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Review

A Comprehensive Review of AI-Based Digital Twin Applications in Manufacturing: Integration Across Operator, Product, and Process Dimensions

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Abstract: Digital twins (DTs) represent a transformative technology in manufacturing, facilitating significant advancements in monitoring, simulation, and optimization. This paper offers an extensive bibliographic review of AI-Based DT applications, categorized into three principal dimensions: operator, process, and product. The operator dimension focuses on enhancing safety and ergonomics through intelligent assistance, utilizing real-time monitoring and artificial intelligence, notably in human–robot collaboration contexts. The process application concerns itself with optimizing production flows, identifying bottlenecks, and dynamically reconfiguring systems through predictive models and real-time simulations. Lastly, the product dimension emphasizes the applications focused on the improvements in product design and quality, employing lifecycle and historical data to satisfy evolving market requirements. This categorization provides a structured framework for analyzing the specific capabilities and trends of DTs, while also identifying knowledge gaps in contemporary research. This review highlights the key challenges of technological interoperability, data integration, and high implementation costs while emphasizing how digital twins, supported by AI, can drive the transition toward sustainable, human-centered manufacturing systems in line with Industry 5.0. The findings provide valuable insights for advancing the state of the art and exploring future opportunities in digital twin applications.

Keywords: digital twin; human digital twin; Industry 4.0; Industry 5.0; framework

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1. Introduction

A digital twin (DT) is a virtual representation of a physical system that enables the simulation and analysis of different process variants in real time, without interfering with the physical environment. This facilitates the optimization of production and supports decision-making [1]. This virtual representation is in sync with the physical system, accurately reflecting its behavior and responding to changes in the real environment [2]. In industrial applications, such as CNC machines, the digital twin not only monitors and simulates machine performance but also predicts its condition, facilitating predictive maintenance decision making and improving operational efficiency [2]. Moreover, the digital twin spans the entire product lifecycle, from design to service, using large volumes of data to optimize product development and maintenance [3]. According to [4], a DT is not merely a virtual representation of a physical component, but is characterized by a bidirectional data flow between the virtual and real models. This dynamic enables advanced data analytics. In work environments, digital twins integrate various ergonomic factors, simulating interactions between operators and machines to optimize safety and human performance in the design of the workstation [5].

Digital twins have become a cornerstone of digital transformations in companies, playing a pivotal role in both Industry 4.0 and the transition to Industry 5.0. Within Industry 4.0, digital twins improve the autonomy and control of interoperable machines and production systems [6]. Technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing facilitate a more efficient use of manufacturing resources and enable greater customization in production [7], which, in turn, demands greater resilience in production systems. Originally, digital twins were designed to replicate physical assets. However, their scope has expanded to encompass not only industrial processes but also human operations. By integrating real-time data, digital twins optimize decision making, improve operational efficiency, refine production scheduling, and improve safety.

Digital twins (DTs) represent a dynamic bridge between the physical and digital world through a bidirectional connection in real time, allowing continuous synchronization of data and their analysis to optimize processes and make informed decisions. It is important to note that the principal action in this is the data, which can come from multiple sources and multiple sensors, as will be discussed later. This bidirectional connection is possible to establish through a series of communication protocols which will depend on the use case. Originally conceived by NASA to monitor space missions, DTs have evolved into a core technology in modern manufacturing, enabled by advances such as IoT, Big Data, and multidisciplinary simulation models. The sensors installed in physical systems collect operational data, which are transferred to the digital model by implementing a communication protocol that enables advanced simulations and predictive analytics, as well as AI algorithms that enable advanced data analysis [8,9].

This continuous flow not only reflects the current state of the system, but also anticipates its future behavior, generating actionable recommendations that directly impact physical assets, creating a continuous cycle of optimization. Practical examples, such as the integration of advanced simulations and semantic models in projects such as H2020 MAYA, illustrate how a DT transforms manufacturing by reducing production times and improving operational performance, while intuitive interfaces and communication networks ensure effective interaction between operators and digital systems [10].

The evolution from Industry 4.0 to Industry 5.0 marks a shift toward human-centered technology and sustainability [11]. Although Industry 4.0 emphasized automation, connectivity, and data analysis powered by artificial intelligence, Industry 5.0 places humans at the center of production processes. This shift introduces values such as resilience and adaptability into digital twin systems [11,12]. Achieving this transition requires not only technological advancements, but also a rethinking of how digital twins are conceptualized and constructed, emphasizing models that optimize processes while integrating human factors [11,12].

Despite the growing interest in digital twins, previous studies have explored specific areas, such as human–robot collaboration [13], plant reconfiguration, production scheduling, and monitoring [14]. However, the literature lacks a structured framework for analyzing the specific capabilities and trends of DTs while identifying knowledge gaps in current research.

The main contribution of this work lies in providing a comprehensive classification of digital twin applications along three fundamental dimensions: operator, product, and process. This classification facilitates the identification of potential gaps in each dimension and the purpose of the application. In addition, it enables recognition of the technologies and tools used in their design and implementation. The proposed framework guides the selection of appropriate technologies aligned with the specific objectives of each dimension. It also offers a clear perspective on the areas within the manufacturing industry where digital twins have been widely adopted, as well as those that remain relatively unexplored.

As part of this research, academic databases, including Web of Science and Scopus, were queried using the keywords "digital twin and manufacturing" and "digital twin and framework". The search was restricted to articles published from 2020 onward, with an additional filter applied to open-access publications to ensure the accessibility of sources. Further criteria were used to isolate studies that specifically addressed digital twin applications within the three proposed axes: operator, product, and process.

A total of 75 scientific articles were reviewed. Among these, 48 articles focused on applications of digital twins within the process d. The other 17 articles explored the operator dimension, primarily investigating applications related to intelligent assistance, monitoring, and safety enhancement. Finally, 10 studies addressed the product dimension, emphasizing the use of digital twins for feedback mechanisms and iterative product development throughout the product lifecycle. Figure 1 provides a graphical summary of this distribution.

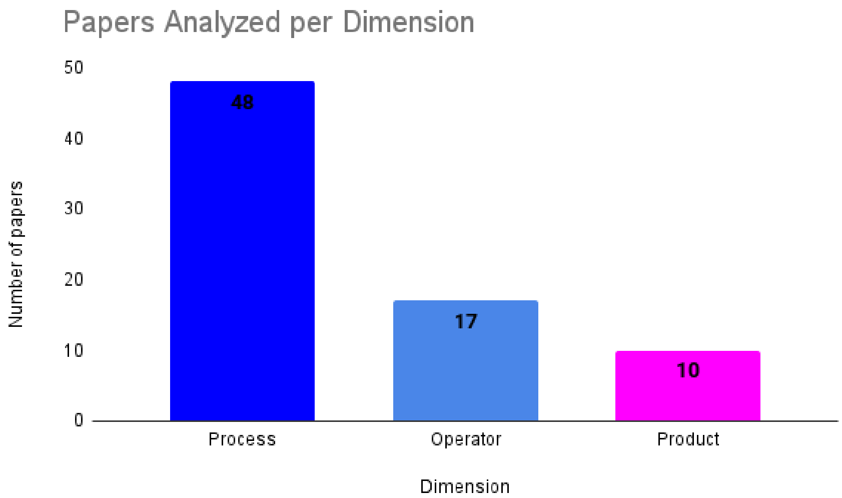

Figure 1. General summary of the papers analyzed by dimension.

The rest of the document is organized as follows. Section 2 describes the methodology used to select and classify the analyzed articles. Section 3 presents the proposed classification model broken down into operator, product, and process axes, together with representative examples of each dimension. Section 4 discusses the main findings, highlighting key opportunities and challenges. Finally, Section 5 concludes the paper, summarizing the contributions of the study and suggesting directions for future research.

2. Methodology

The proposed classification is grounded in an exhaustive analysis of recent scholarly literature, with an emphasis on digital twins (DTs) within the manufacturing domain. Articles that examine specific applications of DTs in conjunction with artificial intelligence (AI) across the domains of operator, product, and process axes were selected, taking into account their practical relevance and contributions to advancing the state of the art.

The selection of operator, product, and process dimensions as the primary focal points of this study is grounded in their significance and widespread discussion within the scholarly literature concerning digital twins (DTs) in the context of manufacturing. These dimensions represent the most pivotal elements of industrial production systems:

the operator, representing the human element whose safety, ergonomics, and performance are crucial in a human-centered setting; the product, constituting the tangible outcome of the process that necessitates optimization concerning design, quality, and life cycle; and the process, comprising the array of activities and resources employed to convert raw materials into finished products.

