufacturing machines to detect heterogeneous data through fault diagnosis and prediction. Big data analytics can handle multi-source and massive data with increased adjustability, precision, and decreased computing time across robotic wireless sensor networks. Shop floor operational performance can be supervised by monitoring operational indicators and correcting system errors. IIoT can supervise operations on the shop floor [65–67] and harmonize the real and virtual settings. Gathering, processing, and inspecting shop floor data is challenging when the system functions under fluctuating state conditions (e.g., alterations in demand, equipment failure, postponement, or plant reconfiguration). Data from the manufacturing undertakings are assimilated with input from orders and operational plans. Real-time data can clarify which equipment necessitates service, restoration, or replacement.

Digital twin-based CPPSs in virtual plants can prevent performance deterioration and equipment failure of the manufacturing system in physical factory operations, resulting in enhanced operational processes, real-time monitoring, and production planning. Manufacturing plant operation efficiency can be attained by real-time monitoring of data acquisition and production process planning, reducing unsatisfactory product quality, abnormal situations, and equipment failure. Digital twin-based CPPS operations and IIoT-based technologies configure networked manufacturing systems in terms of advanced production planning and scheduling, data processing, and device control. CPPSs gather real-time manufacturing data and network with computation modules in smart factory production operations [78–81] by use of digital twin and virtual mapping. Cyber-physical integration of digital twin and data-driven manufacturing service in the digital factory [71–74] optimize smart production and data fusion. Digital twin assists in the cyber-physical incorporation of smart manufacturing big data in terms of predictive maintenance and production planning and design. The conjunction of digital twin and big data can harmonize various stages of the product lifecycle, reducing product development and assessment sequence, facilitating manufacturing planning improvement and production process real-time regulation through robotic wireless sensor networks. Real-time monitoring and upgrading of production processes, innovative product design and lifecycle, and quality traceability optimize and improve the smart manufacturing process across robotic wireless sensor networks. Digital twin decreases the product development cycle, enhances manufacturing performance, and ensures precision, coherence, and quality. Digital twin concatenates physical system modeling, algorithmic decision-making, and cyberspace simulation to configure digital designs of manufacturing operations. Digital twin can attain data distribution and integration between heterogeneous stages of product lifecycle [75–77], increasing the extent of deployment of manufacturing data, and preventing repetition and waste. Digital twin is suitable as regards visualization and outcome assessment, assisting in the interdependence and dynamic remodeling between production planning and implementation while furthering fault prediction, operational diagnosis, and predictive maintenance digitally. Together with the precise analysis and prediction performance of big data analytics, digital twin-driven smart manufacturing is increasingly responsive and conjecturing, upgrading manufacturing management.

Industry 4.0-based smart factories require machine data generation, collection, mining, assessment, and integration across connected manufacturing systems by use of visualization techniques, process automation, planning, and monitoring, and machine learning algorithms, increasing factory performance digitalization. Automation technologies can optimize productivity across Industry 4.0-based manufacturing systems, resulting in efficient and swift data integration and distribution across robotic wireless sensor networks. Production planning and scheduling developed on real-time manufacturing data [82–85] can enhance task distribution, operational resources and processes, and IoMT-enabled shop floor management, through sensing machines. IoMT can swiftly and dynamically adapt scheduling [89–92] to satisfy fluid demands throughout production execution. IoMT-based sensing devices generate large-scale production data streams. Smart sensors assist production planning and scheduling developed on deep learning and robotic wireless sensor networks with manufacturing big data with regard to dynamic production status and predictive modeling. Operational performance indicators can assess, track, and enhance interconnected CPPSs. Operational performance assessment articulates value-creation processes in digitalized production systems. Performance-optimizing functionalities are instrumental in managing, planning, and monitoring operations [86–88] throughout the production plant lifecycle in collaborative manufacturing environments. Smart manufacturing systems necessitate data production process analysis across life cycle management by use of predictive maintenance.

