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Review

Artificial Intelligence-Based Decision-Making Algorithms, Internet of Things Sensing Networks, and Deep Learning-Assisted Smart Process Management in Cyber-Physical Production Systems

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Citation: Andronie, M.; Lăzăroiu, G.; Iatagan, M.; Uță, C.; Ștefănescu, R.; Cocoșatu, M. Artificial Intelligence-Based Decision-Making Algorithms, Internet of Things Sensing Networks, and Deep Learning-Assisted Smart Process Management in Cyber-Physical Production Systems. *Electronics* **2021**, *10*, 2497. https://doi.org/10.3390/electronics10202497

Academic Editors: Matteo Golfarelli and Enrico Gallinucci

Received: 13 September 2021
Accepted: 11 October 2021
Published: 14 October 2021

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Abstract: With growing evidence of deep learning-assisted smart process planning, there is an essential demand for comprehending whether cyber-physical production systems (CPPSs) are adequate in managing complexity and flexibility, configuring the smart factory. In this research, prior findings were cumulated indicating that the interoperability between Internet of Things-based real-time production logistics and cyber-physical process monitoring systems can decide upon the progression of operations advancing a system to the intended state in CPPSs. We carried out a quantitative literature review of ProQuest, Scopus, and the Web of Science throughout March and August 2021, with search terms including "cyber-physical production systems", "cyber-physical manufacturing systems", "smart process manufacturing", "smart industrial manufacturing processes", "networked manufacturing systems", "industrial cyber-physical systems," "smart industrial production processes", and "sustainable Internet of Things-based manufacturing systems". As we analyzed research published between 2017 and 2021, only 489 papers met the eligibility criteria. By removing controversial or unclear findings (scanty/unimportant data), results unsupported by replication, undetailed content, or papers having quite similar titles, we decided on 164, chiefly empirical, sources. Subsequent analyses should develop on real-time sensor networks, so as to configure the importance of artificial intelligence-driven big data analytics by use of cyber-physical production networks.

Keywords: cyber-physical; production; system; artificial intelligence; Internet of Things; algorithm

1. Introduction

There is an emergent body of literature in relation to how Cyber-Physical Systems (CPS) address the integration of Internet of Things sensing networks, computational applications, and artificial intelligence-based decision-making algorithms with physical devices, being engineered as an interconnection between cyber and physical components. This is crucial in the advancement of smart manufacturing by use of cloud computing, social networking, and big data [1–3]. Cyber-Physical Production Systems (CPPSs) develop out of the deployment of CPS principles to manufacturing environments. CPPSs represent an elaborate and fluid network [4–7] of services and shop floor components (e.g., sensors and actuators), can adjust swiftly to new manufactured items or product variants, can optimize networking among smart connected devices in the production environment, and can provide self-governance, self-organization, and interoperability across smart networked factories, thus optimizing the resilience of manufacturing systems. CPPSs are crucial in advancing sustainable manufacturing Internet of Things and smart factories [8–11], by harnessing wireless sensor networks for controlling objectives, facilitating integration of industrial data, and supervising and coordinating real objects and operations.

The purpose of this research is to inspect the recently published material on CPPSs and integrate the understandings associated with Internet of Things-based decision support systems, interconnected sensor networks, deep learning-assisted smart process planning, and automatic big data-driven real-time production logistics. By analyzing the latest (2017–2021) and most important (ProQuest, Scopus, and the Web of Science) sources, our systematic review has attempted to determine that cyber-physical production systems (CPPS) are adequate in managing complexity and flexibility, configuring the smart factory. CPPSs inspect, supervise, and automate business operations, optimizing manufacturing and logistic processes across smart shop floor environments. Smart autonomous devices are pivotal in planning and control systems as Internet of Things elements of CPPSs. The substantiality and uniqueness of the research are highlighted by clarifying how cyber-physical system-based smart factories optimize the networking among equipment, sensors and big data-driven systems, constituting a research issue of high interest. Cyber-physical system-based manufacturing configures knowledge-intensive industrial autonomous settings in which smart customized items are produced through deep learning-assisted smart process planning [12–17], real-time advanced analytics, and cognitive automation. Cloud computing, robotic wireless sensor networks, and artificial intelligence data-driven Internet of Things systems are essential in enabling cyber-physical process monitoring systems.

The research topic advanced throughout our research is whether sustainable cyber-physical production systems developed on functional and behavioral patterns [18–23] can address the inconveniences of disruptive Industry 4.0-related production environments. Accurate and reliable assessments of product quality through cyber-physical system-based real-time monitoring assist in optimizing manufacturing processes and big data-driven decision-making instantaneously. In this article, previous findings were gathered, indicating that Internet of Things-based real-time production logistics, automated production systems, industrial big data analytics, and deep learning-assisted smart process planning [24–29] facilitate continuous monitoring of smart shop floors. Sustainable Industry 4.0 wireless networks can shape effective and robust manufacturing by automatically monitoring production equipment in a flexible fashion. Our chief purpose is to clarify that artificial intelligence data-driven Internet of Things systems necessitate high-performance operations and adjustable production systems [30–35] by use of flexible and real-time scheduling. CPPSs and sustainable manufacturing Internet of Things reconfigure how shop floor operations are designed and carried out. This research contributes to the literature on cyber-physical system-based smart factories by clarifying that manufacturing process monitoring systems have advanced as decentralized reconfigurable networked entities by use of cutting-edge intelligent machines. Industrial enterprises advance as wireless sensor networks to constantly control the operations of their plants. We specifically show that cyber-physical production systems develop by the integrative processes of sustainable industrial big data, artificial intelligence-based decision-making algorithms, and Internet of Things sensing networks in cyber-physical system-based smart factories. This systematic review endeavors to elucidate whether the interoperability between Internet of Things-based real-time production logistics, big data-driven decision support systems, and cyber-physical process monitoring systems can decide upon the progression of operations [36–38] advancing a system to the intended state in CPPSs. As a result of the advancement of CPPSs, self-governing monitoring of manufacturing processes is indispensable in smart production processes. Our contribution is analyzing and interpreting connected research findings which prove that industrial cyber-physical systems are pivotal in sustainable smart manufacturing, and integrating control engineering with artificial intelligence-based decision-making algorithms to set up cognitive and self-configuring plants. Smart connected devices have heterogeneous processing and manufacturing capabilities and optimization operation mechanisms. We clarify that leveraging artificial intelligence data-driven Internet of Things systems is pivotal in achieving smart industrial value creation through real-time process monitoring, sustainable Industry 4.0 wireless networks, and Industry 4.0-based manufacturing systems. Condition-based monitoring and predictive maintenance require real-time sensor data through Internet of Things-based decision support systems.

2. Methodology

We carried out a systematic review covering recently published material on artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, cognitive automation, and deep learning-assisted smart process management in cyber-physical production systems by harnessing Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines. We considered only recent original empirical research or review articles (2017–2021) written in English, indexed in ProQuest, Scopus, and the Web of Science, and covering particular search terms. We used the Systematic Review Data Repository, a software program for the acquisition, processing, and analysis of data. The quality of the indicated scientific sources was appraised by deploying the Mixed Method Appraisal Tool. Extracting and inspecting publicly available documents (scholarly articles) as evidence, we required no procedural ethics permission before initiating our research (Figure 1).

