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Review

Shop Floor Digital Twin in Smart Manufacturing: A Systematic Literature Review

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Abstract: The digital twin is currently recognized as a key technology allowing the digital representation of a real-world system. In smart manufacturing, the digital twin enables the management and analysis of physical and digital processes, products, and people in order to foster the sustainability of their lifecycles. Although past research addressed this topic, fragmented studies, a lack of a holistic view, and a lack of in-depth knowledge about digital twin concepts and structures are still evident in the domain of the shop floor digital twin. Manufacturing companies need an integrated reference framework that fits the main components of both physical and digital space. On the basis of a systematic literature review, this research aims to investigate the characteristics of the digital twin for shop floor purposes in the context of smart manufacturing. The "hexadimensional shop floor digital twin" (HexaSFDT) is proposed as a comprehensive framework that integrates all the main components and describes their relationships. In this way, manufacturing organizations can rely on an inclusive framework for supporting their journey in understanding the shop floor digital twin from a methodological and technological viewpoint. Furthermore, the research strengthens the reference literature by collecting and integrating relevant contributions in a unique framework.

Keywords: digital twin; smart manufacturing; shop floor; systematic literature review; framework

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1. Introduction

The concept of smart manufacturing has existed in literature since 1980, but in recent years has gained more interest due to the growth of digital technologies and the integration of information and operational technologies within industrial environments [1]. Industry 4.0 tends to leverage different enabling technologies for reaching high levels of productivity by transforming traditional organizations in smart and hyper-connected business models. Moreover, the increasing competition, the need to reduce the time to market and to increase innovation require the organization to continuously adapt and its behavior to respond to this dynamically changing context [2]. The concept of digital twin was introduced for the first time by Grieves [3], in 2003, with the Information Mirror Model for explaining the elements that compose this virtual reflective model. The author defines the digital twin as "a sensor-enabled digital model of a physical object that simulates the object in a live setting" [4]. In this context, the digital twin is recognized as one of the most promising and emerging technologies for supporting and changing a traditional factory in a smart shop floor, focused on achieving high production efficiency, low production costs, and high product and process quality. Several other benefits coming from the adoption of this technology are currently recognized: from the improvement of operations to the optimization of production quality and costs and the shortening of product development, and from the early verification and validation of production processes to the possibility to develop innovative services [5,6].

The digital twin is considered in literature as a breakthrough technology, acting as a mirror of a real system (e.g., product, machine, plant, process, factory, people) by building a virtual counterpart able to provide a means for simulating physical manufacturing systems and objects [7]. In these terms, the digital twin technology allows for analyzing, monitoring, and predicting the behavior of a system, controlling its status in real time, simulating a desired environment, and supporting in a sustainable way the management of the product and service lifecycle. Several authors provide different definitions of the digital twin concept and emphasize some distinctive elements. For instance, Boschert and Rosen [8] highlight the simulation activity allowed by this technology; Schluse and Rossmann [9] and Schroeder et al. [10] focus on the virtual representation of physical objects; Stark, Fresemann, and Lindow [11] consider a broader view of production systems, including their interoperability; Negri, Fumagalli, and Macchi [12] analyze the physical side of the model; Kunath et al. [13] pay attention to manufacturing systems and data flows; Shafto et al. [14] and Kraft [15] construct a multidimensional concept of the technology; Lee et al. [16] represent the virtual counterpart of a machine; and, finally, Rosen et al. [17] focus on processes.

However, the development of a shop floor digital twin remains often limited because of the complex convergence of the physical space with the virtual one, which also includes some integration issues [18]. The National Aeronautics and Space Administration (NASA) was the first company that explored and exploited digital twin technology in the aerospace field mainly for prediction, safety, and diagnosis purposes [19]. It is clear that some critical aspects have to be considered such as the interoperability and the bidirectional connection of physical and virtual assets for ensuring a real-time response of the whole system. The Internet of Things (IoT), cyber–physical systems (CPS), information and communication technologies, including artificial intelligence, big data, and analytics, are only some of the most important enabling technologies that contribute to design and shape a digital twin [20]. Furthermore, other important aspects need to be included when applying this technology, such as solution modularity, modeling consistency and accuracy, simulation improvements, integration with immersive technologies, efficient mapping of cyber–physical data and cloud/edge computing integration [21].

Past research reported potential applications of the digital twin in different contexts, such as safety [22,23], occupational health [24], environment [25], high-tech machining sector [26,27], healthcare [28,29], smart city [30], advanced production and robotics [31], and civil engineering [32]. Research about digital twin is still growing and under continuous development and new directions are emerging for further investigation, such as the digital twin as a service paradigm, the massive inclusion of unique assets, the involvement of the human world and unprecedented global challenges [33], the exploitation of different types of data generated during the various lifecycle phases [34], and the sustainability of intelligent production systems [35].

In smart manufacturing, an in-depth knowledge of the digital twin concept, structure, and development methods is still scarce [7,36,37]. In particular, the need for a more comprehensive conceptualization of the digital twin technology is more evident in the context of shop floor and smart manufacturing because of the presence of fragmented previous studies [38,39]. Companies need to successfully support the use of their knowledge in order to improve organizational learning [40]. Manufacturers need to consider an inclusive framework for supporting them in the conceptual application of the shop floor digital twin technology. They require a reference framework that fits all the main components belonging to the physical and the digital spaces that also explains their relationships. For these reasons, this research focuses on investigating the connotations of the digital twin for shop floor purposes in the context of Industry 4.0. The research is based on a systematic literature review useful to develop a knowledge base of references upon which to propose an original and comprehensive framework—“hexadimensional shop floor digital twin” (HexaSFDT)—that includes all the main components of a shop floor digital twin. The HexaSFDT framework aims to support industries in understanding the digital twin for the shop floor from a methodological and a technological point of view.

Moreover, this research strengthens the reference literature by collecting and integrating relevant contributions in a unique framework.

The paper is structured as follows: the next session describes the research methodology adopted in this paper; following that, the results of the literature background are presented and organized in a structured way. On the basis of this knowledge, a comprehensive and integrated framework for the shop floor digital twin is proposed. The conclusion, Section 5, discusses final remarks, including implications and limitations.

2. Materials and Methods

This study adopts the systematic literature review (SLR) approach, which is considered a transparent, scientific, and replicable process that allows researchers to control decisions, procedures, and conclusions [41], with the aim of investigating frameworks developed in the context of smart manufacturing for the digital twin of the shop floor. To achieve this objective, the paper focuses on the following areas of analysis: (1) conceptual models theoretically describing the digital twin technology; (2) benefits and challenges regarding the implementation of the digital twin in the shop floor; and (3) frameworks supporting the digital twin implementation in the shop floor.

A number of different SLR strategies exist in the literature. According to Tranfield et al. [42], the main steps of the systematic review process include: (i) question specification and review planning, (ii) review execution, and (iii) reporting and dissemination. On the other hand, Cerchione et al. [43] propose a literature review organized into main phases (i.e., paper acquisition and selection, and descriptive and content analysis of the selected papers), each of which is further divided into two steps (i.e., material search and selection for the first phase, and descriptive and content analysis for the second phase). Furthermore, the literature review process carried out by Lezzi et al. [44], based on keywords and search terms with a replicable and defined search strategy, consists of three main phases: (1) definition of search criteria, (2) paper selection, and (3) paper assessment. Corallo et al. [45] instead define a systematic literature review procedure consisting of four main steps (i.e., review planning, search execution, document analysis, and results reporting) that are composed of different activities.