Industry 4.0 technologies are instrumental in data sharing, enhancing decision-making performance by monitoring and inspecting collected input across the manufacturing environment. IoMT is decisive in monitoring robust manufacturing operations and collecting real-time data [93–96] in production logistics planning. IoMT facilitates remote management of production scheduling and planning [101–103], supply chain operations, data-collecting storage, and predictive maintenance. In IoMT-enabled real-time shop floor scheduling and operations, disturbances such as machine breakdown require real-time control of optimal scheduling, machine tools, sensing technologies, and product development cycle across robotic wireless sensor networks. A sustainable manufacturing shop floor integrates distributed and smart production equipment in the IoMT environment [97–100] by use of scheduling and processing data, optimization algorithm, and operational resources. Manufacturing supply chain delivery operations, management and processes require quality-controlled product tracking, maintenance, logistics, and inventory accuracy of smart products and machines. The real-time scheduling and monitoring of plant systems integrate product manufacturing, equipment, and management. Distributed control systems develop on dynamic scheduling optimization algorithms and shop floor manufacturing data, tracking the management of production tasks and processes. Smart manufacturing facilitates big data-driven decision-making and coherent operations across shop floor and supply chain traceability developed on real-time information by use of robotic wireless sensor networks (Table 4).

Table 4. Synopsis of evidence regarding analyzed topics and descriptive outcomes (research findings).

Smart sensors assist IoMT-driven smart manufacturing in the performance of production and logistics operations, and machining processes, by use of massive volumes of data generated by interconnected devices.	Zhong et al., 2021; Ismail et al., 2019; Park et al., 2019; Rossit et al., 2019; Qu et al., 2019; Hohmann and Posselt, 2019
CPPSs integrate groundbreaking computational tools, facilitating real-time networking between shop floors and decision support systems in terms of scheduling procedures and production planning.	Brown, 2021; Evans and Horak, 2021; Pera, 2019; Androniceanu et al., 2021

Table 4. *Cont.*

Performance of IoMT systems requires harnessing edge analytics, smart connected devices, and shared computational resources to provide real-time decision-making.	Bui and Jung, 2019; Guo et al., 2020; Jung, 2019; Li et al., 2020; Munín-Doce et al., 2020; Tian et al., 2020
Predictive production planning deploying big data enhance resource performance in manufacturing, assisting enterprises in configuring competitive advantages.	Hu et al., 2020; Ma et al., 2020; Zhang et al., 2020a; Zhang et al., 2020b
Decentralized and real-time operational processes assist dynamic production decision-making and market prediction, furthering big data-driven business networking across the shop floor.	Bacalu, F. 2021; Nica et al., 2021
Manufacturing requirements and equipment operations can be reconfigured swiftly throughout a flexible production system, and thus monitoring and assessment tools have to adapt and perform concertedly across the shop floor.	Saez et al., 2018; Tao et al., 2018
IIoT can supervise operations on the shop floor and harmonize the real and virtual settings.	Androniceanu, 2020; Nica, 2021; Popescu et al., 2021
Intelligent algorithms and predictive models improve manufacturing operations through big data analytics that facilitates smart material assignment, product tracking, predictive maintenance, and performance management.	Andronie et al., 2021; Blake and Frajtova Michalikova, 2021; Clayton and Kral, 2021
Cyber-physical integration of digital twin and data-driven manufacturing service in digital factory optimize smart production and data fusion.	Chen et al., 2020; Cheng et al., 2018; Park et al., 2020; Qi et al., 2018
Digital twin can attain data distribution and integration between heterogeneous stages of the product lifecycle, increasing the extent of deployment of manufacturing data, and preventing repetition and waste.	Durica et al., 2019; Johnson and Nica, 2021; Peters, 2022
CPPSs gather real-time manufacturing data and network with computation modules in smart factory production operations by use of digital twin and virtual mapping.	Androniceanu, 2019; Bekken, 2019; Gray and Kovacova, 2021; Tucker, 2021
Production planning and scheduling developed on real-time manufacturing data can enhance task distribution, operational resources and processes, and IoMT-enabled shop floor management, through sensing machines.	Fang et al., 2020; Osterrieder et al., 2020; Pinzone et al., 2020; Wang et al., 2020a
Performance-optimizing functionalities are instrumental in managing, planning, and monitoring operations throughout the production plant lifecycle in collaborative manufacturing environments.	Ionescu, 2021; Vrbka, 2020; Woodward and Kliestik, 2021
IoMT can swiftly and dynamically adapt scheduling to satisfy fluid demands throughout production execution.	Matsumoto et al., 2020; Wang et al., 2020c; Wang et al., 2022; Zhang et al., 2022
IoMT is decisive in monitoring robust manufacturing operations and collecting real-time data in production logistics planning.	Ben-Daya et al., 2019; Feng et al., 2020; Huang et al., 2019c; Tian et al., 2019
Sustainable manufacturing shop floor integrates distributed and smart production equipment in the IoMT environment by use of scheduling and processing data, optimization algorithms, and operational resources.	Lăzăroiu et al., 2021; Lewis, 2021; Meyers et al., 2019; Pelau et al., 2021
IomT facilitates remote management of production scheduling and planning, supply chain operations, data-collecting storage, and predictive maintenance.	Hashemkhani Zolfani et al., 2021; Rogers and Zvarikova, 2021; Wallace and Lăzăroiu, 2021