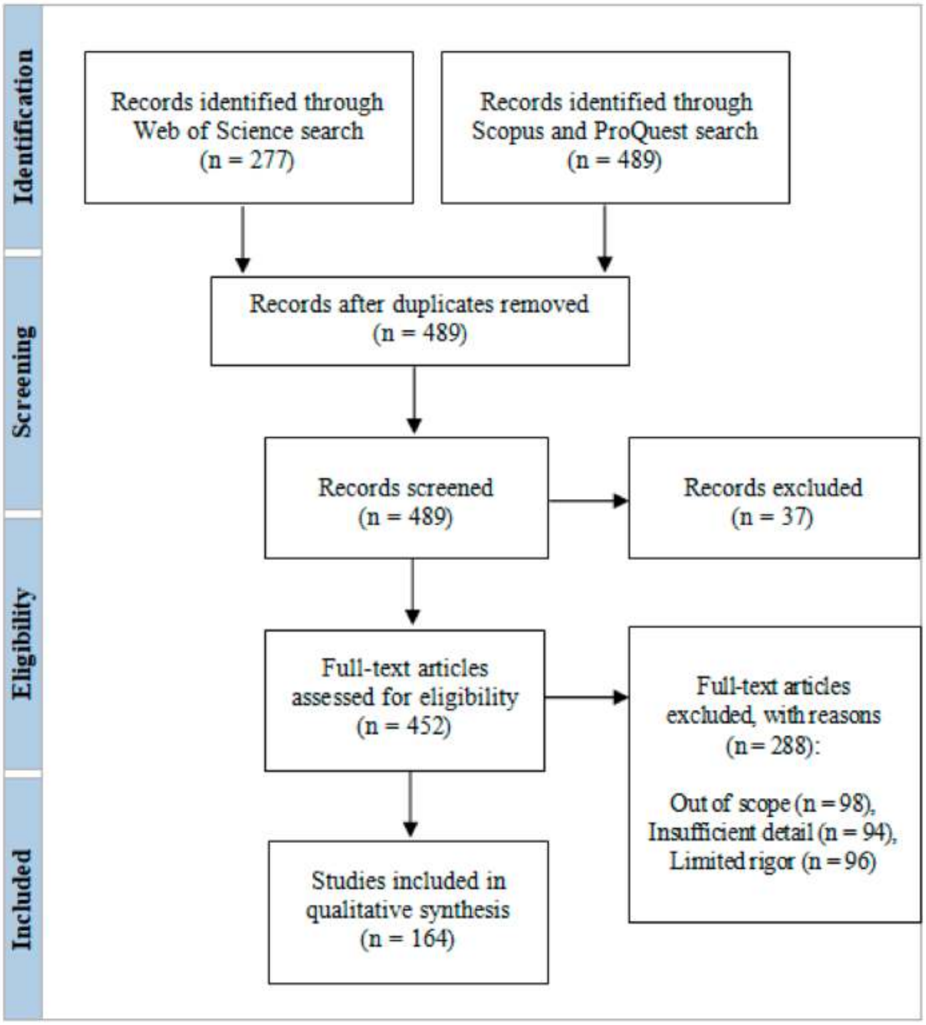

Figure 1. PRISMA flow diagram describing the search results and screening.

We carried out a quantitative literature review of ProQuest, Scopus, and the Web of Science throughout March and August 2021, with search terms including "cyber-physical production systems", "cyber-physical manufacturing systems", "smart process manufacturing", "smart industrial manufacturing processes", "networked manufacturing systems", "industrial cyber-physical systems", "smart industrial production processes" and "sustainable Internet of Things-based manufacturing systems". The search terms were determined as being the most employed words or phrases across the investigated literature. As we analyzed research published between 2017 and 2021, only 489 papers met the eligibility criteria. By removing controversial or unclear findings (scanty/unimportant data), results unsupported by replication, undetailed content, or papers having quite similar titles, we decided on 164, chiefly empirical, sources (Tables 1 and 2).

Table 1. Topics and types of scientific products identified and selected.

Topic	Identified	Selected
Cyber-physical production systems	98	42
Cyber-physical manufacturing systems	82	30
Smart process manufacturing	63	19
Smart industrial manufacturing processes	58	16
Networked manufacturing systems	53	16
Industrial cyber-physical systems	50	15
Smart industrial production processes	46	14
Sustainable Internet of Things-based manufacturing systems	39	12
Type of Paper		
Original research	423	159
Review	29	5
Conference proceedings	22	0
Book	8	0
Editorial	7	0

Source: Processed by the authors. Some topics overlap.

Table 2. General synopsis of evidence regarding focus topics and descriptive outcomes (research findings).

Intelligent plant modules and smart factory automation have advanced CPPSs that are pivotal in collision identification, impedance monitoring, and assimilating machine learning-based tasks. Wireless sensor technology monitor manufacturing assets and networked production or logistics business operations in real time. Cyber-physical system-based manufacturing configures knowledge-intensive industrial autonomous settings in which smart customized items are produced through deep learning-assisted smart process planning, real-time advanced analytics, and cognitive automation. Groundbreaking technologies furthering cyber-physical enterprise systems regarding real-time decision-making determined from streamlined data necessitate networked sensor and operational systems. The scheduling algorithms can become cognizant of the heterogeneous data coming from the industrial unit in relation to relevance and convenience of the resources when carrying out assignments.	Bell, 2020; Brown et al., 2020; Cohen, 2021; Edwards, 2021; Graessley et al., 2019; Grant, 2021; Hamilton, 2021; Islam et al., 2019; Keane et al., 2020; Lewis, 2020; Ma et al., 2021; Mircică, 2019; Mitchell, 2021; Nelson, 2020; Panetto et al., 2019; Popescu Ljungholm, 2019; Preuveneers and Ilie-Zudor, 2017; Townsend, 2021; Walker, 2020; Wu et al., 2021; Yao et al., 2019
Adaptive production systems are crucial in sustainable manufacturing Internet of Things, deriving from the demand for robust characteristics of the system to react to disruption as product changes or alterations to operational parameters. CPPSs autonomously identify and react to inconstant and unplanned situations on the shop floor. Because of the growing volume of modular components and systems, interwoven and heterogeneous factory systems are required for big data-driven decision-making processes and collaborative control in sustainable manufacturing routines. Internet of Things-based real-time production logistics, robotic wireless sensor networks, and deep learning-assisted smart process planning facilitate continuous monitoring of smart shop floors.	Ansari et al., 2018; Balica, 2019; Bennett et al., 2020; Berger et al., 2021; Bergs et al., 2020; Engel et al., 2018; Gibson, 2021; Konecny et al., 2021; Lewis, 2021; Otto et al., 2018; Panetto et al., 2019; Peters et al., 2020; Riley et al., 2021; Sanderson et al., 2019; Stehel et al., 2021; Suler et al., 2021; Suvarna et al., 2021; Valaskova et al., 2021; Wells et al., 2021; Yao et al., 2018