The analysis of the studies reviewed reveals that most research on digital twins in manufacturing predominantly focuses on the process dimension, with comparatively less attention given to the operator and product axes. This imbalance highlights potential underexplored areas and underscores the relevance of the current classification. Such a structured framework not only organizes digital twin applications systematically, but also identifies areas that have been extensively studied and those requiring further exploration.

In the same way that the applications of digital twins are categorized by dimension, whether they pertain to supporting the operator, analyzing and monitoring the production process, or improving a product's operational performance, each dimension is further subcategorized. These subcategories will be discussed and analyzed in the following sections.

The operator dimension, which has gained significant relevance with the evolution toward Industry 5.0, is characterized by the implementation of digital twin applications that enable real-time worker monitoring, provide intelligent assistance, improve ergonomics, and ensure safe operations. Human–robot collaboration is another critical aspect, with research focusing on the safe and efficient integration of robots into human work environments [15].

3. Taxonomy Proposal

This section presents a detailed analysis of each dimension of the classification and its respective subcategories. For each dimension, a subclassification is proposed to systematically organize the digital twin applications.

Figure 2 illustrates the relationship between the three main dimensions of the proposed classification: process, operator, and product. The machinery depicted represents the process dimension, emphasizing the interactions required to transform raw materials into a final product. This dimension includes applications focused on monitoring, process optimization, and production control and scheduling. Within this dimension, subcategories such as process optimization, simulation and monitoring, and scheduling are explored, providing a framework for understanding how these activities contribute to efficient manufacturing workflows. The operators shown in the figure represent the dimension of the operator, which highlights applications aimed at improving the safety, ergonomics, and efficiency of human work. In line with industry 5.0 principles, digital twin applications in this category support human operators by monitoring physical and mental fitness and providing intelligent tools that assist them to perform tasks effectively and safely. Finally, the manufactured product is depicted as a dynamic entity that represents the dimension of the product. This dimension focuses on analyzing the product's performance during its lifecycle, both during final use and in subsequent iterations. Applications in this dimension collect product-related information, enabling iterative improvements that enhance quality and functionality based on operational feedback.

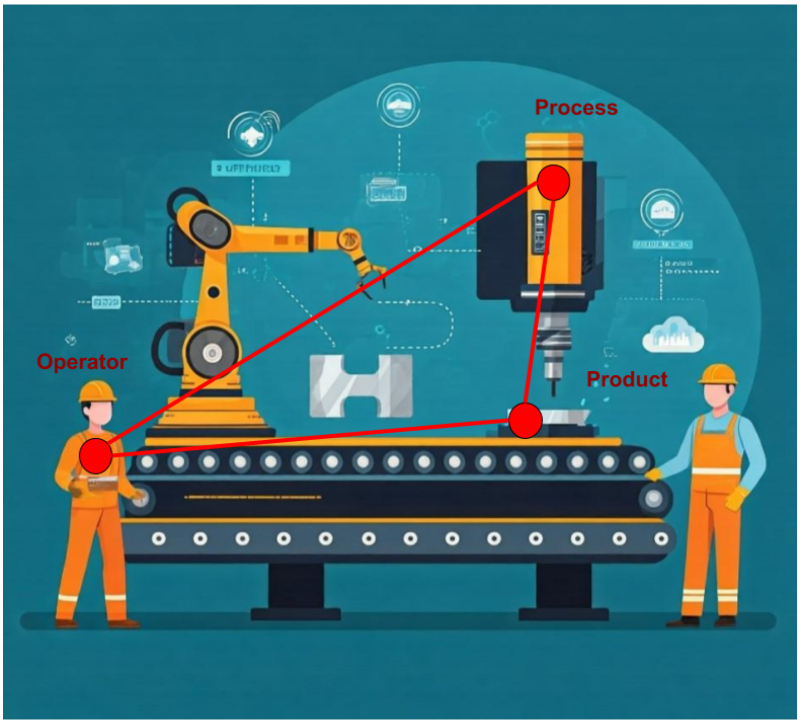

Figure 2. Relationship between the three axes of the proposed classification.

3.1. Process

The process dimension encompasses all activities involved in the manufacturing of products within a company, spanning from production planning and execution to real-time control and operational adjustments. This dimension plays a critical role in ensuring that production processes are both efficient and effective. By monitoring, analyzing, and controlling these activities, companies can optimize operational efficiency, maximize resource utilization, and improve responsiveness to changes within the production environment. The adaptability and flexibility provided by real-time, data-driven process adjustments are essential to address the challenges posed by an increasingly dynamic and competitive manufacturing landscape.

The classification criteria proposed for process implementations, illustrated in Figure 3, organize digital twin applications in industrial processes around several decision variables. These variables distinguish the level of intervention and the objectives of each analyzed digital twin application.

- The first variable, "Active Optimization", determines whether the digital twin is limited to a monitoring and simulation role, merely observing the system, or if it is designed for active optimization, dynamically adjusting process, or operational parameters. This distinction separates digital twins that passively monitor from those that actively influence the behavior of the system.
- For applications engaged in active optimization, the next classification variable, "Operational Optimization", assesses whether the digital twin's interventions target immediate operational improvements, such as production scheduling and flow control. Digital twins in this category directly optimize daily operations, including resource allocation and task sequencing, to improve real-time efficiency and reduce production bottlenecks.
- If optimization is not operational, the "Strategic Optimization" variable is introduced to evaluate whether the digital twin focuses on long-term strategic goals. Digital twins in this category are oriented towards overall system planning, process reconfiguration,

or high-level strategic decisions that significantly impact long-term performance. Examples include redesigning processes or establishing new production models.

- Finally, if the application is not aimed at strategic optimization, the "Resource Optimization" variable applies. This variable identifies whether the primary objective of the digital twin is resource efficiency, such as optimizing the use of energy or material resources.

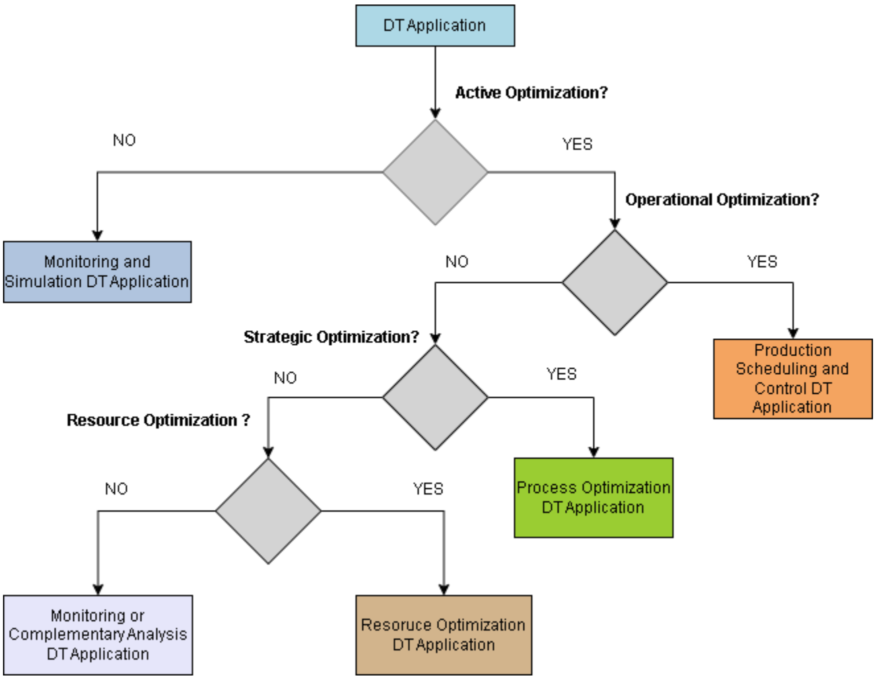

Figure 3. Classification criteria within the process dimension.

3.1.1. Simulation and Monitoring

Simulation and monitoring represent fundamental applications of digital twins in manufacturing, enabling the integration of virtual models with real-time data to optimize processes and improve decision making. These applications are essential for achieving dynamic synchronization between physical and digital environments, facilitating activities ranging from predictive fault diagnosis to quality improvement in manufactured parts. This section explores various implementations of simulation and monitoring in digital twins, highlighting their impact on operational efficiency and their potential to drive more agile, flexible, and resilient manufacturing systems in response to modern challenges.