Summarizing the above contributions and considering the objective of this research work, a schematic view of the main steps of our literature review is shown in Figure 1.

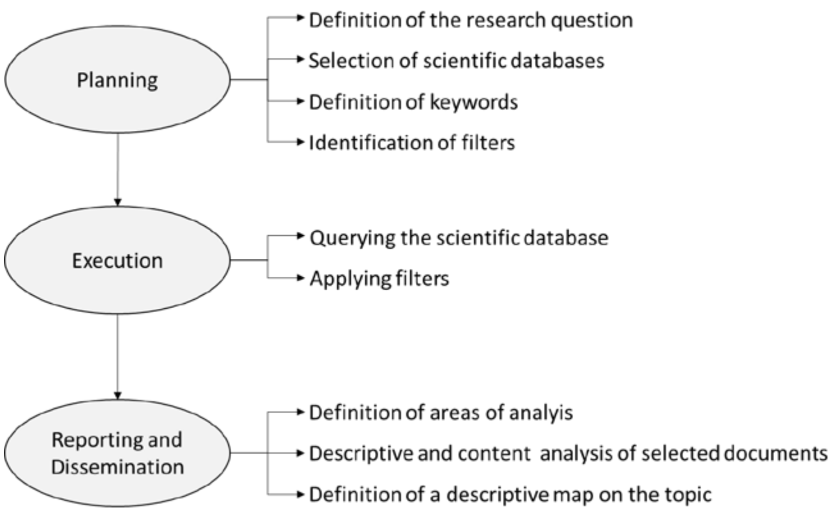

Figure 1. Systematic literature review: the main steps.

Planning and Execution Phases

The first planning phase consists of defining the research question (RQ) on which to base the whole research path. The RQ that the paper intends to answer is: "What are the current frameworks for the shop floor digital twin?". Thus, the need to undertake a systematic literature review in the area of shop floor digital twin stems from the necessity to define a unified method of modelling the digital twin in the context of smart manufacturing.

Therefore, the search process involved the selection of scientific papers from the two main electronic scientific indexed databases, namely, Scopus (www.scopus.com) and Web of Science (www.webofknowledge.com), accessed on 31 March 2021.

The second phase concerning the execution of the review, involves carrying out a comprehensive, unbiased search based on keywords and search terms. For this reason, to give the research question an answer, the keywords "digital twin", "shop floor", "smart manufacturing" have been inserted, in both portals, to search for the title, abstract, and keywords (see Figure 2).

QUERY A

Search in SCOPUS

search in Title / Keywords / Abstract
(TITLE-ABS-KEY ("digital twin") AND ((TITLE-ABS-KEY ("shop floor") OR TITLE-ABS-KEY ("smart manufacturing") OR TITLE-ABS-KEY ("factory"))))

Filters

Document type	Conference Paper / Article / Review
Subject area	Engineering / Computer Science / Business, Management and Accounting
Language	English

(TITLE-ABS-KEY ("digital twin") AND ((TITLE-ABS-KEY ("shop floor") OR TITLE-ABS-KEY ("smart manufacturing") OR TITLE-ABS-KEY ("factory")))) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "BUSI"))

QUERY B

Search in WOS

TS= (digital twin) AND ((TS= (shop floor) OR TS= (smart manufacturing) OR TS= (factory)))

Filters

Document type	Proceeding paper / article / review
Subject area	Engineering Manufacturing / Computer Science Interdisciplinary Applications / Computer Science Theory Methods / Computer Science Information Systems / Management / Information Science Library Science
Language	English

TS= (digital twin) AND ((TS= (shop floor) OR TS= (smart manufacturing) OR TS= (factory)))
Refined by: LANGUAGES: (ENGLISH) AND DOCUMENT TYPES: (PROCEEDINGS PAPER OR ARTICLE OR REVIEW) AND WEB OF SCIENCE CATEGORIES: (ENGINEERING MANUFACTURING OR COMPUTER SCIENCE INTERDISCIPLINARY APPLICATIONS OR INFORMATION SCIENCE LIBRARY SCIENCE OR COMPUTER SCIENCE INFORMATION SYSTEMS OR MANAGEMENT OR COMPUTER SCIENCE THEORY METHODS)
Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI

Figure 2. Queries for databases search.

The search in Scopus and Web of Science (WoS) was based on the selected keywords appearing in the title, abstract, and keywords, identifying 262 and 144 publications, respectively. Thus, we restricted the field to the English language (obtaining 249 results in Scopus and 143 results in WoS). Moreover, the search was limited to "articles", "review", and "conference papers"; this resulted in 226 papers in Scopus and 141 in WoS. However, in order to achieve the established aims, only documents included in the fields of "Engineering", "Computer Science", and "Business, Management and Accounting" were considered on Scopus (resulting in 215 relevant publications). For the same reason, only documents included in the fields of "Engineering Manufacturing", "Computer Science Interdisciplinary Applications", "Computer Science Theory Methods", "Computer Science Information Systems", "Management", and "Information Science Library Science" were selected in Wos (obtaining 89 papers). After this first selection, papers published before 2018 that did not have at least one citation were not included in the analysis, thus only reducing the sample of papers found in Scopus to 190. This choice was made in order to include in the analysis only those contributions with a higher relevance recognized in the scientific community, considering that the topic has been strongly addressed in recent years.

An overall check of all the documents was carried out in order to avoid the multiple inclusion of the same document obtained from different sources (a total of 198 documents were identified). Subsequently, the revision of the title and the abstract was conducted, obtaining 72 publications from both portals. At this point, the articles were excluded mainly because they did not focus only on the topic of digital twin applied to: factory, manufacturing process, production, assembly shop floor, or factory behavior.

After reading the remaining papers, only 41 were accepted as relevant, credible, insightful, and rigorous enough to be included in the literature review that will be carried out in the next section.

The whole process of selecting papers from both scientific databases is shown in Figure 3.