6. Geospatial Big Data Management Algorithms in Internet of Manufacturing Things

IoMT environment can collect real-time data on shop floor production through scheduling algorithms and process monitoring [104–107] to detect abnormal events so as to achieve optimal production efficiency. IoMT carries out large-scale sensing, fluid sharing, and real-time data analysis, leading to improvement of production efficiency. Real-time performance and predictability in manufacturing management are related to production planning, execution, management, and process control. As a result of the underlying forces and unpredictability of the processing environment, shop floors may undergo unanticipated disturbances in the production systems. Predictable, manageable, and adjustable production operations [108–111] require robust resource allocation, coherent task execution, and continuous decision-making support. Smart manufacturing operations integrate production process enhancement and geospatial big data management algorithms, performance evaluation, and distribution and configuration of production resources by use of machine operation and simulation data, quality prediction, and fault diagnosis, thus decreasing machine downtimes and equipment failures. Real-time performance supervision, inspection, and control of IoMT-based industrial systems necessitate smart sensors, devices, and actuators in terms of manufacturing optimization through geospatial big data management algorithms. Plant real-time visualization management developed on IoMT integrates production decision-making and sensor data integration. Factory automation requires product digital design, data sharing and integration, real-time data gathering and distribution technologies, interconnected and big data-driven operations, digital process modeling, and product lifecycle, maintenance, and service. The production process can be assessed, enhanced, and predicted in conformity with real-time simulation and production data, together with historical manufacturing data. For example, the digital management of twin-based factories detects, inspects, monitors, and optimizes integrated and interconnected machining behavior in manufacturing operations. The assimilation and enhancement of business processes, machine tools, information systems, and plant resources [112–114] can carry out synergy during product design, maintenance and fault data, manufacturing, dynamic machining process control, and service. Real-time manufacturing data gathering, management, and production process optimization are pivotal in planning and controlling big data-driven production and resource scheduling.