In [16], the digital twin concept is applied to discrete manufacturing shops, improving the perception of the production status by synchronizing a virtual model of the shop floor with the real-time behavior of physical production.

Digital twins also play a crucial role in the implementation and maintenance of lean manufacturing systems, as demonstrated by [17]. Using sensors, digital twins provide continuous streams of real-time information, facilitating informed decision making and system updates.

Additional applications of digital twins are found in machine tool operations, where the integration of virtual and real-time data enables the simulation and monitoring of process variables. In [18] This integration optimizes material removal rates, minimizes deformations, and enhances the overall quality of machined parts. Effective monitoring of production equipment not only supports control and supervision, but also aids decision-making through real-time data analysis powered by artificial intelligence algorithms, increasing accuracy and depth of insight [6,19].

In the work of [20], a framework was developed to improve steel robotic prefabrication through the use of Semantic Digital Twins (SDT). An SDT is a digital model that not only replicates the physical state of the system but also includes semantic information that enables a deeper, contextual understanding of the fabrication process. These semantics are essential because they allow the digital twin to interpret and adapt real-time manufacturing data, such as tolerances and deviations, to optimize robotic control.

The proposed framework integrates process data, detects anomalies, and adjusts controls in real time, enabling greater interoperability along the value chain, from prefabrication to assembly construction.

Game theory has also been applied to digital twins, as shown in the research by [21], where it enhances decision making by taking advantage of the concept of cooperative strategies. This study highlights the ability of game-theoretical approaches to improve coordination within digital twin systems, benefiting collective outcomes.

In the maintenance domain, digital twins provide innovative solutions for predictive maintenance through process simulation and monitoring. By integrating real-time data from physical assets with virtual models, digital twins enable the development of robust diagnostic systems [1,22,23]. For example, ref. [24] explores the use of digital twins to address data scarcity in machinery by creating virtual representations that are continuously updated with real-world information. This approach simulates potential failure conditions and generates comprehensive training databases, improving predictive maintenance processes. In [25], vibration data are utilized within a digital twin framework for predictive and preventive maintenance.

The study by [26] investigates how digital twin technology can enhance maintenance decision support by capturing and reusing knowledge embedded in maintenance work orders (MWOs). These textual records often contain valuable but unstructured information, making them challenging to process. The research employs a digital twin model to simulate maintenance environments, enabling the validation of solutions before physical implementation. An adapted BERT language model combined with the sequential auto-encoder TSDAE identifies patterns and similarities within MWOs, retrieving maintenance solutions based on prior experiences. By integrating digital twins with large language models (LLMs) such as BERT, the study develops a decision support system that centralizes human knowledge for effective problem solving.

In [27,28], digital twins are applied to machine tools to create intelligent machinery. This research examines various methods for data capture and transmission, critical components of digital twins, and explores AI algorithms to analyze machine operating conditions. The objective is to optimize operating parameters, improving overall machine performance.

The implementation of digital twins in machine tools is further explored in [29], which highlights the use of a digital twin to monitor a micromachining tool and predict tool wear in real time.

Similarly, [30] proposes an approach for developing digital twins in industrial assembly lines, focusing on improving production flexibility and agility through real-time monitoring, prediction of failures and optimization. A methodology for discrete manufacturing lines integrates a digital twin architecture with four dimensions, geometric, physical, behavioral, and information control, to synchronize and optimize workflows.

In parallel, [31] addresses the need for flexibility in production systems during the design phase, adapting to market changes and customization demands. This study combines static and dynamic digital models to evaluate structural characteristics and system resilience to failures. Using the Plant Simulation platform, adverse scenarios are modeled to predict system performance, allowing optimized early-stage decisions that improve operational flexibility.

In additive manufacturing, digital twins enable real-time monitoring, simulation, and testing of the printing process, providing critical insights and adjustments to improve product quality. The creation of a DT ecosystem for an FDM 3D printer using the Unity 3D platform is presented in [32]. This ecosystem allows monitoring, testing, and managing the manufacturing process in a simulated virtual environment, providing remote access to key process information and operational parameters.

In healthcare, [33] presents a digital twin framework to improve the production of CAR T cell therapies, an advanced cancer treatment. This system addresses challenges in personalizing therapies and managing complex biotechnological processes, facilitating detailed real-time monitoring throughout the production stages, from cell extraction to genetic modification.

The study by [34] describes a digital twin system for monitoring and diagnosing failures in thermal turbine rotors. Geometric models and dynamic simulations integrate real-time sensor data, including vibration and displacement, to reflect the rotor behavior in real time. This system reduces downtime, optimizes performance, and supports predictive maintenance.

In [35], a digital twin system is designed for real-time communication and control between digital and physical twins. Unity is used to create a 3D simulation of a robotic arm, while ROS (Robot Operating System) ensures seamless data exchange. A case study involving an ABB IRB 1200-5/0.9 robotic arm demonstrates effective synchronization using the EtherNet/IP protocol, highlighting the system's capability to bridge digital and physical environments.

Finally, ref. [36] addresses the challenge of detecting and monitoring small objects in complex manufacturing environments with varying object sizes, positions, and movement. The proposed model combines neural networks to detect three key elements: equipment, products, and operators. MobileNetv2 reduces computational costs, while a modified YOLOv4-M2 performs static detection of small objects. Additionally, OpenPose enables long-distance pose recognition, even under challenging conditions with complex lighting and backgrounds.

In the research of [37], a digital twin modeling methodology oriented to discrete manufacturing lines is presented, the proposal of an architecture based on the integration of four dimensions: geometric, physical, behavioral, and information control. The objective is to improve the symbiosis between the physical and virtual worlds, allowing intelligent control and optimization. The geometric model describes the spatial and topological characteristics of physical entities, the physical model reflects the mechanical and material attributes, the behavioral model maps the operational logics, and the information control model defines the control rules and information flow between the physical and virtual worlds.

3.1.2. Production and Control Planning

In the literature reviewed for this research, a category of digital twins focused on production control and scheduling has been identified. In the study by [38], digital twins are proposed to validate key decision-making processes, particularly in areas such as manufacturing process planning, sequencing and operations scheduling, and capacity planning.

Digital twins facilitate the identification of bottlenecks in production systems, as demonstrated by [39,40]. By combining real-time data with simulation models, digital twins enable the prediction of system bottlenecks before they occur. This foresight allows for dynamic adjustments to order release policies and dispatching rules, ultimately optimizing workflow and enhancing productivity.

In [41], a study presents the use of digital twins to monitor the condition of the tool in machining processes by anomaly detection. This monitoring is critical for product quality, as tool wear directly affects manufacturing tolerances. The proposed system enables real-time tracking of tool condition, ensuring adherence to quality standards. Similarly, ref. [42] introduces an online simulation system designed to predict distortions during metal additive manufacturing. This system utilizes a diffusion model architecture based on a quantized variational autoencoder (VQVAE) combined with a generative adversarial network (GAN) to capture spatial and temporal distortion patterns.

Another study, [43], presents a digital twin model for dynamic scheduling in flexible workshops with multi-memory processes, incorporating the learning and forgetting behaviors of workers. The proposed architecture integrates physical and virtual workshops using cyberphysical systems. The experiments demonstrate significant improvements in production throughput, reduced processing time, and reduced carbon emissions and production costs.

The study by [44] introduces a digital twin (DT) architecture for decentralized real-time scheduling that adapts to production line interruptions. The primary aim is to enhance the flexibility and responsiveness of production by integrating DT models. Similarly, ref. [45] proposes a framework for predicting production capacity in discrete manufacturing shops using digital twins and long-short-term memory (LSTM) networks. This approach addresses the limitations of traditional methods, offering greater accuracy and adaptability in dynamic production settings.

In line with capacity prediction, ref. [46] presents a system that enables continuous, real-time evaluation of equipment resources. This model integrates sensors and IoT devices to collect data that support resource allocation predictions, improve accuracy, and reduce operational costs.

The job scheduling problem is addressed in [47], which examines task rescheduling in the event of equipment failures, such as machine faults. The study proposes implementing a digital twin that uses IoT to gather real-time equipment data and AI to predict potential failures before they occur, allowing proactive task rescheduling.