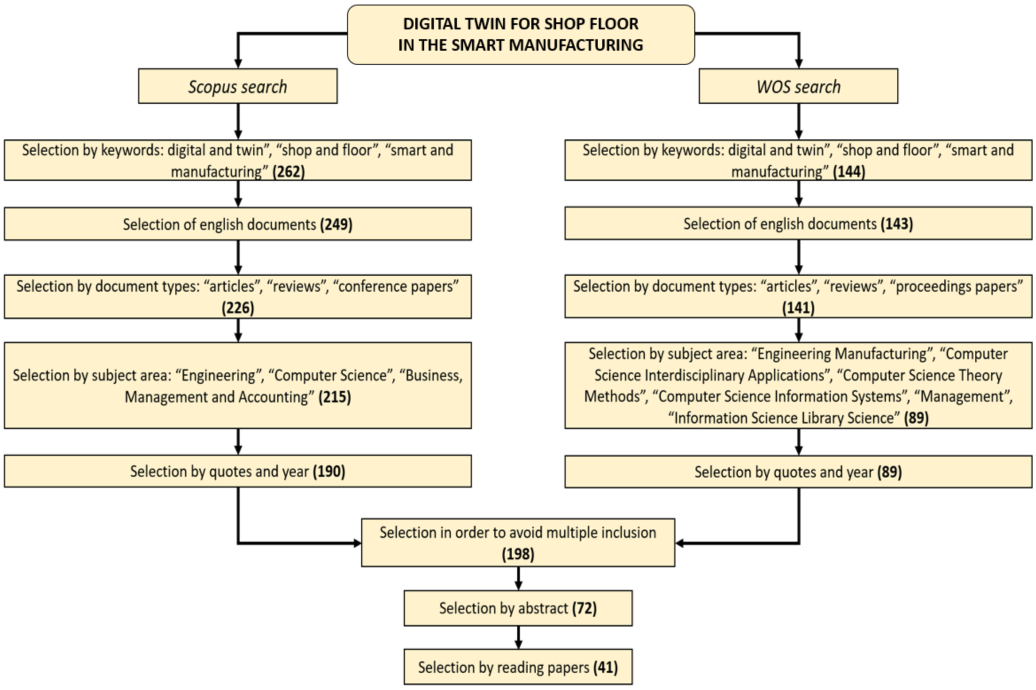

Figure 3. Selecting papers process.

3. Results

3.1. Reporting and Dissemination Phase

The final phase of reporting and dissemination of research results involves making a descriptive map on the topic, including who the contributors are, where they are located, and in what period the main research activities on the topic took place.

In order to evaluate the selected papers, a matrix was firstly defined to record authors' notes about them. This matrix is composed of 11 records, in which the following information was collected: title; authors with affiliations; publication year; source; reference; abstract; keywords; study focus; conceptual models underlying the digital twin technology; benefits and challenges related to the implementation of the digital twin in the shop floor; and frameworks guiding the digital twin implementation in the shop floor (an extract of the matrix with the most relevant information is available in Appendix A).

Therefore, the same categories of information were analyzed in a comparative way between the different papers and the main results were discussed. In Table 1, the three main areas of analysis considered in this study are outlined; while, the results of the comparative review are reported in the following sections.

Table 1. Areas of analysis.

Topic		Focus
1	Digital twin conceptual models	• Conceptual models describing the digital twin technology
2	Benefits and challenges of the digital twin	• Benefits and challenges related to the implementation of the digital twin in the shop floor
3	Digital twin frameworks	• Frameworks that guide the digital twin implementation in the shop floor

3.1.1. Digital Twin Conceptual Models

In this section, the conceptual models, which theoretically describe digital twin technology, are collected. These models emerged from the analysis of the 41 papers resulting from the process of selecting literature resources.

Kuehn [46] presents a Digital Twin approach concept containing an interaction of six steps. These steps complete a closed loop connection between the physical world and the virtual model of the digital twin: (i) create—with multiple sensors various inputs from the physical process and its environment are measured; (ii) communicate—network communication enables a seamless real-time connectivity between the physical process and the digital platform; (iii) aggregate—the real-time data have to be sent to a data repository, processed, and prepared for the analytics; (iv) analyze—the aggregated data are analyzed by use of advanced analytics technologies in order to analyze that data on an ongoing basis to identify opportunities for possible improvements; (v) insight—based on the analyzed data, models for decision making are created; (vi) act—the knowledge and recommendations from the insights step can be fed back to the physical world in order to transform the real enterprise.

The conceptual model proposed by Modoni et al. [47] aims at enhancing the understanding of the digital twin, putting in evidence the continuous synchronization between the real factory and its digital counterpart. This synchronization is realized by means of two streams of data. The first one represents the real-time monitored data flow and includes all physical variables sensed at the factory shop floor level by ubiquitous sensors attached to various physical components of the factory and transmitted with a high-frequency towards the digital space. The second stream involves actions to be performed in real time or near real time at shop floor level, representing the feedback returned from the digital space to the real factory.

Moreover, Park, Easwaran, and Andalam [48] propose developing a cyber–physical production system case study called the IMPACT line, which consists of four linear modules with parallel conveyors and seven processing stations for manufacturing smart phones, to illustrate its proposed model and discuss open issues. The proposed model comprised five main components: a factory; a digital twin and its runtime environment; a factory interface to extract sensor/actuator data from the physical space; an application interface that provides application programming interfaces (APIs) to applications that wish to utilize the digital twin; and the applications themselves.

Finally, Stark, Fresemann, and Lindow [11] explore the dimensions by which the intended behaviors and the context of digital twin can be described. Thus, a structured approach for planning the scope and type of digital twin has been developed; this is called the "digital Twin 8-dimension model". One side of the 8-dimension model can distinguish the dimensions with a focus on digital context and environment and the other side can distinguish the dimensions with a focus on behavior and capability richness. The area of digital twin environment and context is represented by four dimensions: integration breadth, connection mode, update frequency, and product life cycle. On the other hand, the digital twin behavior and capability richness comprises four other dimensions: cyber–physical systems intelligence, simulation capabilities, digital model richness, and human interaction.

3.1.2. Benefits and Challenges of the Digital Twin

Some of the analyzed papers dealt mainly with the review of articles on the theme of the digital twin, exploring the benefits and challenges of implementing this on the shop floor.

In particular, according to Negri, Fumagalli, and Macchi [12], the relevance of digital twin for the manufacturing industry lies in its definition as virtual counterparts of physical devices. These are digital representations based on semantic data models that allow running simulations in different disciplines, that support not only a prognostic assessment at design stage (static perspective), but also a continuous update of the virtual representation of the object by a real-time synchronization with sensed data. This allows the representation to reflect the status of the system and to perform real-time optimizations, decision making, and predictive maintenance according to the sensed conditions. In line with this view, Kuehn's [46] study claims that companies embracing digital twins have the opportunity to better understand and continuously improve products, services, and processes, which gives them a competitive advantage.

Moreover, Shao et Kibira [49] propose the "digital surrogate" as an alternative to digital twin and define this as "an integrated model that represents, connects, and synchronizes a part of or the whole physical manufacturing system or process, enabled by historical and real-time data from the physical system or process". The main goal of digital surrogates is to analyze and optimize a manufacturing system or a process in the cyber space. In particular, the digital surrogates can monitor the status of production systems or processes, predict system performance, and prescribe system behavior or control actions without interrupting production operations in the physical space. By integrating data from both the cyber space and the physical space, digital surrogates can help evaluate alternative plans and schedules, schedule maintenance, optimize operations in real-time, and prescribe future operations. However, the application of relevant standards is needed to improve the interoperability of data exchange among different applications within the digital surrogate.