Industry 4.0-based manufacturing resource reconfiguration results in unrestricted interconnection and real-time data collection through collaborative networks and IoMT, monitoring order demand and abnormal disturbance. Industry 4.0-based manufacturing equipment and processes require smart technologies. CPPS-based reconfigurable manufacturing systems can be optimized and integrated on cutting-edge modules or functions, facilitating increased monitoring of production operations through IoMT to enhance model-based condition assessment and bias detection, and to carry out dynamic manufacturing tasks. Smart factories develop on CPPSs and big data-driven integrated manufacturing systems by use of heterogeneous data, sensor networks, business process management, and decentralized decision making. The management of CPPS-based smart manufacturing plants and decision-making in IoMT are developed on data acquisition and on distributed smart devices and systems [121–124] across the product value chain. Shop floor logistics networks with smart manufacturing planning and control during the production process [115–120] to attain conjoinedly integrated operations. Smart manufacturing can supply a service-oriented sustainable production for shop floors. Exemplary distribution of smart manufacturing services prevents inactive production resources and enables extensive distribution and on-demand deployment of operational performance. Data sensing, modeling, and assessment can predict events that are monitored to reduce uncertainty risk by the use of geospatial big data management algorithms. Production-related data, resource monitoring, and predictive maintenance assist in identifying manufacturing exceptions and ensuring standard task execution through geospatial big data management algorithms.

Industry 4.0 technologies influence supply chains by increasing digitalization and automation. CPPS technologies enable plants to maintain manufacturing traceability and monitoring for increased quality and output [125–127], while production disturbances can be detected and fixed swiftly. Real-time and heterogeneous production data can supply accurate support throughout manufacturing logistics decision-making. The real-time status of equipment and networked devices can be sensed and tracked by operational production systems and geospatial big data management algorithms. Intelligent algorithms and predictive analytics upgrade CPPS-enabled production management, decision making, and manufacturing shop floor in terms of resource allocation, production data, and decision execution. CPPS and predictive analytics technologies facilitate active perception and precise sharing of production data as regards machine status and the dynamic production environment. Smart sensing devices, robust decision support, prediction algorithms, and big data analytics assist enterprise information systems in improving manufacturing resources, machine maintenance, computational abilities, production efficiency, advanced planning, and logistics schedule adjustment. Smart manufacturing processes real-time data as regards production scheduling and decisions by use of geospatial big data management algorithms. In a CPPS-enabled plant, production status can be tracked and sensed rapidly, and production fluctuations and exceptions can be identified timely. To handle constant alterations and disturbances, plants can harness cutting-edge CPPS technologies across production management [128–130] to maintain first-rate production traceability and monitoring on the shop floor through optimized manufacturing machine data and operations. Shop floor production smoothness and performance in terms of accurate prediction enable effortless simulation and checking of production decision output in dynamic autonomous systems.

IoMT technologies carry out large-scale integration of physical operations and production data in a shop floor through the real-time collection of information and smooth equipment networking [131–135], boosting plant productivity. IoMT technologies integrate fluid perception, adaptive enhancement, and real-time management of production processes, monitoring abnormal events and critical machine workload through geospatial big data management algorithms. IoMT aims to improve shop floor operations, logistics, and production, decreasing machine downtime and system failure, and optimizing data acquisition and product quality through geospatial big data management algorithms. Acquired data can be leveraged to make optimal decision-making on production processes, decreasing downtime and maintenance expenses by monitoring unexpected behaviors. Manufacturing systems and enterprises monitor dynamic events and process planning across flexible shop floors to prevent equipment breakdown. Machine learning algorithms can support behavioral control, perception, product maintenance, analysis, and intelligent decision-making. Smart manufacturing requires production planning and lifecycle management, plant governance, and warehouse logistics, aiming for sustainable development. Digital transformation and computation across industrial plants require that components of the production line are networked with enterprise applications [136–138], to collect and analyze real-time production line data across manufacturing phases. Data analytics of large-scale manufacturing operations can derive significant business values.