Another application of digital twins in production estimation and scheduling is presented in [48]. This system combines computer vision, ultrasonic sensors, machine learning, and 3D simulation to create a virtual replica of the factory, improving the accuracy of scheduling and optimization of the production flow. In [49], the focus shifts to production planning for the manufacture of ocean platforms using graph neural networks (GNN). Here, the digital twin functions as a predictive and optimization tool, providing visual simulations of production processes.

The study by [50] explores the influence of Industry 5.0 on manufacturing, emphasizing the role of digital twins in improving sustainability, resilience, and operational efficiency. This digital twin replicates both the product and the manufacturing system in a virtual environment, allowing real-time simulation and optimization of physical processes.

In industries focused on steel beam manufacturing, digital twins improve process flexibility through robotic arm programming, real-time control of process variables, and dynamic adjustments to these factors.

In production programming and control, quality control becomes a critical aspect in ensuring that products meet specifications. It also helps to identify non-compliant products that may require discarding or reprocessing. Studies such as [51,52] propose the use of digital twins for real-time quality prediction. This predictive capability enables prompt adjustment of process parameters, ensuring that quality standards are met consistently.

Digital twin applications are also prominent in battery cell manufacturing, as demonstrated by [53], where digital twins facilitate real-time monitoring and process adjustments, enhancing production efficiency. Similarly, ref. [54] explores the usage of digital twin in metal additive manufacturing, where data collection, processing, and analysis optimize process yield and product quality. In [55], a digital twin system is applied to a collaborative painting robot, allowing simulation of the process and prediction of the results prior to physical execution.

Digital twins also play an important role in collaborative robotics applications. For example, ref. [56] introduces a flexible and collaborative manufacturing system for circuit breaker assembly, supported by a digital twin (DT). This system employs cooperative robots to optimize the assembly of components, increasing production efficiency. The digital twin acts as an interface between the physical plant and its digital simulation, providing real-time data to ensure precise synchronization between the physical shop floor and its virtual counterpart.

In the research of [57], a digital twin is proposed for order processing that addresses key problems in production and logistics networks, such as lack of transparency, data fragmentation, and visibility in real time. This model uses artificial intelligence (AI) and simulation to optimize the planning, control, and execution of operations. AI algorithms analyze real-time data, identify patterns and predict outcomes in material flows, while AI-based simulations model alternative scenarios to support informed decisions. The DTOP implementation consolidates data into a structured relational database, allowing dynamic management of order changes, optimizing resources, and reducing redundancies, thus improving efficiency and accuracy in complex manufacturing environments.

In the work conducted by [58] the use of AI in the implementation of DTs in manufacturing shops is analyzed. In the study, a framework for AI-enabled manufacturing shop floor digital twins is proposed, focusing on solving real-time synchronization and optimization problems. AI models play a central role, using neural networks to predict the future state of equipment, identify patterns in operational data, and correct for sensing and control delays. In addition, genetic algorithms are used to optimize control strategies in collaborative human-machine tasks, while computer vision and natural language processing (NLP) techniques allow human activities to be evaluated and voice commands to be recognized in real time. Implementing these models in a Digital Twin System enables advanced capabilities, such as predictive maintenance, process optimization, and improved energy efficiency, ensuring greater precision in decision making and reducing operational errors.

3.1.3. Process Optimization

In the field of manufacturing, particularly within industries where demand is typified by intermediate production volumes and a substantial level of customization, the implementation of flexible production systems is paramount. Such systems are required to possess the capability for rapid reconfiguration in order to address evolving market demands effectively. The digital twin (DT) applications discussed in this section present essential instruments that aid in the restructuring of production facilities, thereby enabling efficient adaptation to these requirements while optimizing resource utilization and minimizing response time.

Among digital twins designed for simulation and monitoring, ref. [7] addresses the challenge of reconfiguring and optimizing production processes within complex and flexible manufacturing systems in response to external changes, such as shifting market demands, supply chain disruptions and new product requirements. The study proposes a reconfiguration framework that identifies the most suitable devices and optimized configurations based on various criteria. This framework allows manufacturing systems to be reconfigured initially in a simulation environment before implementing changes in the physical system. By enabling dynamic reconfiguration, the framework adjusts design, process parameters, and operating times for multiple assets, facilitating real-time decision making to meet evolving customer and market needs.

Another example of a digital twin application for reconfiguring production systems is presented in [59], which introduces a digital twin-based framework to evaluate and optimize flexible and reconfigurable automotive production lines. This framework addresses the need for manufacturing systems that can quickly adapt to rapid changes in demand and product diversity. The proposed approach enables the assessment of different production line configurations through automated simulations combined with real-time data.

Similarly, ref. [60] describes a self-organizing manufacturing system based on digital twins to enhance reconfiguration capabilities and responsiveness within production environments. This system addresses the growing demand for customized products and aims to overcome interoperability challenges between the physical and digital realms in manufacturing systems.

The study by [61] describes a methodology for developing a distributed control system capable of detecting sensor failures and automatically switching to a degraded mode, allowing the system to maintain operation. Supervisory Control Theory (SCT) is utilized to design controllers for both normal and degraded modes. The proposed methodology consists of several key steps: modeling system behavior in both operating modes, formal verification using a model checker, simulation on a digital twin, and eventual implementation on a real programmable logic controller (PLC). This reconfiguration process allows the system to adapt to sensor failures by substituting lost information with time estimates. As a result, the system continues to function under degraded conditions without relying on expensive redundancies, thus improving efficiency and reducing costs.

In a Delphi study, ref. [62] explores the role of interconnected digital twins and information sharing between companies to improve, accelerate, and stimulate innovation within organizations. Similarly, ref. [63] presents a conceptual approach for the implementation of digital twins in supply chain processes, using Business Process Modeling Notation (BPMN) to model and simulate current and prospective processes. In a case study focused on order fulfillment within a manufacturing company, the digital twin demonstrated significant improvements in production planning, inventory management, and predictive maintenance. The results highlighted a notable reduction in lead times and increased operational efficiency.

Aligned with the new pillars introduced by Industry 5.0, digital twins provide real-time insights into production processes, incorporating principles such as human inclusion, sustainability and resilience, as demonstrated in [64]. This study emphasizes the integration of Industry 5.0 principles into the selection and optimization of manufacturing processes.

In [65], a framework is proposed for the development of digital twins in small and medium enterprises (SMEs). This approach provides relevant and personalized information to decision-making roles at all levels (operational, tactical, and strategic) through a digital infrastructure solution that is adaptable, scalable, and customized to the specific needs of each company. The research describes how small businesses face challenges in accessing and managing information due to data fragmentation and a lack of integrated tools to support effective decisions.

Table 1 presents a summarized categorization of digital twin applications within the process dimension discussed in this section. This categorization highlights various uses of digital twins, including simulation, monitoring, production control, and process optimization. Each subcategory outlines specific applications, from real-time synchronization of manufacturing environments to advanced predictive maintenance and dynamic system reconfiguration. In the following subsections, the subcategories are analyzed.

Table 1. This table shows the summary of digital twin applications for the process dimension; there are 3 main subcategories, Production Programming and Control (PPC), Monitoring and Simulation (MS), Process Optimization (PO).The column entitled "Data Types" displays the categories of data employed in each DT implementation. The three data types are Real-Time Data (RTD), Simulation Data (SD), and Historical Data (HD).