In the same way, Lu et al. [7] believe that constructing a digital twin smart manufacturing needs a standardized information model, high-performance data processing, and industrial communications to work together. In particular, they state that research on standards, communication protocols, time-sensitive data processing, and reliability need to be the priorities for the next stage of the research while focusing on application scenarios of digital twin. Furthermore, they also highlight the key research issues for advancing the research of digital-twin-driven smart manufacturing, such as the need to: (i) define an architecture pattern for a digital twin; (ii) define a communication latency requirement for a digital twin; (iii) define a data capture mechanism and the standards for digital twin; and (iv) understand the role of humans in digital twin applications and the functionalities of a digital twin.

Modoni et al. [47] identify numerous challenges to be addressed in order to make a fully-synchronized factory twin a viable solution. The major obstacles derive from the nature of the digital, as it represents a complex system in high-dimensional spaces, thus requiring integrated multiphysics, multidomain, and multiscale modelling technology and ultra-high synchronization and fidelity between the virtual and physical space.

Furthermore, Park, Easwaran, and Andalam [48], in their work, highlight some problems associated with the digital twin, such as the discrepancy between the definition of a model and the physical system, and the issues associated with the concept of security and safety. With reference to the latter issues, since digital twins are closely coupled with the physical environment, an attack on a cyber–physical system can endanger the safety of people and cause significant economic loss.

Finally, according to Tao et al. [50], the most popular application area of digital twin is the prognostics and health management (PHM) area, where the current applications mainly focus on the high-value equipment. This aspect limits the broader applicability of digital twins. In general, they believe that digital twins are not only useful for fault diagnosis and prediction of equipment lifetime, but also for equipment maintenance and repair. However, a unified modelling framework for digital twins is needed.

Table 2 shows the most significant benefits and challenges associated with the implementation of digital twin on the shop floor found in the literature.

Table 2. Benefits and challenges of digital twin on the shop floor.

Benefits	Challenges
• Decision making [12] • Real-time optimizations [12,49] • Predictive maintenance [12,49,50] • Better understanding and continuous improvement of products, services, and processes [46] • Evaluate alternative plans and schedules [49] • Prescribe future operations [49] • Fault diagnosis [50] • Prediction of equipment lifetime [50]	• Definition of an architecture pattern [7] • Definition of a communication latency requirement [7] • Definition of a data capture mechanism and standards [7] • Understanding the role of humans in digital twin applications and the functionalities of a digital twin [7] • Need of a standardized information model, high-performance data processing, and industrial communications [7] • Need of integrated multi-physics, multi-domain, multiscale modelling technology, and ultra-high synchronization and fidelity between the virtual and physical space [47] • Discrepancy between the definition of a model and the physical system [48] • Security and safety issues [48] • Improvement of the interoperability of data exchange among different applications [49] • Need of a unified modelling framework for digital twins [50]

3.1.3. Digital Twin Frameworks

Most of the 41 analyzed papers provided a framework or an architecture able to act as a guide for the implementation of the digital twin within a shop floor. The review of the papers that were of fundamental importance for the definition of the framework proposed in this work is here discussed.

Zhuang, Liu, and Xiong [1] propose a framework of digital twin-based smart production management and control approach for complex product assembly shop floors, such as a satellite assembly shop floor. It consists of four components: physical assembly shop floor; assembly shop floor digital twin; assembly shop floor big data storage and management platform; and digital twin and big data-driven assembly shop floor service/ application platform. The physical assembly shop floor is the collection of existing physical entities. The assembly shop floor digital twin in virtual space is the reconstruction and digital mapping of the physical assembly shop floor. They exchange data/information/knowledge through the assembly shop floor big data storage and management platform. On the other hand, the assembly shop floor service/application platform refers to the collection of technologies that support the functional and target requirements of smart production management and control.

Wang, Zhang, and Zhong [51] present a proactive material handling method for a cyber–physical system enabled shop floor (CPS-PMH) to address the issues of using passive material handling strategies, which lead to excessively long occupation or idle time of machines. The overall architecture of the proposed CPS-PMH strategy mainly consists of three modules: physical shop floor, shop floor digital twin, and proactive material handling. In particular, the physical shop floor is responsible for constructing a smart shop floor by adopting CPS technologies. The shop floor digital twin is instead used to construct a digital twin model for the physical shop floor. Finally, the proactive material handling is responsible for making material handling decisions based on the prediction of the future status of manufacturing systems, including future logistics tasks prediction and trolley status prediction.

Fang et al. [52] introduce the architecture of DT-based job shop scheduling to deal with the uncertain events, information asymmetry, and abnormal disturbance, that affect the actual process of production scheduling, causing the execution deviation and undermining the efficiency and quality of the planning execution. The proposed architecture consists of two parts: physical space and virtual space. The two parts communicate with each other through CPS units. In the virtual space, the scheduling data can be obtained from the monitored resource in the physical space, such as equipment, workers, task information, etc. In the physical space, the plan is decomposed into machine execution, operator distribution, and material transportation, etc.

The conceptual framework developed by Chen et al. [36] for the new paradigm called smart factory based on CPS applies virtual-real mapping and fusion, digital twin, big data driven, virtualization, and edge-to-cloud service technology to the manufacturing system. It consists of a physical domain, a digital twin body, a model body and a service body. The physical domain is mainly composed of workshop equipment, product production process, information system and so on. On the other hand, cyber domain is characterized by a virtual space composed of a digital twin body and a model body.

With the aim to realize the intelligent interconnection and interaction between physical shop floors and virtual ones, Zhang et al. [53] propose an architecture of digital twin-driven CPPS (cyber–physical production system). This architecture consists of five layers: (i) physical layer, which refers to physical entities in the shop floor; (ii) network layer, that refers to the network infrastructure, which is the bridge between the physical space and the virtual space; (iii) database layer, that includes the multisource and heterogeneous data; (iv) application layer, that includes various services of the production system, which are responses for decision support; and (v) model layer, that is a very important layer to digital-twin-driven CPPS.

Zhang, Zhang, and Yan [18] aim to provide a practical insight into intelligent manufacturing by introducing a data and knowledge-driven framework for DTMC (digital twin manufacturing cell). It consists of five dimensional-limited intelligent manufacturing spaces: physical space, digital space, data space, knowledge space, and social space. Physical space is a container that brings together manufacturing resources involved in a processing sequence of a product's natural flow; while, digital space is a container of virtual digital twin models; it could first simulate, then understand, then predict and finally optimize the performance. On the other hand, data space is a container of massive real-time manufacturing data; knowledge space equips DTMC with the capacities of self-thinking and self-improving and with the capacity of self-decision-making, handle various manufacturing problems in physical space, digital space or social space. Finally, social space integrates a variety of service systems, such as customer relation management (CRM) and enterprise resource planning (ERP), which bridges the gap between the supply of DTMC and demand of customers in service-oriented manufacturing.

Furthermore, Zhang et al. [54] present a digital twin-enabled reconfigurable modelling for smart manufacturing systems (RDTMS) with a five dimensional fusion model, to build a digital-twin-based manufacturing system with high fidelity, high practicability, high flexibility, high intelligence, and high capability of reconfiguration. In particular, they define a digital twin framework for robotics-based smart manufacturing systems that supports automatic reconfiguration. The framework mainly contains four layers: physical layer, which consists of manufacturing equipment and which is responsible for executing actual production tasks based on instructions and strategies and feeding back operating data in real time; model layer, which contains the five models: geometric model (GM), physical model (PM), capability model (CM), behavior model (BM) and rule model (RM), which realistically describe all kinds of entities in the physical layer; service layer, which is also the human–computer interface, is composed of kinds of services and functions in RDTMS; and data layer, which includes various databases, data structures and data flows, which integrates multi-source heterogeneous real-time data and information from the above three layers.