Table 2. *Cont.*

In CPPSs, smart connected devices team up automatically to constantly optimize manufacturing processes, manage disturbances, and adjust to variable conditions. The demand for increasingly customized, smart, and sustainable manufactured items and the swift growth of cyber-physical system-based real-time monitoring have resulted in the development of Internet of Things-based decision support systems. The capacity of sustainable cyber-physical production systems to reconfigure in conformity with variable demands enables a rise in deployment and a decrease in expenses and alterations in time. Advancing data-driven monitoring systems and leveraging them across a CPPS platform may result in large-scale supervision and an increase in efficiency during the sustainable product lifecycle management in plants.	Biró et al., 2021; Clarke, 2020; Costea, 2020; Davidson, 2020; Dawson, 2021; Deng et al., 2018; Ionescu, 2019 a; Jiang, 2018; Johnson, 2020; Kovacova et al., 2019; Lăzăroiu et al., 2021; Leiden et al., 2021; Lowe, 2021; Miller, 2020; Mircică, 2020; Moghaddam et al., 2018; Novak et al., 2021; Rojas and Rauch, 2019; Russell, 2020; Taylor, 2021; Walker et al., 2020
CPPSs constitute cutting-edge technologies for the adoption of smart manufacturing that is effective only when processing standards and application procedures for the heterogeneous data, which can modify instantaneously due to the character of a factory, are carried out. CPPSs are redesigning hierarchical control arrangements into distributed structures in which the components operate autonomously. Data processing to collect significant information and physical value creation in the production operations can be attained through the assimilation of the enterprise resource coordination and manufacturing execution systems. Embedded and coordinated value networks provide customers with sustainable mass-personalized products and services, and further real-time adaptation to fluid alterations in user demand, shop floor environments, and supply/value networks.	Brown, 2021; Chessell and Neguriță, 2020; Cooper et al., 2021; Cruz Salazar et al., 2019; Dias-Ferreira et al., 2018; Elhabashy et al., 2019; Gordon, 2021; Gödri et al., 2019; Green and Zhuravleva, 2021; Harris, 2021; Jiang et al., 2018; Kang et al., 2019; Morgan and O'Donnell, 2018; Pera, 2019; Popescu et al., 2021; Throne and Lăzăroiu, 2020; Tomiyama and Moyen, 2018; Vrabič et al., 2018; Wang et al., 2018
Companies expand their product portfolio and try to decrease their manufacturing time to maximize earnings and market presence, indirectly exacerbating the intricacy of the operational processes. The production system has to inspect the tasks to integrate with the smart connected devices and perform them unsupervised and automatically. CPPSs and sustainable manufacturing Internet of Things reconfigure how shop floor operations are designed and carried out. Deployment of artificial intelligence-based decision-making algorithms, deep learning-assisted smart process planning, real-time sensor networks, and cloud technologies are instrumental in remote maintenance support.	Bekken, 2019; Coatney and Poliak, 2020; Davies, 2020; Jantunen et al., 2018; Lyons and Lăzăroiu, 2020; Miller, 2020; Morgan and O'Donnell, 2017; Neubauer et al., 2017; Nica et al., 2020; O'Donovan et al., 2019; Peters, 2020; Popescu et al., 2020; Rossit and Tohmé, 2018; Scott et al., 2020; Suvarna et al., 2021; Vogel-Heuser et al., 2021
Cloud computing and service-oriented designs can network and develop physical factory performance to the cyber world in terms of engineering. By harnessing data-driven modeling, cyber-physical process monitoring systems will reshape manufacturing as intuitive and automated. Smart manufacturing harnesses predictive production systems systematically. In smart industrial units, CPPSs control physical operations, configure a digital duplicate of the physical world, and decisions are decentralized.	Davis et al., 2020; Duffie et al., 2017; Francalanza et al., 2017; Hawkins, 2021; Ionescu, 2020 a, b; Jiang et al., 2018; Kral et al., 2019; Lee et al., 2017; Mladineo et al., 2017; Moore, 2020; Nica et al., 2019; Schneider et al., 2019; Shaw et al., 2021; Tang et al., 2018; Williams, 2020
Variable manufacturing systems and product demands derive from inconstant customer behavior. Tools for assessing and managing enhancements in the performance, the soundness, and the responsiveness of manufacturing systems are required. CPPSs improve the flexibility and output of smart manufacturing, adjusting the design and quality of products to fluid market demands and customized requirements. The convergence of standard automation systems within CPPSs, together with service-oriented designs and fog, edge, and cloud computing technologies, are developing sustainable manufacturing Internet of Things and cyber-physical process monitoring systems.	Bourke et al., 2019; Davidson, 2020; Duft and Durana, 2020; Engelsberger and Greiner, 2018; Gray-Hawkins and Lăzăroiu, 2020; Harrower, 2019; He et al., 2021; Kovacova et al., 2019; Lăzăroiu et al., 2020; Liu et al., 2019; Noack, 2019; Sinha and Roy, 2019; Tan et al., 2019; Wingard, 2019; Yu et al., 2017 a, b
Cyber-physical machine tools can develop Industry 4.0-based equipment regarding intelligence and self-governance, by integrating physical devices and machining operations with computation and networking performance. CPPSs provide the technological basis for the digitalization and decentralization of manufacturing processes, and their integration across plant networks. Heterogeneous instantaneous transmission scheduling algorithms handle the distribution of the channel resources, but cyber and physical units have distinct demands to enhance the quality of network performance. The fluid assessment, integration, and positioning of services across CPPSs constitute elements of the process control throughout the consolidated modeling and appraisal of operational phases.	Adamson et al., 2017; Andreev et al., 2021; Durana et al., 2021; Freier and Schumann, 2021; Grundstein et al., 2017; Ionescu, 2019 b; Ionescu, 2020 c; Kannengiesser et al., 2021; Kliestik et al., 2020; Liu et al., 2017; Meyers et al., 2019; Penas et al., 2017; Taylor, 2020; Tucker, 2021; Vogel-Heuser et al., 2017; Wade et al., 2021; Welch, 2021, Zahid et al., 2021

Table 2. *Cont.*

CPPSs can be thoroughly and steadily engineered and during their lifecycle in smart manufacturing through Internet of Things sensing networks, real-time process monitoring, and artificial intelligence-based decision-making algorithms. Artificial intelligence data-driven Internet of Things systems necessitate high-performance operations and adjustable production systems by use of flexible and real-time scheduling. Sustainable Industry 4.0 wireless networks can shape effective and robust manufacturing by automatically monitoring production equipment in a flexible fashion. CPPSs ensure a thorough networking of the smart connected devices and resources integrated in manufacturing processes and, consequently, enhanced availability of collected data. Computational devices can be deployed as monitoring and interaction technologies and as heterogeneous collaborative devices and modes of networking to configure crucial tools in operating, maintaining, and upgrading data-driven CPPSs.	Allen, 2020; Bennett, 2021; Bordel et al., 2017; Cunningham, 2021; Davies et al., 2020; Grayson, 2020; Harrison et al., 2021; Hyers, 2020; Mourtzis and Vlachou, 2018; Pivoto et al., 2021; Popescu et al., 2020; Robinson, 2020; Sinha and Roy, 2021; Tomiyama and Moyen, 2018; Smith, 2020; Watkins, 2021; Weichhart et al., 2021; Williams et al., 2020; Wright and Birtus, 2020 Dhiman and Röcker, 2021

Source: Processed by the authors.

3. Artificial Intelligence-Based Decision-Making Algorithms, Smart Factory Performance, and Industry 4.0-Based Manufacturing Systems in CPPSs

Intelligent plant modules and smart factory automation [39,40] have advanced CPPSs that are pivotal in collision identification, impedance monitoring, and assimilating machine learning-based tasks. For collective decision-making, CPPSs necessitate processing of collective data, taking into account the feasible knowledge, operational analysis, and fluid systems resilient to the instantaneous dynamic alterations across the shop floor and within the networked infrastructure. Because of the growing volume of modular components and systems [41–43], interwoven and heterogeneous factory systems are required for big data-driven decision-making processes and collaborative control in sustainable manufacturing routines (e.g., closed-loop supply chains). The inconstant environment necessitates adjustable patterns through learning, while additional mechanisms comprise self-regulation by smart agents. Operational infrastructure should enable loose coupling, cyber-physical system-based real-time monitoring, and supply networks.

In CPPSs, smart connected devices team up automatically to constantly optimize manufacturing processes, manage disturbances, and adjust to variable conditions [44–47], articulating the relevance of networking and control systems. Increased collected data would lead to configuring resilient manufacturing systems adjustable to market demand and holding patterns in the logistic chains to obtain exemplary values of the intended key performance indicators. Industry 4.0-based manufacturing systems require the networking of all devices integrated across the shop floor. Data processing to collect significant information and physical value creation in the production operations [48–50] can be attained through the assimilation of the enterprise resource coordination and manufacturing execution systems. The deployment of networked monitoring systems across smart factories configures big data-driven manufacturing control architecture. The interoperability between Internet of Things-based real-time production logistics and cyber-physical process monitoring systems can decide upon the progression of operations advancing a system to the intended state in CPPSs. Internet of Things-based decision support systems will enhance the quality of big data-driven decision-making processes, due to the extensive convenience of information regarding smart networked factories. Smart autonomous devices are pivotal in planning and control systems as Internet of Things elements of CPPSs.