As a result of the difficulties in handling large volumes of gathered data, heterogeneity environment, and instantaneous alterations across IoMT [32,139,140], a data-driven production-oriented platform can supply manufacturing services and process monitoring, articulating the continuous configuration of services. Sensing data can be harnessed from large-scale IoMT-networked machines [141–143] to advance cutting-edge tools for diagnostics, prognostics, and upgrading of smart manufacturing systems through machine information processing, adaptive equipment control, real-time data acquisition, network modeling, predictive maintenance systems, and condition monitoring. The increasing demand for swift feedback to customers' orders requires the assimilation of planning, flexible job-shop scheduling, and monitoring in flexible production systems through optimization algorithms, context awareness, and instantaneous maintenance in smart manufacturing. Networked machines are deployed to perform manufacturing operations by use of geospatial big data management algorithms. The interoperability between networked machines may be articulated dynamically to boost adjustability to customized tasks. The data-driven interconnection of networked machines enhances the performance of sensor-based production systems.

Articulating CPPSs, IoMT data include significant information to be extracted and processed from interconnected machines [31,32] by use of networked operations and manufactured item lifecycles across supply chains. IoMT and big data result in the configuration of cyber-physical connected networks of production systems [144–146] by use of processing, modeling, and simulation. Industrial plants have progressively invested in IoMT for process supervision, operation upgrading, fault detection, and production monitoring. Data pertinent to certain processes should be coherently identified and retrieved to assist manufacturing analytics. IoMT sensing networks can be deployed and assimilated [147–149] to further data-driven manufacturing. IoMT and cloud computing provide inexpensive and adjustable data gathering, storage, and processing support throughout the manufacturing data lifecycle. Smart manufacturing develops on data-driven breakthroughs to carry out increased levels of self-governance and optimization of shop floors through virtual machine networks and geospatial big data management algorithms. The quantity of data acquired throughout the production value chain and manufactured item lifecycle is increasing significantly. Data can enable the supervision and optimization of product quality. Data sharing is decisive in maintaining networking across distributed production systems and resources through geospatial big data management algorithms. Big data analytics can assist in configuring informed decisions as regards the optimization of production operations and machines, and evaluating and upgrading technological processes (Table 5).

Table 5. Synopsis of evidence regarding analyzed topics and descriptive outcomes (research findings).

IoMT environment can collect real-time data on shop floor production through scheduling algorithms and process monitoring to detect abnormal events so as to achieve optimal production efficiency.	Bao et al., 2019; Gulati and Kaur, 2019; Qian et al., 2019; Wu et al., 2019
Predictable, manageable, and adjustable production operations require robust resource allocation, coherent task execution, and continuous decision-making support.	Barbu et al., 2021; Gibson, 2021; Hopkins and Siekelova, 2021; Noack, 2019
The assimilation and enhancement of business processes, machine tools, information systems, and plant resources can carry out synergy during product design, maintenance and fault data, manufacturing, dynamic machining process control, and service.	Goodman and Frajtova Michalikova, 2021; Ionescu, 2020; Janovská et al., 2021
Shop floor logistics networks with smart manufacturing planning and control during the production process to attain conjoinedly integrated operations.	Guo et al., 2021; Jwo et al., 2021; Yao et al., 2019; Zhang et al., 2021a; Zhang et al., 2021b; Zhang et al., 2021c
The management of CPPS-based smart manufacturing plants and decision-making in IoMT are developed on data acquisition and on distributed smart devices and systems across the product value chain.	Barnes and Zvarikova, 2021; Konhäusner et al., 2021; Lowe, 2021; Rogers and Kalinova, 2021
CPPSs technologies enable plants to maintain manufacturing traceability and monitoring for increased quality and output, while production disturbances can be detected and fixed swiftly.	Hopkins, 2021; Wang et al., 2021a; Wang et al., 2020b
To handle constant alterations and disturbances, plants can harness cutting-edge CPPS technologies across production management to maintain first-rate production traceability and monitoring on shop-floor through optimized manufacturing machine data and operations.	Bailey, 2021; Kovacova and Lăzăroiu, 2021; Stanley and Kucera, 2021