Zhang and Zhu [55] propose a novel application framework of a digital-twin-driven product smart manufacturing system. The framework mainly consists of the following content: system layer, information processing layer, physical layer, and model layer. The physical layer refers to physical entities sets existing objectively, which mainly includes manufacturing equipment and data acquisition apparatus. Model layer is instead the real mapping of product manufacturing in cyberspace, including mainly product digital twin model, machine digital twin model, process digital twin model, and so on. The information layer is the information management platform for product manufacturing, including mainly digital twin data, manufacturing service information, and product service information; while the system layer is composed of the manufacturing service platform system and the digital twin application subsystem.

Finally, Guo et al. [56] introduce a digital-twin-enabled graduation intelligent manufacturing system (DT-GiMS) with the aim of reducing complexity and uncertainty in fixed-position assembly islands by utilizing information visibility and visualization. They define a unified digitization approach to create the digital representations with appropriate sets of information at object level, product level, and system level in fixed-position assembly islands. At object level, the manufacturing status of the object (e.g., ID, attribute, status, and service) can be captured, mapped, and converged on a real-time basis. The light weight 3D model and manufacturing status of the product assembly process can be synchronously published on the web on a real-time basis at product level. System level focuses on the production system, which provides an effective way to achieve real-time synchronization between the production system and its corresponding digital representation. Therefore, the proposed overall framework of DT-GiMS presents a physical layer, a digital layer, and a service layer. Real-time convergence and synchronization among them ensure that the right resources are allocated and utilized to the right activities at the right time with enhanced visibility and that the managers and onsite operators could easily make near-optimal production decisions and efficiently complete their daily tasks with nearly error-free operations.

4. Discussion

4.1. The Hexadimensional Shop Floor Digital Twin Framework

Starting from the results of the literature review, all the relevant contributions have been analyzed and combined in a unique integrated framework. Past research identified different components of the digital twin but presented them in a fragmented view. For instance, while some authors focused on the physical elements [18,56], some others stressed the virtual ones [53,54]. Moreover, a common approach identified in the literature is based on the multi-layer construction of a digital twin model that encompasses both physical and digital issues.

The hexadimensional shop floor digital twin (HexaSFDT) is proposed (Figure 4) as a comprehensive conceptual framework that integrates all aspects in a unique, holistic, and integrated view. The multi-layered framework describes the digital twin components and their relationships in smart manufacturing. The HexaSFDT consists of two main environments: the physical space and the digital space.

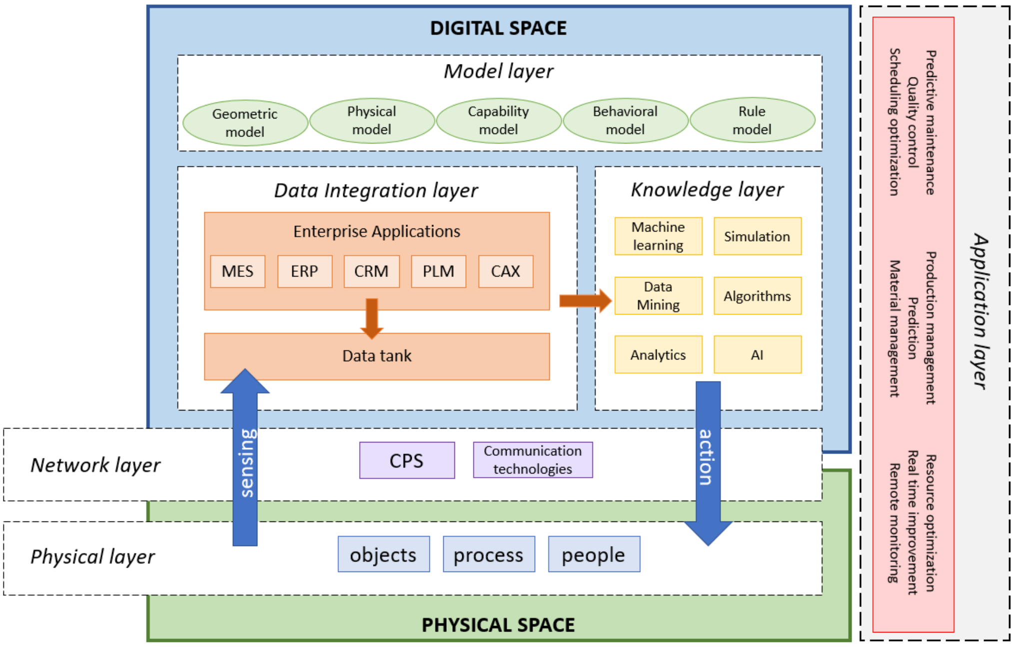

Figure 4. Hexadimensional shop floor digital twin.

The physical space is mainly represented by the physical layer containing all the potential existing physical entities. It refers to objects, processes, and people that exist in the shop floor such as: machines, tools, robots, workers, parts, materials, resources, and manufacturing assets. The physical entities can be sensed to dynamically collect data, monitor their status in real time, and exchange information and instructions.

The digital space represents the virtual counterpart of the physical space and it is composed of different layers focused on mirroring its behavior. It digitally maps the manufacturing system allowing for analyzing its working conditions with different constraints and requirements and without stopping the operations.

The bidirectional communication and interaction between these two spaces is enabled by the network layer. The IoT, CPS, and communication technologies enable the synchronization between the physical and digital spaces, ensuring the reflectivity characteristic and establishing a real-time interaction. In these terms, a closed-loop digital twin is modelled from the representation of the "sensing" and the "action" arrows [51,54]. The former allows the connection from the physical to the digital space and it is mainly responsible for collecting and transmitting data sensed from the physical entities. The latter creates a link from the digital to the physical space in order to communicate the results of the decision-making process and of the services requested by the users. Therefore, the HexaSFDT works in a cyclical process with the characteristics of continuous monitoring, dynamic adjustment, and iterative optimization.

As suggested by the literature, the HexaSFDT has been designed in a multi-layered approach in order to structure all the contributions that this technology enables in conceptualizing a digital twin for the shop floor (see Figure 5).

In the following, a detailed description of each layer of the HexaSFDT framework is provided.