CPPSs and sustainable manufacturing Internet of Things reconfigure how shop floor operations are designed and carried out [51–54], decentralizing production by deploying networked cyber-physical production resources. Heterogeneous smart connected devices and processes across industrial monitoring interact in product decision-making information systems. Industrial cyber-physical systems are pivotal in sustainable smart manufacturing, by integrating control engineering with artificial intelligence-based decision-making algorithms to set up cognitive and self-configuring plants. Cloud computing and service-oriented designs can network and develop physical factory performance to the cyber world in terms of engineering, monitoring and Internet of Things sensing networks [55–57] for increased reliability and resilience. The latency and soundness of cyber-physical system-based real-time monitoring implemented by using cloud and fog computing can result in instantaneous integrated deep learning-engineering applications. High accuracy production necessitates the leverage of cutting-edge signal processing and analytics to supervise, handle, and control manufacturing processes. CPPSs are instrumental in instantaneous heterogeneous data collection, inspection, and distribution by use of interoperability support integrated in process monitoring systems. Multi-scalable signal processing and big data-driven decision-making operations can be deployed for both user-driven and partially autonomous manufacturing support systems. CPPSs redesign decision-making processes (e.g., dynamic, distributed, and inverse scheduling) across manufacturing environments, assimilating heterogeneous functionalities in Internet of Things sensing networks.

Cyber-physical system-based manufacturing configures knowledge-intensive industrial autonomous settings [58–61] in which smart customized items are produced through deep learning-assisted smart process planning, real-time advanced analytics, and cognitive automation. CPPSs inspect, supervise, and automate business operations, optimizing manufacturing and logistic processes across smart shop floor environments: big data performance, cloud services, and cyber-physical predictive decision support connected devices can boost productivity and efficiency. Industrial enterprises advance as wireless sensor networks to constantly control the operations of their plants. Wireless sensor technology monitors manufacturing assets and networked production or logistics business operations in real time [62–64], increasing output, improving resource efficiency, diminishing interruptions, or reducing discontinuation. Wireless sensor networks are multipurpose and inexpensive to install for impermanent and gradual gathering of further data points, facilitating rapid continuous integration into industrial production networks comprising Internet of Things smart devices, mobile applications, and cloud services. Context-aware behavior is decisive in industrial manufacturing settings to set up smart production systems and applications across robotic wireless sensor networks, in terms of operational tracking, zero-defect manufacturing, and data-driven maintenance optimization. Effective and robust data gathering is essential in configuring context-adaptive decision support connected systems that incessantly supervise production processes in flux. Context-awareness and robotic wireless sensor networks assist in integrating smart connected devices and can decrease manufacturing errors. Internet of Things-based real-time production logistics and deep learning-assisted smart process planning [65–67] facilitate continuous monitoring of smart shop floors. Effective upgrading of business operations and computational resource use typically depends on data intensive processes. Cloud computing, real-time sensor networks, and artificial intelligence data-driven Internet of Things systems are essential in enabling cyber-physical process monitoring systems: a massive volume of industrial device data are assimilated and product decision-making information systems are analyzed, providing the adjustability to customize scale to heterogeneous workloads to automate and enhance business operations and facilitating big data analytics, articulating predictable performance across industrial wireless networks of production facilities and manufacturing processes that are interconnected, thus leading to a cost-efficient supply chain. Data-driven software and intelligence are integrated into industrial manufacturing systems to cut down expenses and optimize the quality, performance, and adjustability of production.

The demand for increasingly customized, smart, and sustainable manufactured items, and the swift growth of cyber-physical system-based real-time monitoring [68–71], have resulted in the development of Internet of Things-based decision support systems. The manufacturing sector is driven by big data-driven decision-making processes that enable accelerated production, decreased expenses, and diminished downtime by harnessing artificial intelligence data-driven Internet of Things systems across industrial enterprises and integrated sensing and computing technologies. Embedded and coordinated value networks that harmonize and distribute manufacturing resources online, digitalization and assimilation of manufacturing resources on the Internet of Things-based real-time production logistics as dynamic, reliable, and on-demand micro-services, and data-driven and networked CPPS entities capable of instantaneous and self-governing decision-making facilitated by cognitive automation [72–74] provide customers with sustainable mass-personalized products and services, and further real-time adaptation to fluid alterations in user demand, shop floor environments, and supply/value networks. As the physical resources of data-driven production systems are formalized as smart factory components with heterogeneous features, the supplied operations or functions should be set up as conventional services to facilitate robust and on-demand production for value network assimilation and assistance. The demand for customized, networked, smart, and sustainable products and services supported by artificial intelligence-based decision-making algorithms are progressively restructuring the manufacturing sector. Digitalization and assimilation of manufacturing resources on the Internet of Things-based real-time production logistics as on-demand services further value network consolidation and cooperation throughout the industrial unit.

Deployment of artificial intelligence-based decision-making algorithms, deep learning-assisted smart process planning, real-time sensor networks, and cloud technologies [75–77] are instrumental in remote maintenance support. Leveraging massive volumes of data gathered on equipment and their processing through product decision-making information systems enable the adoption of groundbreaking techniques for condition-based maintenance. Artificial intelligence-based decision-making algorithms, robotic wireless sensor networks, and Internet of Things-based real-time production logistics are decisive in the development of smart CPPSs and Industry 4.0-based manufacturing systems. Industry 4.0-based manufacturing systems aim for breakthroughs, cognitive automation, increased feedback to customer demands, and artificial intelligence-based decision-making algorithms. By harnessing data-driven modeling, cyber-physical process monitoring systems will reshape manufacturing as intuitive and automated [78–80], leading to the decentralization of production processes. Real-time big data analytics, cognitive automation, Internet of Things-based decision support systems, and production process optimization are pivotal in configuring CPPS-enabled data-driven manufacturing. Smart networked factories will be driven by the integration of robotic wireless sensor networks and industrial big data analytics for cyber-physical process monitoring systems. Throughout the organized layers of CPPS-enabled smart networked factories, big data-driven manufacturing facilitates decentralized production through automation and interconnected industrial units. The subsystems throughout decentralized production collect and share data with heterogeneous industrial units to make coherent decisions. Leveraging descriptive, causal, predictive, and prescriptive analytics is reconfiguring manufacturing into value-based and big data-driven production facilities by use of designed and informed decision-making (Table 3).

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

Intelligent plant modules and smart factory automation have advanced CPPSs that are pivotal in collision identification, impedance monitoring, and assimilating machine learning-based tasks. Wireless sensor technology monitor manufacturing assets and networked production or logistics business operations in real time. Cyber-physical system-based manufacturing configures knowledge-intensive industrial autonomous settings where smart customized items are produced through deep learning-assisted smart process planning, real-time advanced analytics, and cognitive automation.	Brown et al., 2020; Edwards, 2021; Hamilton, 2021; Islam et al., 2019; Mitchell, 2021; Panetto et al., 2019; Popescu Ljungholm, 2019; Preuveneers and Ilie-Zudor, 2017; Townsend, 2021
Because of the growing volume of modular components and systems, interwoven and heterogeneous factory systems are required for big data-driven decision-making processes and collaborative control in sustainable manufacturing routines. Internet of Things-based real-time production logistics and deep learning-assisted smart process planning facilitate continuous monitoring of smart shop floors.	Gibson, 2021; Konecny et al., 2021; Lewis, 2021; Suler et al., 2021; Valaskova et al., 2021; Wells et al., 2021