Reference	Classification	AI Implementation	Visualization Tool	Data Types	Network Protocols
[1]	MS	-	-	-	-
[6]	MS	-	Siemens Tecnomatix	RTD	OPC-UA,TCP/IP,Ethernet
[7]	PO	GA	Siemens Tecnomatrix	RTD	OPC-UA, MQTT, and TCP/IP
[10]	PO	-	-	RTD	REST-API
[14]	MS	CNN	-	RTD	-
[16]	MS	-	-	RTD	-
[19]	MS	-	-	RTD	-
[20]	PPC	-	Rhinoceros 3D	RTD	MQTT
[22]	MS	RNN	-	RTD	-
[23]	MS	RNN	MapleSim	RTD	TCP/IP
[24]	MS	VAE	Simulink Simscape	RTD	-
[26]	MS	GAN	HD	REST-API	
[27]	MS	CNN, SVM	OpenGL	RTD	OPC-UA and MTConnect
[28]	MS	-	-	RTD	OPC-UA
[29]	MS	-	Simulink Simscape	RTD	OPC-UA
[30]	MS	-	-	RTD	OPC-UA
[31]	MS	-	Plant Simulation	RTD	-
[32]	MS	-	Unity	RTD	REST API
[33]	MS	-	-	RTD	-
[34]	MS	CNN and GAN	Unity	RTD	OPC-UA
[35]	MS	-	Unity	RTD	Ethernet/IP
[36]	MS	DNN	-	HD	-
[37]	MS	Math Models	-	RTD	OPC-UA
[38]	PPC	RLN	-	RTD	REST-API
[39]	PPC	-	Siemens Tecnomatrix	RTD	OPC-UA
[40]	PPC	-	-	RTD	REST-API
[41]	PPC	SVM	-	RTD	OPC-UA
[42]	PPC	RNN	-	SD and RTD	-
[43]	PPC	IMOLSA Algorithm	AnyLogic 8.7	RTD	-
[44]	PPC	GA	-	RTD	TCP/IP and Modbus
[45]	PPC	RNN	-	RTD	RFID
[46]	PPC	ENN	-	HD and RTD	-
[47]	PPC	LVQ	Unreal Engine	RTD	-
[48]	PPC	DNN	Simio	RTD	-
[49]	PPC	GNN	Unity	HD and RTD	-
[50]	PPC	-	-	RTD	ZigBee, Bluetooth, NFC, REST API
[51]	PPC	LR	Three.js	HD and RTD	MQTT
[52]	PPC	CNN	-	SD	EtherCAT
[53]	PPC	Math Models	-	RTD	-
[54]	PPC	CNN	-	HD	Ethernet, TCP/IP, and REST API
[55]	PPC	-	CoppeliaSim	RTD	-
[56]	PPC	RLN	Unity	-	Ethernet
[59]	PO	-	-	RTD	TCP/IP
[60]	PO	RLN	Blender and Unity3D	RTD	OPC-UA, Ethernet/IP
[61]	PO	-	CellFlex4.0	Profinet	-
[63]	PPC	-	ProModel	HD and RTD	-
[64]	PO	-	-	RTD	-
[65]	MS	-	Arena Simulation	RTD	-

3.2. Operator

Within the operator dimension, digital twin applications focus on improving the skills, efficiency, and safety of production floor operators throughout their workday. In this section, the applications of digital twins are categorized into three primary areas: safety, intelligent assistance, and production planning. Human Digital Twins (HDTs) in manufacturing environments provide valuable opportunities for operator training, skill acquisition, and real-time monitoring. Furthermore, HDTs can contribute to improving ergonomics through digital twin-based pose analysis, although this area remains relatively underexplored in current research.

The research paper by [66,67] presents digital twins within the new Industry 5.0 paradigm as a platform that enhances human capabilities by adapting digital tools to the specific needs of each user. The paper explores the potential of DTs in Industry 5.0, with a focus on the design of systems that integrate artificial intelligence (AI) and extended reality (XR) to optimize human-system interaction. DTs are conceptualized as central platforms that consolidate historical, real-time, and predictive data, providing operators, engineers, and managers with personalized and adaptive interfaces. The implementation of AI enables predictive analytics, advanced simulations, and process optimization through machine learning, helping to predict failures, optimize resources, and provide accurate recommendations. On the other hand, XR, through augmented reality (AR) and virtual reality (VR) devices, provides immersive and adaptive experiences, facilitating intuitive interaction with digital systems and allowing users to access relevant information efficiently.

3.2.1. Operator Safety

In the category of operator safety, digital twin applications focus on human–robot collaboration (HRC) and monitoring operators for factors such as fatigue and ergonomics that impact personal safety during work tasks.This section discusses and analyzes TD applications that have among their objectives the safety of operators while performing their work activities.

An essential aspect of HRC is the accurate recognition of operator actions. In [68], a digital twin framework is introduced to enhance HRC in customized manufacturing environments. This research presents a human mesh recovery algorithm and an improved action recognition system with uncertainty estimation to optimize collaborative assembly processes [68].

The research by [69] explores the human–robot collaboration (HRC) within the manufacturing industry, emphasizing the role of digital twins (DTs) in enhancing worker safety. The study highlights that HRCs enabled by DTs contribute to improved safety by monitoring operator actions, predicting potential risks, and ensuring secure interactions between humans and robots. Although the study also identified benefits such as process optimization and reduced operational costs, it emphasizes the challenges related to accurate modeling and data integration, which are critical to creating reliable digital twins. These challenges, including the need for effective human–robot interaction and robust safety protocols, highlight the complexity of ensuring operator safety in dynamic manufacturing environments. The findings stress the importance of developing standardized and interoperable platforms to maximize the safety potential of DT applications in HRC.

The study by [70] examines a human digital twin (HDT) architecture designed to improve operator integration and safety in manufacturing, particularly in HRC scenarios. The HDT centralizes human data and models, enabling simulations of ergonomics and predictive behaviors. Experiments in a production environment using automated guided vehicles (AGVs) demonstrate that HDTs can predict human motion trajectories, thereby optimizing both operational efficiency and safety.

A related application in action recognition is presented in [71], which introduces a digital twin framework using deep learning to improve safety and reliability in HRC manufacturing. This system allows for the detection and classification of actions performed by human operators and robots during the manufacturing process, enabling autonomous decision making within the robot control system.

A conceptual framework for cognitive digital twins (C-DT) in smart manufacturing, particularly in HRC, is presented by [72]. This framework consists of three layers: physical, edge, and cloud, built on top of a 5G communication network. Data from physical machines and human operators are collected in the physical layer, transmitted through the edge layer, and virtualized in the cloud. The cloud layer generates inference models through deep learning, which are updated at the edge layer to enhance machine intelligence in real-time. Specifically, cognitive models of human operators are developed using multimodal fusion to support cognitive functions.

Supporting research, such as [73,74], discusses the creation of datasets that serve as foundational resources to develop and test advanced action recognition systems in various domains, including computer vision, machine learning, intelligent manufacturing, and HRC.

Digital twins are increasingly integrated with large language models (LLMs) to enhance HRC in intelligent manufacturing environments, as demonstrated in [75]. This research presents an LLM-based manufacturing system designed to improve HRC, where digital twins provide real-time data and a behavior-based control framework for robot management. The system features two primary agents: the interaction agent, which facilitates communication with human operators, and the manufacturing agent, which oversees task scheduling and management. Additional modules support natural interaction between humans and the system and enable autonomous robot behavior planning. Model training is based on vectorized manufacturing data, allowing precise and contextually relevant responses through the text embossed ada-002 model.

Beyond HRC, digital twins contribute to occupational safety by enabling complete monitoring of operator actions, fatigue, and ergonomics, ensuring overall well-being in the workplace.

In manufacturing settings, operators engage in a multitude of operations daily, necessitating an examination of group dynamics. Tracking operators' trajectories for the purpose of recognizing actions and predicting hazardous situations is essential. Studies, such as [76], introduce a novel approach for the description and recognition of group activities through trajectory analysis coupled with neural network methodologies. The proposed method employs a descriptor, known as the Group Activity Descriptor Vector (GADV), which considers the group's trajectory, individual coherence within the group, and the motion interrelations among distinct groups.

The study by [77] examines the application of HDTs to enhance workplace safety and resilience in production systems aligned with Industry 5.0. This research presents an architecture for real-time monitoring of worker postures and workload using ergonomic sensors integrated into a digital platform. The proposed solution optimizes task allocation and minimizes makespan. Experimental results demonstrate that HDTs can identify awkward postures and occupational hazards, allowing for task reprogramming that improves both safety and efficiency. These findings underscore the potential of HDTs to drive manufacturing toward a more human-centered approach.

The study by [78] introduces a DT framework designed to analyze biomechanical fatigue in operators during manual material handling. The system uses a motion capture (MoCap) setup and biometric suits to gather data on operator movements and biometrics during repetitive tasks. These data are processed using a dynamic time alignment algorithm and control charts to detect variations in joint angles indicative of fatigue. The results reveal that individuals experience fatigue in different joints, highlighting the need for customized digital representations for each operator and further parameter optimization to improve model accuracy.

The research by [79] proposes a conceptual framework to improve worker safety and well-being in industrial environments through HDTs combined with advanced artificial intelligence (AI) techniques. The framework emphasizes real-time monitoring of physical, emotional, and cognitive factors using smart devices and AI analytics to identify and prevent mental health problems. The study highlights the critical role of collaboration and adherence to data-protection regulations to ensure both effectiveness and security.