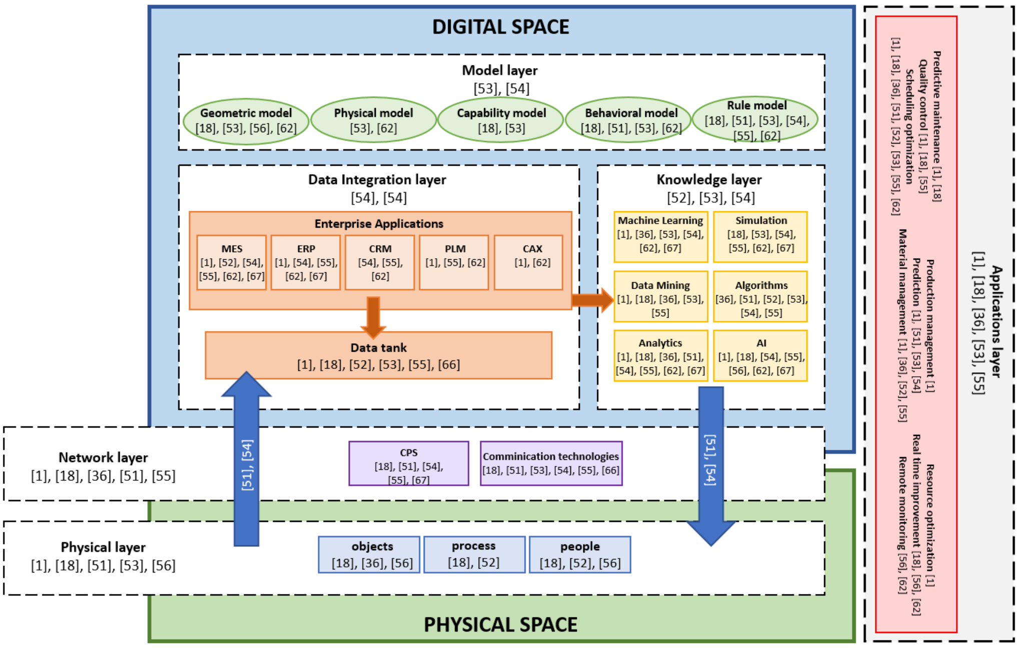

Figure 5. References for HexaSFDT design.

4.1.1. Physical Layer

The manufacturing system is characterized by multiple physical entities from which it is possible to collect heterogeneous, multi-source, and real-time data mainly generated by sensors, smart devices, and IoT. For example, the temperature, voltage, pressure, and speed are some of the parameters that can be sensed from a manufacturing machine. Data can be generated, collected, and transmitted considering all the enabled manufacturing resources and assets, including industrial robots, equipment, materials, products, people, and the environment. It is possible to distinguish:

Objects: tools, machines, conveyors, materials, products, parts, components, etc. [18,36,56], that are equipped with smart devices and technologies, such as RFID, sensors and microprocessors, that allow for the identification, connection, communication, and synchronization of their status in real time.

Process: operations and workflows needed to manufacture the product [18,52].

People: blue, white, and pink collars that operate in the shop floor and can be sensed and tracked within it by using enabling devices such as the wearable devices [18,52,56].

Similarly, data can be conceptually divided into object data (e.g., production, logistics, and equipment data), process data (e.g., data referred to operations and manufacturing process such as completion data, work-hour data, product quality data), and people data (e.g., data concerning the behavior of workers). CPS and communication technologies support the synchronization between physical and virtual environments operating in a synergic way with the network layer [1,18,51,53,56].

4.1.2. Network Layer

The network layer acts as a broker by creating a bidirectional connection between the physical space and the virtual space. Data generated by physical entities are collected, integrated, and transmitted in the virtual counterpart. IoT, CPS [54], and communication technologies [53,54,56] are some of the most important enablers of the network layer that is responsible for the real-time synchronization of the manufacturing system. Both hardware and software are included in this layer such as the industrial Ethernet, Bluetooth, wireless and mobile gateway, Wi-Fi, RFID, mobile internet, and 4G/5G technologies. Firstly, it is necessary to identify all the manufacturing resources and then to design the industrial network, including aspects related to data security and privacy [1,18,36,51,55].

4.1.3. Data Integration Layer

Multiple data-sources are involved in the physical space and generate heterogeneous and multi-types of data. The data integration layer allows to integrate the streaming data coming from the real world with stored data and other information produced by enterprise systems and applications. In this context, a shop floor digital twin deals with big data having typical characteristics of high volume (terabytes of records, transaction, tables, files), high velocity (batch, near time, real time, streams) and high variety (structured, semi-structured, unstructured). This layer is mainly responsible for data ingestion, pre-processing, aggregation, integration, and storing [18].

In particular, the data integration layer consists of two sub-components: the enterprise applications and the data tank. The enterprise applications include the set of applications and systems implemented and used in the manufacturing organization such as the ERP (enterprise resource planning) [1,54,55], MES (manufacturing execution systems) [1,52,55], PLM (product lifecycle management) [1,55], CRM (customer relationship management) [54,55], CAX (computer aided tools) [1], service platforms, and HMI (human–machine interface) technologies [54,55]. The data tank represents the repository of all data (e.g., production data, material data, equipment data, tooling data). In particular, different databases store data coming from the physical world, representing the direct interface with it, data coming from the enterprise applications, and virtual data generated by the digital counterpart such as model data, simulation data, prediction data, and production plan data [1,18,52,53,55].

4.1.4. Model Layer

The general objective of the model layer is to structure the virtual counterpart starting from the real world and adopting abstraction and encapsulation mechanisms. To model the digital twin, five integrated components are considered with specific variables and abilities in order to reproduce all the characteristics, properties, and attributes of the manufacturing system [53,54].

Geometric model: it describes the geometric characteristics of the smart shop floor entities (e.g., tools, machines, conveyors, materials, products, components) such as: the shape, size, and location; height, width, and length; and the horizontal/vertical and single-spindle/multi-spindle of machine tools, in order to build the 3D models of the virtual visualization. The CAD (computer-aided computer) systems are useful tools for achieving this goal [18,56].

Physical model: it concerns the non-geometrical attributes of the shop floor describing their physical nature, rules and property values, such as speed and mass. The digital twin has the same rules and properties of the physical world in order to accurately mirror the manufacturing entities. It allows digital entities to simulate the same physical task under the different environmental conditions [53].

Capability model: in the physical manufacturing system, each entity deals with specific operations and has different roles and capabilities. The capability model is responsible for clarifying these capabilities in terms of what an entity can do and what can be done on it. In these terms, the description of the available capabilities allows for a dynamic representation of the digital twin [18,53].

Behavioral model: this element describes the mechanisms and the behavioral status of each manufacturing entity, including activities, movements, reactions, and actions of workers, objects, and processes. For example, a machine can be in standby, in running, or out of service; a worker can be available or not; and an operation can include tool setting, emergency, shutting down, parts loading, cleaning. Common tools used to virtualize models of personnel actions, equipment operations, and material transportations are simulation, visualization, and documentation tools [18,51,53].

Rule model: the definition of rules is necessary to ensure a smart digital twin, including safety and security aspects. The rule model also comprises constraints and requirements, such as process energy consumption and spatiotemporal information. Finally, it supports domain knowledge and manufacturing decisions. Rules need to be modeled with the possibility to change over time in order to reflect the development of the manufacturing system. To build the rule model, algorithms for data analysis and for data and knowledge mining are useful tools [18,51,53–55].