Table 3. *Cont.*

In CPPSs, smart connected devices team up automatically to constantly optimize manufacturing processes, manage disturbances, and adjust to variable conditions, articulating the relevance of networking and control systems. The demand for increasingly customized, smart, and sustainable manufactured items and the swift growth of cyber-physical system-based real-time monitoring have resulted in the development of Internet of Things-based decision support systems.	Dawson, 2021; Johnson, 2020; Kovacova et al., 2019; Miller, 2020; Mircică, 2020; Moghaddam et al., 2018; Novak et al., 2021; Rojas and Rauch, 2019
Data processing to collect significant information and physical value creation in production operations can be attained through the assimilation of the enterprise resource coordination and manufacturing execution systems.	Brown, 2021; Cooper et al., 2021; Gordon, 2021; Green and Zhuravleva, 2021; Harris, 2021; Popescu et al., 2021
CPPSs and sustainable manufacturing Internet of Things reconfigure how shop floor operations are designed and carried out. Deployment of artificial intelligence-based decision-making algorithms, deep learning-assisted smart process planning, real-time sensor networks, and cloud technologies are instrumental in remote maintenance support.	Jantunen et al., 2018; Morgan and O'Donnell, 2017; Neubauer et al., 2017; O'Donovan et al., 2019; Rossit and Tohmé, 2018; Suvarna et al., 2021; Vogel-Heuser et al., 2021
Cloud computing and service-oriented designs can network and develop physical factory performance to the cyber world in terms of engineering, monitoring, and Internet of Things sensing networks for increased reliability and resilience. By harnessing data-driven modeling, cyber-physical process monitoring systems will reshape manufacturing as intuitive and automated.	Hawkins, 2021; Ionescu, 2020 a, b; Moore, 2020; Shaw et al., 2021; Williams, 2020

4. Internet of Things Sensing Networks, Sustainable Product Lifecycle Management, and Real-Time Big Data Analytics in CPPSs

CPPSs improve the flexibility and output of smart manufacturing [81–84], adjusting the design and quality of products to fluid market demands and customized requirements. Cyber-physical system-based smart factories optimize the networking among equipment, sensors and big data-driven systems, and enhance the self-governance, soundness, agility, and responsiveness of sustainable smart manufacturing. Real-time wireless networks can collect heterogeneous information in the underlying applications and perform mining, inspection, and assessment of supply chain logistics data. The variable dynamics of industrial wireless sensor–actuator networks across CPPSs necessitates incessant amendments of the system states and continuing operations by sharing high-priority and event-driven data to preserve the stability of the system so that the shop floor does not shut down. Heterogeneous instantaneous transmission scheduling algorithms handle the distribution of the channel resources [85–87], but cyber and physical units have distinct demands to enhance the network performance. Industrial robot applications are developing swiftly as a result of cyber-physical system-based real-time monitoring. As demands with agile product iterations are progressively variable and purpose-built, the assembly operations of industrial robots confront fluctuating restructuring and redesign, ubiquitous sensing, and networking in real time. Industrial robot assembly process designing, coordination, and scheduling developed on instantaneous data collection and fusion is pivotal in groundbreaking plant communication and computing technologies (e.g., edge computing, wireless connected sensors, and actuator networks). The integration, networking, and interaction of connected devices with instantaneous data collection and fusion articulate the multi-agent pattern of industrial robot assembly process by use of smart planning and scheduling algorithms.

CPPSs can be thoroughly and steadily engineered during their lifecycle in smart manufacturing through Internet of Things sensing networks, cognitive automation, real-time process monitoring, and artificial intelligence-based decision-making algorithms [88–93], even though inconstant integration routines may lead to variable data patterns at heterogeneous levels of production processes. The shift from planning to the operational phase impacts the harnessing of physical tools on the industrial unit and brings about a relevant realignment of logistical requirements throughout the plants. Pervasive sensing technologies and wireless sensor networks are pivotal in CPPSs. In CPPSs, heterogeneous equipment, actuators, sensors and monitoring systems are networked to manufacture items efficiently. Monitored industrial wireless sensor–actuator networks are pivotal in CPPSs. Groundbreaking technologies furthering cyber-physical enterprise systems regarding real-time decision-making determined from streamlined data [94–96] necessitate networked sensor and operational systems. Networking, physical/virtual joint performance, interoperability, self-organization, and smart big data-driven decision making are key in furthering Industrial Internet of Things. The digital transformation aims to advance Internet of Things sensing networks, smart industrial value creation, deep learning-assisted smart process planning, and CPPSs architectures that can connect smart devices from heterogeneous data-driven technologies, virtualizing manufacturing enterprises' assets and integrating them across production sectors and plants. Processing devices and systems are crucial in ensuring vertical and horizontal integration.

Adaptive production systems are crucial in sustainable manufacturing Internet of Things [97–99], deriving from the demand for robust characteristics of the system to react to disruption as product changes or alterations to operational parameters. Functional and behavioral modeling assists in the reshaping of Industry 4.0-based manufacturing systems. Sustainable cyber-physical production systems developed on functional and behavioral patterns can address the inconveniences of disruptive Industry 4.0-related production environments. Self-adaptive reconfigurable manufacturing systems are crucial in the operational modeling design, where the processes have to be assimilated into the system monitoring behavior. The capacity of sustainable cyber-physical production systems to reconfigure in conformity with variable demands [100–102] enables a rise in deployment and a decrease in expenses and alterations in time, leading to increased output across disruptive production environments. To thoroughly capitalize on Industry 4.0-based manufacturing systems, production, data-driven, and biological systems have to network. Sustainable Industry 4.0 aims to optimize the adjustability of manufacturing systems so that customized items can be made within a large-scale production regime. Manufacturing systems thus resemble natural organisms, both regarding their structural planning and the achievable computational and sensing capabilities. Unfolding digitalization expedites the reconfiguration and assimilation of physical manufacturing and computing systems into smart entities and their networking, constituting artificial intelligence data-driven Internet of Things systems. In sustainable manufacturing Internet of Things, the cross-linking of integrated systems sets up flexible and self-organizing CPPSs. As a result of growing cross-linking, swift technological breakthroughs, and multifunctionality, the intricacy and structural impenetrability of CPPSs are intensifying at a fast pace.

The convergence of standard automation systems within CPPSs, together with service-oriented designs and fog, edge, and cloud computing technologies [103–105], are developing sustainable manufacturing Internet of Things and cyber-physical process monitoring systems. For the purpose of ensuring robust manufacturing processes, any disruptions throughout the system have to be monitored by operational technology and big data services. The fluid assessment, integration, and positioning of services across CPPSs constitute elements of the process control [106–108] throughout the consolidated modeling and appraisal of operational phases. The reliability of manufacturing and service integration and positioning in dynamically variable system environments is impacted by engineering production processes. CPPSs develop on heterogeneous connected computers, devices, and applications having diverse conditions, performance, and latency, while necessitating data management in relation to deficiency detection and diagnosis through cyber-physical process monitoring systems at a complexity level unrelated to Internet of Things-based real-time production logistics in smart networked factories. Cyber-physical machine tools are smart, networked, broadly available, highly robust, and thoroughly autonomous devices.

Artificial intelligence data-driven Internet of Things systems necessitate high-performance operations and adjustable production systems [109–112] by use of flexible and real-time scheduling. Sustainable manufacturing Internet of Things enables robust and dynamic planning and monitoring of production systems by leveraging efficient and sound real-time data gathering, handling, and analysis from the industrial unit. Accumulated data can be deployed in a sound decision making system that encompasses a multi-criteria supervising algorithm and a condition-based assistance approach, endeavoring to optimize shop floor operations. The scheduling algorithms can become cognizant of the heterogeneous data coming from the industrial unit in relation to relevance and convenience of the resources when carrying out assignments [113–115], concerning machine tools status by the coherent integration between controlling and planning systems and adaptive and real-time scheduling algorithm. Instantaneous data collection and monitoring can be configured from heterogeneous sources, data analysis, assimilation of planning and supervision, in addition to streamlined, precise, and dynamic scheduling suited to managing real-time information from the industrial unit, furthering the digitalization of manufacturing enterprises efficiently. Robust, affordable, and reconfigurable controlling systems that gather and deliver meaningful data are pivotal in CPPSs for flexible time management and condition-based maintenance.