Table 5. *Cont.*

IoMT technologies carry out large-scale integration of physical operations and production data on a shop floor through the real-time collection of information and smooth equipment networking, boosting plant productivity.	Dai et al., 2020; Dall'Ora et al., 2021; Lv et al., 2021; Qian et al., 2021; Wang et al., 2021b
Digital transformation and computation across industrial plants require that components of the production line are networked with enterprise applications, to collect and analyze real-time production line data across manufacturing phases.	Cohen and Macek, 2021; Ford, 2021; Phillips, 2021
As a result of the difficulties in handling large volumes of gathered data, heterogeneity environment, and instantaneous alterations across IoMT, a data-driven production-oriented platform can supply manufacturing services and process monitoring, articulating the continuous configuration of services.	Dong et al., 2018; Yang et al., 2019; Yao et al., 2018
Sensing data can be harnessed from large-scale IoMT networked machines to advance cutting-edge tools for diagnostics, prognostics, and upgrading of smart manufacturing systems through machine information processing, adaptive equipment control, real-time data acquisition, network modeling, predictive maintenance systems, and condition monitoring.	Hurley and Popescu, 2021; Mihăilă and Braniște, 2021; Novak et al., 2021
Articulating CPPSs, IoMT data include significant information to be extracted and processed from interconnected machines by use of networked operations and manufactured item lifecycles across supply chains.	Tao et al., 2018; Yang et al., 2019
IoMT and big data result in the configuration of cyber-physical connected networks of production systems by use of processing, modeling, and simulation.	Costea, 2020; Holmes and Cug, 2021; Małkowska et al., 2021
IoMT sensing networks can be deployed and assimilated to further data-driven manufacturing.	Dawson, 2021; Morrison, 2021; Woods and Miklencicova, 2021

7. Discussion

The relevance of deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in relation to IoMT is to a large extent in consonance with, and provides a further substantiation of, previous articles, e.g., [1–11], clarifying that the IoMT-based real-time plant environment integrates the status of machines, flexible manufacturing systems, and processing performance [12–21] to handle operational scheduling and enhance production tasks in [22–32] conformity with machine status, improving factory planning, execution, and monitoring. IoMT-based production information management systems can optimize shop floor scheduling. Real-time manufacturing data can shape production decision-making [33–45] across smart factories, optimizing quality management.

The outcomes of this systematic review are derived from empirical research [46–58] contending that manufacturing process data and execution systems integrate digitization of production services and equipment, enterprise data management and resource planning [59–68], supervising and inspecting process input for quality control. Smart machines integrate sensor networks and data management to monitor production disturbances and logistics capability [69–78] by determining real-time manufacturing status by use of deep learning-assisted smart process planning. Smart manufacturing processes real-time data as regards production scheduling and decisions by use of geospatial big data management algorithms.

There has been a developing volume of studies [79–91] claiming that big data-driven applications facilitate smart design and planning, stuff sharing and tracking, production process supervision, quality monitoring, and smart machine maintenance. IoMT carries out large-scale sensing, fluid sharing, and real-time data analysis [92–108], leading to improvement of production efficiency. Manufacturing control systems necessitate management and planning, robust processes, and suitable equipment [109–117] that are decisive in production scheduling, quality control, and assessment.

Certain empirical studies [118–130] systematically indicate that Industry 4.0 technologies are instrumental in data sharing [131–138], enhancing decision-making performance [139–149] by monitoring and inspecting collected input across the manufacturing environment. Cutting-edge automatic production systems and cognitive automation technologies [150–154] are adopted on shop floors [155–161] to upgrade smart manufacturing. Operational performance assessment [162–167] articulates value-creation processes [168–172] in digitalized production systems. IoMT articulates sustainable smart manufacturing by the use of data-driven predictive algorithms, deep learning-based sensing technologies, and big geospatial data analytics [173–178].