4.1.5. Knowledge Layer

This layer integrates dynamic knowledge with the capabilities of self-decision-making to manage different issues of the manufacturing system [54]. The knowledge layer interacts with the data integration layer and processes data by adopting methodologies, techniques, and technologies for data analysis such as algorithms [36,51–55], machine learning [1,36,53,54], big data analytics [1,18,36,51,54,55], data mining [1,18,36,53,55], simulation tools [18,53–55], and artificial intelligence (AI) [1,18,54–56]. The retention of data and the mechanisms to extract their value is essential for the decision-making process. In this context, it is also possible to autonomously or semi-autonomously support actions in the physical world.

4.1.6. Application Layer

The application layer refers to the collection of techniques and tools that support the functionalities of the shop floor digital twin, including solutions for its management, control, and improvement. Multiple services can be implemented for a rapid analysis of the manufacturing system such as job scheduling optimization [1,18,36,51–53,55], real-time monitoring of manufacturing resources [18,56], quality control [1,18,55], tool life prediction [1,51,53,54], predictive maintenance [1,18], logistic optimization, and material delivery management [1,36,52,55]. These services are elaborated in the digital space and are available and accessible by the users in the physical space [1,18,36,53,55].

5. Conclusions

The achievement of a digital–physical synchronization is a driving factor in smart manufacturing, and the adoption of digital twin solutions is a sustainable strategy for monitoring, analyzing, and improving the operation performances in real time.

The systematic literature review allows for investigating digital twin frameworks developed in the context of smart manufacturing and, in particular, for the shop floor. By structuring the results in three main areas of analysis, it has been possible to build a knowledge base of reference upon which to consider the most important contributions in the reference domain. Starting from the awareness of the potential benefits and challenges related to this technology, this research provides a comprehensive framework to support organizations in their digital twinning journey. In particular, the HexaSFDT framework integrates the components and their relationships that shape the shop floor digital twin in smart manufacturing. On the basis of six main layers, the design of the framework includes the concept of a closed-loop digital twin for a continuous bidirectional communication and interaction between the physical and the digital spaces. This is a concept not widely mentioned in the literature.

Different advantages can be recognized in considering the HexaSFDT framework. First, it aids the conceptual modelling of a real scenario by reducing its complexity. Second, by leveraging the availability of data and the adoption of technologies, it allows the definition of data flows, from the physical to the virtual spaces and vice-versa. Third, it supports manufacturing companies in understanding the digital twin from the methodological and technological viewpoint. It stimulates the identification of all the elements in a unique reference framework.

On the other hand, this research strengthens the relative literature by collecting and combining relevant contributions in an integrated framework.

However, limitations and future research need to be highlighted. First, the proposed framework needs to be validated to test its effectiveness. The qualitative research methodology does not allow a complete evaluation of the results. The application of the HexaSFDT framework in manufacturing scenarios is warmly suggested in order to collect quantitative data. Second, future empirical work should be addressed in complex manufacturing systems and in specific industrial case studies. Third, the technological application of the digital twin solution requires advanced and heterogeneous digital competences because of the integration of different technologies such as IoT, CPS, analytics, and simulation tools. In this sense, future research could follow this direction. Fourth, despite the research growth, a commonly recognized methodology, including an implementation roadmap and standard of reference, seems to be missing in this domain.

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Appendix A

Table A1. Details of the results obtained by the systematic literature review.

ID	Authors	Title	Year	Focus	DT Conceptual Model	DT Framework	DT Benefits and Challenges	Reference
1	Negri, Fumagalli and Macchi	A Review of the Roles of Digital Twin in CPS-based Production Systems	2017	The paper analyzes the definition of the digital twin concept in the literature, considering the aerospace and manufacturing domains.			X	[12]
2	Tao and Zhang	Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing	2017	The concept of Digital Twin Shop-Floor (DTS) is proposed to provide an effective way to reach the physical–virtual convergence model.	X			[57]
3	Tao et al.	Digital twin-driven product design, manufacturing and service with big data	2017	It discusses the digital twin shop floor (DTS) as a new paradigm for product manufacturing. DTS is composed of physical shop floor, virtual shop floor, shop floor service system, and shop floor digital twin data.	X		X	[58]
4	Shao and Kibira	Digital manufacturing: Requirements and challenges for implementing digital surrogates	2018	The "digital surrogate" concept is introduced and explores the relationships with digital thread, simulation, AI, and IoT.			X	[49]
5	Zhuang, Liu, and Xiong	Digital twin-based smart production management and control framework for the complex product assembly shop-floor	2018	The paper proposes a framework of digital twin-based smart production management and control approach for predicting complex product assembly shop floors.		X		[1]
6	Nikolakis et al.	The digital twin implementation for linking the virtual representation of human-based production tasks to their physical counterpart in the factory floor	2018	The study proposes an implementation of the digital twin approach as part of a wider cyber–physical system to enable the optimization of the planning and commissioning of human-based production processes using simulation-based approaches.	X		X	[59]

Table A1. *Cont.*

ID	Authors	Title	Year	Focus	DT Conceptual Model	DT Framework	DT Benefits and Challenges	Reference
7	Bao et al.	The modelling and operations for the digital twin in the context of manufacturing	2018	The paper develops three types of digital twins (product digital twin, process digital twin, and operation digital twin) in the manufacturing context, for simulating the state and behavior of the physical object and optimizing production process.	X			[38]
8	Ellgass et al.	A digital twin concept for manufacturing systems	2018	The paper develops a framework for a digital-twin-based manufacturing system, with its supported real-time simulation and optimization of shop floor. It includes four main components: virtual shop, physical shop, big data storage and management platform, and service provider.		X		[60]
9	Cheng et al.	Cyber–physical integration for moving digital factories forward towards smart manufacturing: a survey	2018	It provides an overview of digital twin factories. It proposes a systematical framework of cyber–physical integration for manufacturing service.			X	[20]
10	Leng et al.	Digital twin-driven manufacturing cyber–physical system for parallel controlling of smart workshop	2018	The paper presents a digital-twin-driven manufacturing cyber–physical system architecture. It also discusses the digital twin use in optimizing system behavior.	X			[61]
11	Kuehn	Digital twins for decision making in complex production and logistic enterprises	2018	The paper discusses the digital twin concept and the interactions of six steps which complete a closed loop connection (physical-to-digital-to-virtual-to-physical) between the physical world and the virtual model.	X		X	[46]
12	Modoni et al.	Synchronizing physical and digital factory: Benefits and technical challenges	2019	The paper proposes a conceptual model to understand the digital twin by highlighting its main entities and relations.	X		X	[47]
13	Park, Easwaran and Andalam	Challenges in digital twin development for cyber–physical production systems	2019	The paper reviews current state-of-the-art technology on tools and developments of digital twin in manufacturing and then discusses potential design challenges.	X		X	[48]