Similarly, ref. [80] explores the integration of an exoskeletal robotic system with a digital twin for industrial manufacturing applications. This system enables operators to control collaborative robots (cobots) via a haptic interface and virtual reality, optimizing training and task execution. Real-time interaction between the operator and the digital twin supports cobot task execution in the physical world. The cobot sensor feedback is continuously relayed to the digital twin to adjust and enhance operations. The digital twin is implemented using ROS for communication and Unity for visualizing the robotic arm model.

The study by [81] presents an innovative HDT designed to assess both physical and cognitive fatigue in manufacturing operators. For physical fatigue, the system employs action segmentation models to detect task types, movement repetitions, and arm usage during operations. These models, based on an MS-TCN enhanced with LSTM, enable real-time localized fatigue assessment. Cognitive fatigue is measured using a wearable device that monitors physiological signals, including heart rate and electrodermal activity. By integrating these modules, the HDT provides a comprehensive view of the operator's condition, allowing task reassignment based on fatigue levels.

The DTs explored in this section demonstrate a significant impact on improving workplace safety in manufacturing, especially through applications of human–robot collaboration (HRC) and real-time monitoring of operators. Common technologies highlighted include advanced action recognition algorithms, ergonomic and biometric sensors, and artificial intelligence models such as deep learning and LLM language models. These technologies can identify potential risks, optimize assigned tasks, and monitor physical and cognitive factors such as fatigue and work postures.

3.2.2. Smart Assistance

In [82], the role of the field operator is emphasized in enhancing production efficiency within Industry 5.0, where the human factor is central. This study proposes a Decision Support System (DSS) integrated with a digital twin to assist operators in decision-making. Presented as a novel application in production planning and control (PPC), the system is designed for potential industrial implementation, with plans to integrate machine learning and evaluate user experience.

Similarly, ref. [83] introduces an operator-centric digital twin architecture aimed at optimizing automated composite production. This architecture collects real-time data from multiple machines, providing operators with a comprehensive view of the production process. It enables operators to monitor critical parameters and receive adjustment recommendations to improve product quality. By involving operators in the design of the digital twin, the system is tailored for usability and practical effectiveness, evolving from an Industry 4.0 implementation to an advanced Industry 5.0 solution.

The study by [84] introduces the Human-CENTER framework, based on human digital twins (HDTs), to manage human-centered processes within Industry 5.0. This framework integrates humans with both physical and virtual machines to enhance interaction and collaboration, emphasizing collaborative intelligence (CI) patterns such as "humans train machines" and "machines assist humans". Unlike Industry 4.0, which focuses primarily on technology, Industry 5.0 aims to integrate human and machine elements, though it is still a relatively misunderstood and fragmented concept.

The study positions digital twins as a key technology due to their real-time monitoring capabilities, which enable machine-to-operator assistance across three intensity levels. Additionally, it suggests creating virtual models of employees to record their development within the company, as well as to track their skills and competencies.

A human digital twin (HDT) is also proposed to enhance safety and efficiency in process industries by simulating the behavior of control room operators during abnormal situations. This HDT is based on the ACT-R cognitive architecture, employing a symbolic layer for information processing and a sub-symbolic layer to adjust cognitive adaptability. Using declarative and procedural memory structures, it stores information and guides actions through production rules. The HDT was implemented in a MATLAB simulation of a controlled chemical process, with problem-solving capabilities validated by comparing its eye-tracking patterns to those of human operators.

The research of [85] addresses the need to improve safety and efficiency in process industries by evaluating the performance of the operator. This study seeks to develop a human digital twin (HDT) that simulates the behavior of a control room operator during abnormal situations using the ACT-R cognitive architecture.HDT uses production rules to identify and solve problems, going through phases of problem identification and experimentation. For validation is done by Eye Tracking, HDT was validated by comparing its eye tracking behavior with that of human operators in similar tasks.

The research by [86] presents a case study of how DTs can be used to provide intelligent assistance to operators by generating instructions according to the context. The instructions are adapted to the user's context by using a DT-based data model, which integrates information specific to the user, the task, the required resources, and the environment. This system allows customized instructions to be generated in real time, considering the individual characteristics of the user and the work environment. Artificial intelligence (AI) plays a key role in this process by analyzing data in real time, identifying patterns, and optimizing the presentation of information.In the case study presented in the research, a worker is instructed to maintain a switch box in a rolling mill. The system identifies that it is his first time performing this task, so it presents more detailed instructions, includes additional notes, and displays interactive 3D models. The AI, by analyzing previous data, anticipates possible common errors and provides specific warnings.

3.2.3. Production Planning

The literature includes studies such as [87], which examine a Human Digital Twin (HDT) model designed to support production planning and control in sheltered workshops for disabled workers in Germany. These workshops employ more than 310,000 people in 2800 locations and face unique challenges due to the diverse skill levels and support needs of disabled workers. The proposed HDT model includes digital profiles of the dynamic skills and behaviors of workers, allowing person-centered production planning. The results suggest that HDTs can improve the accuracy of production efficiency planning by aligning tasks with individual abilities and integrating assistive systems. However, the study also highlights challenges, including the need for real-time data on workers' emotional and physical states, the integration of smart devices for data collection, and the enhancement of cognitive skills through tailored learning tasks.

Table 2 provides a concise summary of the primary applications of digital twins within the operator dimension, classified into three main areas: operator safety, intelligent assistance, and production planning. It illustrates how digital twin technology enhances worker safety, optimizes decision making, and supports production planning through human-machine collaboration, ergonomics and fatigue monitoring, and customized production planning assistance.In the following subsections, the subcategories are analyzed.

Table 2. This table shows a summary of digital twin applications for the operator dimension; there are 3 main subcategories, Operator Safety (OS), Smart Assistance (SA), Production Planning (PP).The column entitled "Data Types" displays the categories of data employed in each DT implementation. The three data types include Real-Time Data (RTD) and Historical Data (HD).

Reference	Classification	AI Implementation	Visualization Tool	Data Types	Network Protocols
[68]	OS	ST-GCN	SMPL Model	RTD	-
[69]	OS	-	Unity	RTD	-
[70]	OS	-	-	RTD	WLAN, Profinet
[71]	OS	R-CNN	Unreal Engine	RTD	ROS framework
[72]	OS	CNN, LSTM	-	RTD	-
[73]	OS	ST-GCN	-	RTD	-
[75]	OS	LLM	-	RTD	-
[77]	OS	-	-	RTD	-
[78]	OS	-	-	RTD	-
[79]	OS	LLM	-	RTD	APIs
[80]	OS	-	Unity	RTD	ROS framework
[81]	OS	LSTM	-	RTD	-
[82]	SA	-	-	RTD	-
[83]	SA	-	-	RTD	-
[84]	SM	CNN, RNN, LSTM	-	RTD	-
[85]	SA	-	-	RTD	TCP/IP
[87]	PP	-	-	RTD	-

3.3. Product

This section presents the classification of digital twins within the product dimension. Digital twins in this category are classified based on how the information generated is used to enhance subsequent iterations of the product. Specifically, data are collected from the final product to inform and improve the next version.

For example, ref. [88] describes a digital twin developed to control variables in an additive manufacturing process. This digital twin employs AI techniques, such as linear regression and support vector machines (SVM), to predict anomalies and uses sensor data collection to improve print quality.

In [89], the development of a digital twin for a temperature uniformity control system is explored. This system utilizes thermoelectric elements and an infrared camera to measure the temperature distribution across a copper plate, aiming to achieve precise thermal control for industrial applications such as semiconductor manufacturing.

In [90], a novel application is presented, in which AI-driven digital twins are used to optimize the cooling rate during the heat treatment of 42SiCr steel using tensile separation and partitioning (Q-P). The objective is to improve material properties, such as hardness and ductility, by fine-tuning cooling conditions.

In [91], a framework is introduced that represents a significant advance in rapid product development. This framework enables comprehensive and accurate validation within a digital environment before physical production. The approach minimizes development costs and time while improving design precision and manufacturing efficiency. By integrating digital twins of both the product and the manufacturing system, the framework provides tools such as "digital validation as a service," fostering more effective collaboration and greater adaptability throughout the product-development process.

This framework is particularly impactful in advanced manufacturing, where demands for speed, flexibility, and accuracy are critical to achieving commercial success. Its application highlights the transformative potential of digital twins in streamlining processes, improving resource utilization, and driving innovation in highly competitive industrial settings.