CPPSs autonomously identify and react to inconstant and unplanned situations on the shop floor (e.g., machine failure, a sudden deficiency in unprocessed materials, or last-minute request orders), enabling interoperable connections among distributed business applications [40,70,116,117], while rendering supervision of manufacturing processes with first-rate quality and adjustability, and reducing operational risk or unpredictability. Generic and cross-deployable data-driven patterns powered by deep learning-assisted smart process planning, real-time advanced analytics, and artificial intelligence-based decision-making algorithms can exemplarily trace the data derived from sustainable cyber-physical production systems and harness it for Internet of Things-based real-time production logistics, real-time optimization, or cyber-physical process monitoring systems. Accurate and reliable assessments of product quality through cyber-physical system-based real-time monitoring assist in optimizing manufacturing processes and big data-driven decision-making instantaneously. Advancing data-driven monitoring systems and leveraging them across a CPPS platform may result in large-scale supervision and an increase in efficiency [118–120] during the sustainable product lifecycle management in plants, consequently mitigating operational constraints. Industry 4.0 manufacturing and logistics systems require significantly custom-designed supply network monitoring, the setting up of resilient factories to manage risks, advancements in the administration of decision-support systems for the configuration, scheduling and supervision of resilient production networks, adaptable workstations, and shared operational control (Table 4).

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

CPPSs improve the flexibility and output of smart manufacturing, adjusting the design and quality of products to fluid market demands and customized requirements. The convergence of standard automation systems within CPPSs, together with service-oriented designs and fog, edge, and cloud computing technologies, are developing sustainable manufacturing Internet of Things and cyber-physical process monitoring systems.	Engelsberger and Greiner, 2018; He et al., 2021; Liu et al., 2019; Sinha and Roy, 2019, Tan et al., 2019, Yu et al., 2017 a, b
Heterogeneous instantaneous transmission scheduling algorithms handle the distribution of the channel resources, but cyber and physical units have distinct demands to enhance the network performance. The fluid assessment, integration, and positioning of services across CPPSs constitute elements of the process control throughout the consolidated modeling and appraisal of operational phases.	Durana et al., 2021; Ionescu, 2019 a; Taylor, 2020; Tucker, 2021; Wade et al., 2021; Welch, 2021
CPPSs can be thoroughly and steadily engineered during their lifecycle in smart manufacturing through Internet of Things sensing networks, automated production systems, real-time process monitoring, and artificial intelligence-based decision-making algorithms. Artificial intelligence data-driven Internet of Things systems necessitate high-performance operations and adjustable production systems by use of flexible and real-time scheduling.	Bordel et al., 2017; Cunningham, 2021; Harrison et al., 2021; Mourtzis and Vlachou, 2018; Pivoto et al., 2021; Sinha and Roy, 2021; Tomiyama and Moyen, 2018, Watkins, 2021; Weichhart et al., 2021; Wright and Birtus, 2020

Table 4. *Cont.*

Groundbreaking technologies furthering cyber-physical enterprise systems regarding real-time decision-making determined from streamlined data necessitate networked sensor and operational systems. The scheduling algorithms can become cognizant of the heterogeneous data coming from the industrial unit in relation to relevance and convenience of the resources when carrying out assignments.	Cohen, 2021; Grant, 2021; Graessley et al., 2019; Lewis, 2020; Mircică, 2019; Nelson, 2020
Adaptive production systems are crucial in sustainable manufacturing Internet of Things, deriving from the demand for robust characteristics of the system to react to disruption as product changes or alterations to operational parameters. CPPSs autonomously identify and react to inconstant and unplanned situations on the shop floor, enabling interoperable connections among distributed business applications, while rendering supervision of manufacturing processes with first-rate quality and adjustability, and reducing operational risk or unpredictability.	Berger et al., 2021; Bergs et al., 2020; Panetto et al., 2019; Riley et al., 2021; Sanderson et al., 2019; Stehel et al., 2021; Suvarna et al., 2021
The capacity of sustainable cyber-physical production systems to reconfigure in conformity with variable demands enables a rise in deployment and a decrease in expenses and alterations in time. Advancing data-driven monitoring systems and leveraging them across a CPPS platform may result in large-scale supervision and an increase in efficiency during sustainable product lifecycle management in plants.	Davidson, 2020; Ionescu, 2019 b; Lăzăroiu et al., 2021; Lowe, 2021; Russell, 2020; Walker et al., 2020

5. Deep Learning-Assisted Smart Process Planning, Internet of Things-Based Real-Time Production Logistics, and Sustainable Industrial Big Data in CPPSs

CPPSs constitute cutting-edge technologies for the adoption of smart manufacturing [121–124] that are effective only when processing standards and application procedures for heterogeneous data—which can modify instantaneously due to the character of a factory—are carried out. Intelligent production systems gather unprocessed data from a shop floor in real time. The automation of manufacturing requires complete mapping, scaling, and standardization of the collected data of the industrial unit into operational processes across a CPPS environment. The increasing complexity of cyber-physical process monitoring systems necessitates convenient control designs that enable fluid adaptation throughout their runtime. CPPSs are adequate in managing complexity and flexibility, configuring the smart factory. Companies expand their product portfolio and try to decrease their manufacturing time to maximize earnings and market presence [12,125,126], indirectly exacerbating the intricacy of the operational processes. The manufacturing sector frequently builds upon cutting-edge monitoring systems to mitigate quality losses. Redesigning the production systems and optimizing their performance depend significantly on the harnessing of cutting-edge decision support tools so as to satisfy the inconstant demand of high-mix, low-volume manufacturing settings. Assessing the predictable values of the key performance measures is difficult because the intricate structure, performance, and input demand leads to a vastly massive variable area limiting the analysis. A groundbreaking undertaking for supplying simulation-based decision support for enhancing key performance indicators of high-mix, low-volume manufacturing systems would decrease the proportion of the input domain by leveraging unsupervised machine learning algorithms.

Smart manufacturing harnesses predictive production systems systematically [127–132]: cognitive networked assets can predict, identify cause, and redesign malfunctioning events automatically. CPPS-related data are inspected and networked between a physical industrial unit and the cyber computational space, integrating smart analytics to grasp undetectable issues for swift and precise decision-making. CPPSs can be harnessed to predictive production systems to stimulate resilience and coordination, increasing manufacturing productivity. The fusion between data technologies shapes the performance of cyber-physical automation systems. Variable manufacturing systems and product demands derive from inconstant customer behavior [133–135], which is an incessantly moving target impacting product development, and thus CPPSs leveraging condition monitoring, cognitive automation, and reconfigurability have to be designed and adopted. CPPSs are instrumental in the advancement of adjustable and reactive systems. A decentralized monitoring mode can significantly meet the system demands of a CPPS due to its upsides (e.g., flexibility, reconfigurability, swift approachability, and soundness), emerging as the essential control routine of CPPSs. Non-hierarchical manufacturing networks comprising self-governing companies acquire accurate big data-driven technologies or groundbreaking industrial platforms, leading to cyber-physical production structures with heterogeneous automated operations.

Cyber-physical machine tools can develop Industry 4.0-based equipment regarding intelligence and self-governance [136–140] by integrating physical devices and machining operations with computation and networking performance through functional modules such as real-time control, process monitoring and optimization, and manufacturing simulation. Developments in Industry 4.0-based manufacturing systems further the advancement of CPPSs. Industrial production systems and items are perpetually advancing as a result of swift technological breakthroughs and inconstant customer requirements, while a consolidated co-development of both is needed, as otherwise the lifecycles of manufactured items and production systems may be at variance. Sustainable Industry 4.0 wireless networks can shape effective and robust manufacturing [141–143] by automatically monitoring production equipment in a flexible fashion. For joint sharing and deployment of distributed and interconnected production resources, coherent planning and control at heterogeneous levels and locations are needed, advancing feature-based manufacturing for dynamic tool monitoring and resource-task matching throughout Industry 4.0-based manufacturing systems. As a result of the advancement of CPPSs, self-governing monitoring of manufacturing processes are indispensable in smart production processes. Control operations such as order release, systematization, and capacity monitoring can be integrated across subtasks of digital manufacturing supervision to conform to due dates.