Table A1. *Cont.*

ID	Authors	Title	Year	Focus	DT Conceptual Model	DT Framework	DT Benefits and Challenges	Reference
14	Stark, Fresemann and Lindow	Development and operation of Digital Twins for technical systems and services	2019	The paper proposes two development support models that are essential for the design of digital twin solutions: the "digital Twin 8 dimension model" and digital twin design elements.	X			[11]
15	Lu et al.	Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues	2019	The paper provides a literature review about the concept of digital twins in manufacturing.			X	[7]
16	Tao et al.	Digital Twin in Industry: State-of-the-Art	2019	The paper provides a literature review about the concept of digital twins in manufacturing.			X	[50]
17	Wang, Zhang and Zhong	A proactive material handling method for CPS enabled shop-floor	2019	It presents a shop floor digital twin model for simulating real-life production in a virtual environment. It discusses production KPIs and a proactive material handling strategy (CPS-PMH).		X		[51]
18	Fang et al.	Digital-Twin-Based Job Shop Scheduling Toward Smart Manufacturing	2019	An architecture and working principles of new job shop scheduling mode are proposed to reduce the scheduling deviation.		X		[52]
19	Chen et al.	The framework design of smart factory in discrete manufacturing industry based on cyber–physical system	2019	The paper explains four main charateristics of smart factory, and proposes a framework for the design of smart factory CPS-model-based digital twin.		X		[36]
20	Zhang et al.	Digital twin-enabled reconfigurable modeling for smart manufacturing systems	2019	This paper provides a complete set of modelling approaches for DT-based and robotics-based manufacturing systems to reconfigure manufacturing systems at different levels.		X		[53]
21	Zhang, Zhang and Yan	Digital twin-driven cyber–physical production system towards smart shop-floor	2019	The paper provides a reference architecture of a digital-twin-driven cyber–physical production system to enhance the transparency in the smart shop floor and to allow real-time production control.		X		[18]

Table A1. *Cont.*

ID	Authors	Title	Year	Focus	DT Conceptual Model	DT Framework	DT Benefits and Challenges	Reference
22	Zhang et al.	A data- And knowledge-driven framework for digital twin manufacturing cell	2019	The paper introduces a data- and knowledge-driven framework for a digital twin manufacturing cell (DTMC) to support the construction of an autonomous manufacturing cell that aims to maximize the product quality and throughput.		X		[54]
23	Zhang and Zhu	Application framework of digital twin-driven product smart manufacturing system: A case study of aeroengine blade manufacturing	2019	The article proposes a novel application framework of a digital-twin-driven product smart manufacturing system and it analyzes its operation mechanism.		X		[55]
24	Zhang et al.	A reconfigurable modeling approach for digital twin-based manufacturing system	2019	It proposes a reconfigurable digital twin (RDT)-based manufacturing system for improving the operation efficency of systems for carrying out the reconfiguration production tasks, saving time, and costs.	X			[62]
25	Tao et al.	Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison	2019	It analyzes differences and correlation between CPS and digital twin from three different levels: the unit level, the system level (production line, shop floor, or factory), and the system of systems (SoS) level.	X		X	[63]
26	Liu et al.	A digital twin-based approach for dynamic clamping and positioning of the flexible tooling system	2019	The paper proposes a digital-twin-based approach for dynamic clamping and positioning of the flexible tooling system.	X			[64]
27	Liu et al.	Dynamic Evaluation Method of Machining Process Planning Based on Digital Twin	2019	A novel digital-twin-based machining process evaluation (DT-MPPE) framework method is proposed for complex parts simulation and evaluation.		X		[65]
28	Min et al.	Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry	2019	It proposes a digital twin framework for petrochemical production control optimization based on the industrial IoT and machine learning.		X		[66]
29	Delbrügger and Rossmann	Representing adaptation options in experimentable digital twins of production systems	2019	The paper introduces an experimentable digital twin of the factory that tracks production and transport capabilities. The factory EDT is able to create valid production and transport plans that can be updated if the capabilities change.	X			[67]

Table A1. *Cont.*

ID	Authors	Title	Year	Focus	DT Conceptual Model	DT Framework	DT Benefits and Challenges	Reference
30	Ding et al.	Defining a Digital Twin-based Cyber–Physical Production System for autonomous manufacturing in smart shop floors	2019	It defines a digital-twin-based cyber-physical production system (DT-CPPS) that includes a physical shop floor (PSF) configuration and a cybershop floor (CSF) configuration for a transparent management of data flow.	X			[68]
31	Park et al.	Design and implementation of a digital twin application for a connected micro smart factory	2019	The paper proposes a digital twin solution for simultaneously solving the cost and performance hurdles of a personalized production.	X			[69]
32	Xu et al.	A Digital-Twin-Assisted Fault Diagnosis Using Deep Transfer Learning	2019	The paper presents a two-phase digital-twin-assisted fault diagnosis using deep transfer learning (DFDD) which aims to make fault diagnosis more suitable for increasingly autonomous and complex manufacturing.	X			[70]
33	Kousi et al.	Digital twin for adaptation of robots' behavior in flexible robotic assembly lines	2019	The study investigates the use of digital modeling techniques in hybrid production systems. The suggested digital world model infrastructure includes the dynamic real time updating of the digital twin based on sensors.	X			[71]
34	Pfeiffer, Oppelt, and Leingang	Evolution of a Digital Twin for a Steam Cracker	2019	The paper, through the example of a steam cracker, shows numerous aspects of an integrated application of a digital twin for process plants.	X			[72]
35	Zipper and Diedrich	Synchronization of Industrial Plant and Digital Twin	2019	The paper presents an architecture and an algorithm to synchronize the states of a plant and its digital twin while in the same time still providing the possibility to detect changes.	X			[73]
36	Martins, Costelha, and Neves	Shop Floor Virtualization and Industry 4.0	2019	It describes the virtualization of a typical production process, the digital twin in the scope of Industry 4.0, involving different devices such as robotic arms, conveyors, automatic warehouses, and vision systems.			X	[74]

Table A1. *Cont.*

ID	Authors	Title	Year	Focus	DT Conceptual Model	DT Framework	DT Benefits and Challenges	Reference
37	Park et al.	Digital twin-based cyber–physical production system architectural framework for personalized production	2019	The study focuses on a CPPS to prevent the degradation of production plant performance in the operation stage.			X	[75]
38	Guo et al.	Digital twin-enabled Graduation Intelligent Manufacturing System for fixedposition assembly islands	2020	The paper introduces the digital-twin-enabled graduation intelligent manufacturing system (DT-GiMS) for fixed-position assembly islands, real-time convergence, and synchronization among the physical layer, digital layer, and service layer.		X		[56]
39	Cheng et al.	DT-II: Digital twin enhanced Industrial Internet reference framework towards smart manufacturing	2020	The paper presents the implementation and operation mechanisms of digital twin industrial internet (DT-II) from three perspectives: product lifecycle level, intra-enterprise level, and inter-enterprise level.			X	[39]
40	Leng et al.	Digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model	2020	The paper discusses the digital twin system for a rapid reconfiguration process that allows to find the balance between the maximization of the productivity and the economic efficiency in terms of minimizing costs of machine moving and machine holding.			X	[76]
41	Qamsane et al.	A unified digital twin framework for real-time monitoring and evaluation of smart manufacturing systems	2020	The paper proposes a digital twin architecture for the real-time monitoring and evaluation of large-scale smart manufacturing systems. An application to a manufacturing flow shop is presented to illustrate the usefulness of the proposed methodology.	X		X	[77]

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