In the work of [92], an automated manufacturing tool based on digital twins is presented. This tool employs a Product–Process–Resource model, integrating computer-aided design (CAD), computer-aided manufacturing (CAM) and iterative planning services to generate customized products. By orchestrating skills and capabilities within the production environment, this approach facilitates the efficient creation of highly customized manufacturing solutions.

In [93], a framework that integrates DTs and DTH (Digital Thread) is proposed to improve traceability, data centralization, and collaboration in the product lifecycle. The results show that a DT allows for validation, simulation, and optimization of designs prior to physical creation, reducing costs and errors, while a DTH acts as a centralized data source, avoiding fragmentation and loss of information. In the case study proposed in the research, applied to the design of a beer package, the effectiveness of the framework in complex products is shown.

In the same way, in the work [94] the implementation of DTs in product life cycle management is investigated for the development of new generations of products. It proposes a methodology that integrates the data collected from the DTs and transforms them into actionable information for product design, improving traceability, quality, and efficiency.

In the development of new products, it is possible to take advantage of technologies such as (Extended Reality, XR). In [95] a framework is presented to integrate DTs and XR digital twins into the design of customized product-service systems, with the objective of optimizing collaboration between customers and engineers, improving customization and reducing development times. The methodology proposes a cloud-based platform that combines augmented reality (AR) to capture customer requirements, virtual reality (VR) for real-time collaboration between engineers, and simulations based on digital twins to validate designs and optimize mechanical and geometric properties.

The use of DTs in product development can also be used for production-related cost estimation, as in [96] where a DT-based architecture for cost estimation throughout the product life cycle is presented. This architecture integrates physical and digital data, using ontologies to structure information and ensure interoperability, as well as advanced analysis techniques to optimize design decisions and reduce costs. During a case study with a machine tool, real-time data were captured for events associated with the life cycle, such as maintenance and replacement, highlighting that the "scrap" event represents 75. 61% of total costs. In the product life cycle, there is also research, as in [97] where a DT-based system is proposed that uses classification and simulation models to optimize processes and support decision-making in the context of sustainable manufacturing.

The work of [98] presents a standardized framework for digital twin (DT) quality assurance throughout the product lifecycle, addressing key challenges such as interoperability, data management, cybersecurity, and scalability. They highlight the lack of universal standards as a critical barrier to effective integration of platforms and systems, and propose uniform protocols to ensure fidelity and reliability of DTs for high-impact decisions. In addition, they stress the need for flexible and sustainable architectures, along with interdisciplinary training programs, to overcome the shortage of industry experts. This comprehensive approach not only addresses the technical and organizational barriers that limit the adoption of DTs, but also offers practical guidance to maximize their potential in sectors such as manufacturing, healthcare and recycling, positioning them as essential tools for industrial digital transformation. Table 3 provides a concise summary of the main applications of digital twins within the dimension of the product.

Table 3. This table shows the summary of the digital twin applications for the product dimension; in this table, only the Product Development (PD) subcategory is identified. The column entitled "Data Types" displays the categories of data employed in each DT implementation. The three data types include Real-Time Data (RTD) and Historical Data (HD).

Reference	Classification	AI Implementation	Visualization Tool	Data Types	Network Protocols
[88]	PD	SVM	-	RTD	OPC-UA
[89]	PD	-	Simulink/Simscape	-	-
[90]	PD	ANN	-	HD	-
[91]	PD	-	-	RTD	-
[92]	PD	-	ISG Virtuos	RTD	OPC-UA
[93]	PD	-	-	RTD	-
[94]	PD	-	-	RTD	OPC-UA
[95]	PD	-	Unity	RTD	FTP
[96]	PD	-	-	RTD	-
[97]	PD	-	-	RTD	-

4. Discussion

The classification proposed in this research organizes the applications of digital twins in the manufacturing domain into three distinct dimensions: operator, product, and process. This conceptual framework provides a structured approach that facilitates the analysis and categorization of these technologies. Within the operator, digital twins are characterized by their ability to monitor real-time factors such as fatigue and posture, utilizing advanced sensory data and action analysis algorithms. These applications play a critical role in promoting safety and ergonomics in work environments. In the product dimension, digital twins focus on the iterative improvement of product design and quality. Using historical data, these applications optimize future product versions and enable the customization of features to meet evolving market demands.

The process dimension emphasizes the optimization of production flows and dynamic reconfiguration through real-time simulations. These capabilities improve overall efficiency and minimize downtime, ensuring more resilient and adaptive manufacturing operations. This classification offers a clear and differentiated perspective on the various uses of digital twins in manufacturing while deliberately avoiding the establishment of interactions between the axes, thus maintaining their independence within the proposed framework.

The process dimension stands out as one of the axes with the most extensive applications of digital twins. However, not all applications within this dimension rely on artificial intelligence technologies. Many analyses are guided by rule-based systems established according to the physical processes modeled. Similarly, the approach to modeling within this dimension varies significantly. Although the widely accepted concept of a digital twin involves a virtual replica, in many studies, this "replica" is represented by mathematical equations that model the system. In contrast, other research incorporates 3D modeling and leverages advanced technologies such as Unity, Unreal Engine, and sophisticated visualization tools, including virtual reality (VR) and augmented reality (AR).

The work presented in [99] introduces an innovative approach utilizing vision transformers for the estimation of the pose of six-dimensional objects, showcasing the incorporation of contemporary advancements in computer vision into Digital Twin systems to improve the precision and efficacy of simulations. Similarly, ref. [100] addresses the critical issue of data representation in computer vision for applications involving Digital Twins. Their study specifically investigates the effects of noise and occlusion on the accuracy of Convolutional Neural Networks (CNNs) in the context of three-dimensional object recognition. The authors emphasize the significance of selecting an appropriate three-dimensional data representation to strengthen the robustness of CNNs when subjected to noise and occlusion, conditions commonly encountered in practical manufacturing settings.

In addition, the creation of accurate virtual representations requires an exhaustive visual analysis, which includes the estimation of the pose of six-dimensional objects. Ref. [101] assert that existing reference datasets do not encapsulate the complexities of real-world environments, subsequently hindering the advancement of computer vision algorithms that can be seamlessly integrated into Digital Twins. This deficit underscores the pressing need for robust algorithms capable of managing the inherent noise and complexities present in real-world contexts. Within this framework, the research of [102] is particularly pertinent. They introduce an innovative technique for the estimation of 3D planar models that exploits multi-constraint knowledge within a k-means and RANSAC framework. This method tackles precisely the issue of accurately deriving planar models from noisy 3D point clouds, a frequent necessity in manufacturing settings for tasks such as object reconstruction and scene understanding.

Specifically, studies like [103] offer tools for object recognition in challenging environmental conditions. This enhances the incorporation of intelligent systems into various digital twins (DTs) for object recognition and strengthens the integrated vision systems.

In the operator dimension, artificial intelligence technologies are more widely utilized. Many applications within this dimension aim to enhance operator safety in manufacturing environments, particularly in scenarios involving collaboration with cobots. Critical aspects, such as action recognition and robot movement planning, are addressed using advanced AI algorithms, ensuring safe and efficient human–robot interaction. A pertinent illustration of the adaptability of technology to user requirements is demonstrated by the work of [104], who devised a customized robotic rehabilitation platform to recognize the gestures of each user. This user-centric methodology holds potential significance for the development of more intuitive and personalized user interfaces within Digital Twins applications.

A critical aspect in mobile robotics is SLAM, especially with the challenge of integrating mobile robots into flexible manufacturing systems for navigation and collaboration with operators. Ref. [105] demonstrates using neural networks like GNGs to enhance localization and mapping accuracy. This method can optimize 3D data acquisition and processing in Digital Twins for manufacturing environments.

The development and implementation of a digital twin in manufacturing is a complex and multifaceted process. In [106], the sources of complexity in the development of digital twins are investigated through a case study conducted in a global manufacturing company. The study identifies three primary sources of complexity: the physical environment, the virtual environment, and the development process itself. Factors such as resource interdependencies, human intervention, and frequent changes in production processes significantly challenge the accuracy and reliability of digital models.