CPPSs are redesigning hierarchical control arrangements [90,144–148] into distributed structures in which the components operate autonomously. Agent network operations can be optimized through knowledge assimilation and interaction in distributed monitoring for manufacturing environments. Resilient CPPSs can disregard or repair faults, or function by self-governing reconfiguration facilitated by surplus at state, behavioral, or operational levels. CPPSs can carry out multi-product and small-batch operations intelligently and autonomously by use of processing route generation algorithms, backpropagation neural networks, and scheduling rules. Smart connected devices have heterogeneous processing and manufacturing capabilities and optimization operation mechanisms. The production system has to inspect the tasks to integrate with the smart connected devices and perform them unsupervised and automatically [149–151], configuring a machining route across production system operations through intelligent decision-making. Manufacturing process monitoring systems have advanced as decentralized reconfigurable networked entities by use of cutting-edge intelligent machines. CPPSs integrate high power computation, shared interoperability, and advanced analytics. Biological collective systems have shaped the configuration of manufacturing systems because of their intrinsic features. Industry 4.0 can handle customized demands by setting up CPPSs for smart networked factories.

In smart industrial units, CPPSs control physical operations, configure a digital duplicate of the physical world, and decisions are decentralized [152,153]: the virtual world stores and processes networked data in real time. Physical, logical, and interconnection layers can integrate intelligent operations within manufacturing processes across the smart shop floor. Physical entities on the plant are self-governing intelligent logical units carrying out undertakings directed by distributed control functions in smart networked factories. Computing capacity and optimization operations are integrated in logical units to make decisions so as to smoothly react to constant incidents of unplanned disturbances on the plant. Physical entities can be coordinated and self-governing logical units can automatize manufacturing system processes. Tools for assessing and managing enhancements in the performance, the soundness, and the responsiveness of manufacturing systems are required [154–156], as a decrease in due-date soundness is typically associated with external causes and not with planning behavior. Negative dynamic behavior can happen if imminent declines in due-date reliability are not properly considered. Holding patterns and lead-time-related amendments impact the ensuing system behavior and operations. Autonomous data gathering and integrated patterns can diminish postponement in decision making and implementation of sustainable Industry 4.0 wireless networks.

CPPSs provide the technological basis for the digitalization and decentralization of manufacturing processes [157–160] and their integration across plant networks. Industry 4.0 offers increased adjustability, facilitating inexpensive product and service customization, and enabling lot-size one manufacturing, deep learning-assisted smart process planning, cognitive automation, and data-driven predictive maintenance. Planning an exemplary chain of manufacturing operations constitutes a determining competitive component for the engineering of CPPSs, considering a rise in customization with concomitantly increasing sales volumes, while plants have to handle the issue of the manufacturing of personalized items efficiently. Developed on the swift organization of industrial enterprises, constant digital coordination, and target cost analysis, intelligent engineering focuses on designing CPPSs that ensure the manufacturing of items in conformity with the distinct demands at the target cost, thus improving economic efficiency. The intelligent engineering of manufacturing comprises assessment of requirements for CPPSs, estimation and examination of the target cost, planning of CPPSs in keeping with the customer demands and target cost, setting up of a production digital twin, harnessing of an incessant digital organization strategy, and supervision and appraisal of received data. CPPSs ensure a thorough networking of the smart connected devices and resources integrated in manufacturing processes [161–164] and, consequently, enhanced availability of collected data. Decision support systems facilitate adequate processing and display of the gathered data, with production scheduling being the reason for the swift planning and monitoring of released orders in sustainable manufacturing Internet of Things. Decision support systems and CPPSs can be harnessed in production scheduling on a large scale, capturing real-time data from manufacturing processes. The demands in groundbreaking engineering of CPPSs are difficult to carry out because of massive system proportions, component diversity, integration of heterogeneous machines, and constant advancement. Formal and semi-formal languages, approaches, devices, and arrangements can configure replicable and sound structures for bringing about, clarifying, inspecting, checking, and maintaining CPPS-related requirements. Industrial control systems can carry out distributed, instantaneous system monitoring, and durable stability. Physical operations, together with control-related sensors, actuators, and processors, are networked and distributed across CPPSs. Computational devices can be deployed as monitoring and interaction technologies and as heterogeneous collaborative devices and modes of networking to configure crucial tools in operating, maintaining, and upgrading data-driven CPPSs (Table 5).

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

CPPSs constitute cutting-edge technologies for the adoption of smart manufacturing that is effective only when processing standards and application procedures for the heterogeneous data that can modify instantaneously due to the character of a factory are carried out. CPPSs are redesigning hierarchical control arrangements into distributed structures in which the components operate autonomously.	Cruz Salazar et al., 2019; Dias-Ferreira et al., 2018; Elhabashy et al., 2019; Gödri et al., 2019; Jiang et al., 2018; Kang et al., 2019; Morgan and O'Donnell, 2018; Tomiyama and Moyen, 2018; Vrabič et al., 2018; Wang et al., 2018
Companies expand their product portfolio and try to decrease their manufacturing time to maximize earnings and market presence, indirectly exacerbating the intricacy of the operational processes. The production system has to inspect the tasks to integrate with the smart connected devices and perform them unsupervised and automatically.	Coatney and Poliak, 2020; Miller, 2020; Nica et al., 2020; Peters, 2020; Popescu et al., 2020; Scott et al., 2020
Smart manufacturing harnesses predictive production systems systematically: cognitive networked assets can predict, identify cause, and redesign malfunctioning events automatically. In smart industrial units, CPPSs control physical operations, configure a digital duplicate of the physical world, and decisions are decentralized: the virtual world stores and processes networked data in real time.	Duffie et al., 2017; Francalanza et al., 2017; Jiang et al., 2018; Lee et al., 2017; Mladineo et al., 2017; Schneider et al., 2019; Tang et al., 2018

Table 5. *Cont.*

Tools for assessing and managing enhancements in the performance, the soundness, and the responsiveness of manufacturing systems are required, as a decrease in due-date soundness is typically associated with external causes and not with planning behavior.	Bourke et al., 2019; Duft and Durana, 2020; Gray-Hawkins and Lăzăroiu, 2020; Harrower, 2019; Lăzăroiu et al., 2020; Wingard, 2019
Cyber-physical machine tools can develop Industry 4.0-based equipment regarding intelligence and self-governance by integrating physical devices and machining operations with computation and networking performance through functional modules. CPPSs provide the technological basis for the digitalization and decentralization of manufacturing processes, and their integration across plant networks.	Adamson et al., 2017; Andreev et al., 2021; Freier and Schumann, 2021; Grundstein et al., 2017; Kannengiesser et al., 2021; Liu et al., 2017; Penas et al., 2017; Vogel-Heuser et al., 2017; Zahid et al., 2021
Sustainable Industry 4.0 wireless networks can shape effective and robust manufacturing by automatically monitoring production equipment in a flexible fashion. CPPSs ensure thorough networking of the smart connected devices and resources integrated in manufacturing processes and, consequently, an enhanced availability of collected data. Computational devices can be deployed as monitoring and interaction technologies and as heterogeneous collaborative devices and modes of networking to configure crucial tools in operating, maintaining, and upgrading data-driven CPPSs.	Allen, 2020; Davies et al., 2020; Dhiman and Röcker, 2021; Grayson, 2020; Hyers, 2020; Robinson, 2020; Williams et al., 2020

6. Discussion

The importance of artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, product decision-making information systems, and deep learning-assisted smart process management in cyber-physical production systems is extensively consistent with, and provides additional confirmation of, previous review articles, e.g., [40,44,68,91,93], clarifying that CPPSs are adequate in managing complexity and flexibility, configuring the smart factory. CPPSs inspect, supervise, and automate business operations, optimizing manufacturing and logistic processes across smart shop floor environments. Cloud computing, real-time process monitoring, and artificial intelligence data-driven Internet of Things systems are essential in enabling cyber-physical process monitoring systems. Artificial intelligence data-driven Internet of Things systems necessitate high-performance operations and adjustable production systems by use of flexible and real-time scheduling. Intelligent production systems gather unprocessed data from a shop floor in real time. Industry 4.0-based manufacturing systems require the networking of all devices integrated across the shop floor. The interoperability between Internet of Things-based real-time production logistics and cyber-physical process monitoring systems can decide upon the progression of operations advancing a system to the intended state in CPPSs. Smart autonomous devices are pivotal in planning and control systems as Internet of Things elements of CPPSs.