8. Synopsis of the Main Research Outcomes

IoMT technologies integrate green and sustainable manufacturing processes [1–13] across the product entire life cycle. The operations of manufacturing systems and robotic wireless sensor networks [14–22] are shaped by both the behavior of equipment and networked devices. CPPSs can be deployed in smart manufacturing with regards to customized products and services [23–34] by use of deep learning-assisted smart process planning. The real-time scheduling and monitoring of plant systems [35–46] integrate product manufacturing, equipment, and management. The optimal management, scheduling, and distribution of logistics resources and services [47–58] require real-time data acquisition in terms of feedback, control, and processing. Data analytics of large-scale manufacturing operations [59–71] can derive significant business values. Operational data designed for manufacturing quality supervision and item defect traceability are acquired during production [72–88] through big data analytics. Industry 4.0 comprises process digitization, big data-driven manufacturing, and operational networking [89–102], configuring value creation. Real-time manufacturing data gathering, management, and production process optimization [103–114] are pivotal in planning and controlling big data-driven production and resource scheduling. Automation technologies can optimize productivity across Industry 4.0-based manufacturing systems [115–123], resulting in efficient and swift data integration and distribution across robotic wireless sensor networks. Smart production systems require manufacturing status and resources [124–136] to determine equipment failures, computational resources, and production schedules. Process and efficiency optimization reconfigure operational performance [137–149] as regards productivity and sustainable growth.

9. Conclusions

Significant research has analyzed how smart manufacturing and automation systems are correlated with manufacturing digitization. The architecture and performance of CPPSs can reinforce production system enhancement through context modeling and data. Sensing devices can transfer real-time manufacturing data throughout the shop floor. Data-driven smart manufacturing services and big data technologies integrate operational scheduling, distribution and configuration of production resources, and predictive maintenance in a flexible shop floor, identifying operational deficiencies by use of decision support systems. This systematic literature review examines relevant published peer-reviewed evidence as regards Industry 4.0-based manufacturing equipment and processes assisted by data mining tools and decision support systems. We show how networked machines are deployed to perform manufacturing operations, optimizing the volume of data available to increase output by the use of data-driven decision-making across robotic wireless sensor networks. We clarify that real-time industrial unit scheduling and data processing can result in IoMT-enabled dynamic optimization as regards tool condition monitoring, real-time anomaly detection, event-driven production planning, predictive maintenance, and operational performance. Consequently, CPPS-based decentralized manufacturing and enterprise data systems can reconfigure production big data visualization, abnormal event monitoring, product lifecycle planning and management, industrial manufacturing and logistics, and big data-driven product services in IoMT-based virtual enterprises. The findings obtained from the above explorations clarify that smart sensors assist production planning and scheduling, that geospatial big data management algorithms improve the production process and performance of smart manufacturing operations by use of real-time data and tools, and that production process enhancement and performance evaluation necessitate data production process analysis across life cycle management by use of smart technologies and manufacturing data. Academic implications of this study mainly include the need of advancing research on big data-driven process optimization of IoMT-based real-time monitoring systems, context-aware information services, and predictive production planning. Practical consequences would be for cyber-physical manufacturing systems to integrate enhanced manufacturing execution decisions, real-time shop floor scheduling, and system performance monitoring of supply chain quality management.

10. Limitations, Implications, and Further Directions of Research

As limitations, by analyzing only original research and review articles published in scholarly outlets indexed in aggregators such as ProQuest, Scopus, and the Web of Science between 2018 and 2022, important sources on the Internet of Manufacturing Things developed on deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms may have been omitted. Subsequent interest should be oriented to how geospatial big data management algorithms can optimize resource utilization and enhance productivity in terms of enterprise decision-making. The scope of our systematic review does not advance how dynamic production status and predictive modeling can harness big data acquisition, sensing, processing, storage, analysis, and integration in smart manufacturing systems. Future research should investigate dynamic scheduling and production execution systems advanced by deep learning-assisted smart process planning, data-driven decision making, and robotic wireless sensor networks. More visualization monitoring technologies should be examined and leveraged for real-time data collection in IoMT concerning predictive manufacturing systems and maintenance processes, cyber-physical factory automation, and performance assurance methods and tools, resulting in cutting-edge products and services.

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