The outcomes of our systematic review develop on empirical research [1–11,39,40,44,121–124,136–140,144–148,157–160] contending that sustainable cyber-physical production systems developed on functional and behavioral patterns can address the inconveniences of disruptive Industry 4.0-related production environments. Wireless sensor technology monitor manufacturing assets and networked production or logistics business operations in real time. Accurate and reliable assessments of product quality through cyber-physical system-based real-time monitoring assist in optimizing manufacturing processes and big data-driven decision-making instantaneously. CPPSs and sustainable manufacturing Internet of Things reconfigure how shop floor operations are designed and carried out. Cyber-physical system-based smart factories optimize the networking among equipment, sensors and big data-driven systems. Sustainable Industry 4.0 wireless networks can shape effective and robust manufacturing by automatically monitoring production equipment in a flexible fashion. Cyber-physical system-based manufacturing configures knowledge-intensive industrial autonomous settings where smart customized items are produced through deep learning-assisted smart process planning, real-time advanced analytics, and cognitive automation.

There has been a small but growing volume of studies [51–54,58,68,75–77,128–132,152,153] claiming that industrial enterprises advance as wireless sensor networks to constantly control the operations of their plants. Internet of Things-based real-time production logistics, product decision-making information systems, and deep learning-assisted smart process planning facilitate continuous monitoring of smart shop floors. As a result of the advancement of CPPSs, self-governing monitoring of manufacturing processes is indispensable in smart production processes. CPPSs are instrumental in instantaneous heterogeneous data collection, inspection, and distribution by use of interoperability support integrated in process monitoring systems. Autonomous data gathering and integrated patterns can diminish postponement in decision making and implementation of sustainable Industry 4.0 wireless networks.

As underlying mechanisms between cyber-physical production networks, deep learning-assisted smart process planning, product decision-making information systems, artificial intelligence-based decision-making algorithms, and cognitive automation in sustainable manufacturing Internet of Things are comprehended to a limited extent in the current literature, certain empirical studies [81–84,88–93,97–99,103–105,108,164] systematically indicate that smart connected devices have heterogeneous processing and manufacturing capabilities and optimization operation mechanisms. Manufacturing process monitoring systems have advanced as decentralized reconfigurable networked entities by use of cutting-edge intelligent machines. Sustainable manufacturing Internet of Things enables robust and dynamic planning and monitoring of production systems [165–168], by leveraging efficient and sound real-time data gathering, handling, and analysis from the industrial unit. Physical entities on the plant are self-governing intelligent logical units carrying out undertakings directed by distributed control functions. Industrial cyber-physical systems are pivotal in sustainable smart manufacturing, by integrating control engineering with artificial intelligence-based decision-making algorithms [169–171] to set up cognitive and self-configuring plants.

7. Synopsis of the Main Research Outcomes

CPPSs can be thoroughly and steadily engineered during their lifecycle in smart manufacturing through Internet of Things sensing networks, industrial big data analytics, real-time process monitoring, and artificial intelligence-based decision-making algorithms. CPPSs ensure thorough networking of the smart connected devices and resources integrated in manufacturing processes and, consequently, enhanced availability of collected data. Digital transformation aims to advance Internet of Things sensing networks, cognitive automation, deep learning-assisted smart process planning, and CPPS architectures that can connect smart devices from heterogeneous data-driven technologies in smart factory performance. Industry 4.0-based manufacturing systems aim for breakthroughs, cognitive automation, increased feedback to customer demands, and artificial intelligence-based decision-making algorithms. The demand for increasingly customized, smart, and sustainable manufactured items, and the swift growth of cyber-physical system-based real-time monitoring, have resulted in the development of Internet of Things-based decision support systems. Deployment of artificial intelligence-based decision-making algorithms, real-time sensor networks, and cloud technologies are instrumental in remote maintenance support. Real-time big data analytics, Internet of Things-based decision support systems, and production process optimization are pivotal in configuring CPPS-enabled data-driven manufacturing. Throughout the organized layers of CPPS-enabled smart networked factories, big data-driven manufacturing facilitates decentralized production through automation and interconnected industrial units. Generic and cross-deployable data-driven patterns powered by deep learning-assisted smart process planning, industrial big data analytics, and artificial intelligence-based decision-making algorithms can exemplarily trace the data derived from sustainable cyber-physical production systems and harness it for Internet of Things-based real-time production logistics, real-time optimization, or cyber-physical process monitoring systems.

8. Conclusions

Significant research has attempted to clarify in the recent past whether CPPSs are instrumental in instantaneous heterogeneous data collection, inspection, and distribution by use of interoperability support integrated in process monitoring systems. Intelligent production systems gather unprocessed data from a shop floor in real time. The interoperability between Internet of Things-based real-time production logistics and cyber-physical process monitoring systems can decide upon the progression of operations advancing a system to the intended state in CPPSs. Our systematic literature review puts forward first-rate peer-reviewed evidence concerning how sustainable manufacturing Internet of Things enables robust and dynamic planning and monitoring of production systems by leveraging efficient and sound real-time data gathering, handling, and analysis from the industrial unit. Physical entities on the plant are self-governing intelligent logical units carrying out undertakings directed by distributed control functions. Accurate and reliable assessments of product quality through cyber-physical system-based real-time monitoring assist in optimizing manufacturing processes and big data-driven decision-making instantaneously. The findings derived from the above analyses indicate that Industry 4.0-based manufacturing systems require the networking of all devices integrated across the shop floor. Autonomous data gathering and integrated patterns can diminish postponement in decision-making and implementation of sustainable Industry 4.0 wireless networks. Wireless sensor technology monitor manufacturing assets and networked production or logistics business operations in real time. Internet of Things-based real-time production logistics and deep learning-assisted smart process planning facilitate continuous monitoring of smart shop floors.

9. Limitations, Implications, and Further Directions of Research

By analyzing only articles published in journals indexed in ProQuest, Scopus, and the Web of Science between 2017 and 2021, significant research on artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, cognitive automation, and deep learning-assisted smart process management in smart factory performance and cyber-physical production systems may have been excluded. Limitations of this research comprise particular types of published research (original empirical research and review articles) without considering others (editorial materials, conference proceedings articles, and books). The scope of this systematic review does not approach complex connections between product decision-making information systems, real-time advanced analytics, cyber-physical smart manufacturing, and robotic wireless sensor networks in sustainable Industry 4.0. Subsequent analyses should develop on real-time sensor networks so as to configure the importance of artificial intelligence-driven big data analytics by use of cyber-physical production networks. Future research should consequently investigate how real-time big data analytics enable the advancement of Industry 4.0-based manufacturing systems by use of Internet of Things smart devices and deep learning-assisted smart process planning. Attention should be directed to how sustainable Industry 4.0 wireless networks articulate smart factory performance and Internet of Things-based decision support systems through cognitive automation and cyber-physical system-based real-time monitoring.

Author Contributions: Conceptualization, G.L. and M.A.; methodology, R.Ș. and M.C.; validation, M.I. and M.C.; investigation, C.U. and G.L.; resources, C.U. and M.A.; data curation, C.U. and G.L.; writing—original draft preparation, M.A. and M.I.; writing—review and editing, M.A. and R.Ș.; visualization, G.L. and R.Ș.; supervision, C.U. and M.C.; project administration, R.Ș. and M.I. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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