Moreover, the success of a digital twin implementation project requires consideration of not only its technical aspects but also its alignment with overarching business objectives. As discussed in [107], certain preconditions are critical for the successful realization of digital twin ecosystems. These preconditions encompass both operational factors at the enterprise level and technological factors at the ecosystem level. On the enterprise side, companies must adopt a goal-oriented approach and foster a culture of open information sharing. At the ecosystem level, success hinges on technical responsiveness, clear coordination among stakeholders, shared interests, and defined roles, as well as a customer-centric approach.

In addition to considering the alignment with business objectives for a successful implementation of TD, the research of [108], which highlights the importance of an interdisciplinary approach for the effective implementation of TD, stands out. The authors propose and classify numerical tools at three levels for the representation of engineering processes: physical problem solving, optimization, and decision making, emphasizing the need to integrate mechanistic models, model reduction techniques, model-based predictive control, and uncertainty quantification. Using a case study on an air separation unit, they demonstrated how these tools enable real-time simulations, energy optimization, and operational robustness, achieving a 15 percent reduction in energy consumption and 10 times less computational time. They point out that many DT implementations fail due to insufficient integration between disciplines, computational complexity, and inadequate handling of uncertainties.

At the technical level of development, one of the most complex challenges is the management and analysis of data. To address this, many digital twin solutions leverage artificial intelligence (AI) algorithms to process and analyze large datasets effectively. In [4], a study investigates the application of AI in digital twin systems, highlighting several key findings. The study reveals that AI components in digital twins are used for a variety of tasks, including optimization, classification, regression, and forecasting. The algorithms used most frequently include linear regression models (LR), deep learning (DL) methods, reinforcement learning networks (RLN), and traditional machine learning techniques. Among these, DL approaches such as convolutional neural networks (CNNs), feedforward neural networks, and long-short-term memory (LSTM) networks are particularly prevalent. Furthermore, most studies reviewed in [4] demonstrated the predictive capabilities of their algorithms in specific tasks, validating the potential of AI to improve the functionality and precision of digital twin systems.

With the transition to the new industrial revolution (Industry 5.0), there is a growing interest in the development of Human Digital Twins (HDTs), as highlighted in the operator dimension section. The study by [109] analyzes the enabling technologies for the development of HDTs, categorizing them into several key areas. First, the study discusses human-focused sensors, including optical and non-optical devices for motion tracking, as well as biological sensors such as EOG, ECG, EEG, and EMG, designed to monitor human behavior and physiological states. These sensors form the foundation for the capture of critical data required for the creation of HDTs.

In the classification proposed in this investigation, all dimensions and their applications were independently analyzed. However, digital twins (DTs) share common challenges and opportunities due to their intrinsic nature. Regardless of their application, DTs require the integration of sensors to capture data, the implementation of communication protocols to establish a bidirectional connection, and the use of advanced artificial intelligence (AI) models to analyze the collected data. In addition, they employ modeling technologies to create virtual representations of physical assets.

As a result, common challenges center on issues such as interoperability between systems, massive data loading and handling, and cybersecurity implications for protecting this information. These difficulties are especially relevant given that DTs manage different types of data depending on their application: manufacturing process information, digital representations of operators, or data associated with manufactured product iterations.

A significant challenge in the development of digital twins (DTs), as identified in previous analyses, is the frequent absence of a comprehensive and precise virtual representation of the physical asset. This deficiency limits the ability to accurately reflect the attributes and behavior of the tangible system. This issue is particularly pronounced in the domain of virtual reality (VR) applications, where the creation of detailed and realistic three-dimensional environments constitutes a major challenge. To address this issue, research such as [110] has advocated advanced tools for 3D scene recreation, which improve the precision of virtual modeling and support immersive interaction within industrial and simulation settings.

The technological interoperability among sensors, platforms, and industrial systems constitutes a significant challenge, particularly in environments characterized by heterogeneous infrastructures. This aspect of interoperability is extensively examined in the study conducted by [111], which proposes a six-level conceptual framework to address the interoperability challenges encountered in cyber-physical systems integrated with digital twins. The identified levels include technical, syntactic, semantic, pragmatic, dynamic, and organizational. Each level encompasses specific issues, such as protocol and data format compatibility, semantic nonuniformity, real-time adaptation, and strategic alignment across organizations. To address these challenges, various solutions are suggested, including the adoption of technical standards such as OPC-UA and JSON-LD, the implementation of comprehensive ontologies and semantic analysis tools, the design of optimized workflows utilizing BPMN, and the development of resilient architectures grounded in microservices and continuous learning. Moreover, the necessity for organizational governance that aligns with international standards, such as ISO/IEC 27001 and GDPR, is emphasized.

In the field of cybersecurity, DTs present significant challenges and opportunities, as highlighted by [112–114]. The inherent vulnerabilities of DTs span cyber, physical, and social dimensions, including ransomware attacks, data manipulation, communication breaches, and exploitation of the user interface, which affect their integrity and operational reliability. However, these vulnerabilities also offer opportunities to transform DTs into more secure and resilient tools. The integration of explainable artificial intelligence (XAI) enables threat detection, predictive behavior modeling, and trust reinforcement in critical systems, while blockchain and smart contract technologies decentralize access control, ensure auditability, and protect IoT systems by acting as secure intermediaries. By combining approaches such as AI, blockchain, and holistic governance strategies, DTs can become pillars of security, optimization, and sustainability in diverse sectors such as construction, manufacturing, and smart cities, effectively addressing the risks associated with their interconnectedness.

Furthermore, the high initial implementation costs pose significant barriers, especially for Small and Medium Enterprises (SMEs), limiting widespread adoption. Each dimension also presents unique challenges. In the operator dimension, resistance to organizational change and the need for more intuitive user interfaces impede the effective integration of digital twins. Within the product dimension, capturing relevant and consistent data throughout the product life cycle is a complex task that requires robust and adaptable systems. Finally, in the process dimension, implementing dynamic simulations that accurately reflect changing production conditions remains a formidable technical challenge. Addressing these challenges will be essential to fully realize the potential of digital twins in manufacturing and beyond.

In general, DTs have significant benefits in the manufacturing domain, including process optimization, predictive maintenance, and service customization. However, their adoption faces significant challenges, such as high upfront costs, implementation complexity, lack of modeling and interoperability standards, and issues related to data privacy and security. In addition, integration with legacy systems and the need for advanced technology infrastructures, such as cloud computing, represent additional barriers to mass adoption. Despite these difficulties, DTs offer great opportunities to transform manufacturing. Their integration with emerging technologies such as 5G and blockchain can improve connectivity and security, while the development of more intuitive and accessible tools could democratize their use, benefiting both large corporations and small and medium enterprises. Likewise, DTs have a high potential to expand into unexplored sectors, driving process optimization, sustainable development, and value generation in a constantly evolving business environment [115].

5. Conclusions

This study introduces a comprehensive classification of digital twin applications in manufacturing, organizing them into three dimensions: operator, product, and process. The proposed taxonomy not only provides a conceptual tool for analyzing these technologies and applications, but also identifies patterns and gaps in the existing literature, providing a basis for future research. Within the operator dimension, Digital Twins (DTs) demonstrate remarkable proficiency in monitoring and enhancing worker safety, ergonomics, and efficiency. Applications encompass posture analysis and fatigue detection, extending to secure human–robot collaboration. In the context of product development, DTs play a pivotal role in the continuous advancement of design and quality, leveraging historical and real-time data to refine product iterations. The process dimension hosts the largest number of applications, distinguished by its capability to optimize production flows, forecast bottlenecks, and execute real-time simulations that facilitate dynamic reconfiguration. Nonetheless, challenges persist in achieving interoperability between legacy and modern systems, as well as in maintaining the accuracy of simulations under evolving production conditions. The findings highlight that while DTs have demonstrated significant benefits, such as process optimization, predictive maintenance, and service customization, their implementation is not straightforward and faces significant challenges. These include interoperability, in its different domains, not only technical but also syntactic, semantic, pragmatic, dynamic, and organizational, the management of large volumes of data and cybersecurity, especially in interconnected systems. Addressing these challenges is critical to unlocking the full potential of DTs in manufacturing. In addition, emerging fields have been identified that deserve further attention in future research. In particular, the integration of explainable artificial intelligence (XAI) and blockchain in the design of DT systems offers promising solutions to overcome current security and trust barriers. Finally, the results underscore the importance of developing accessible and scalable frameworks that democratize the use of DTs, enabling their adoption in small and medium-sized enterprises (SMEs). In doing so, DTs will not only transform manufacturing, but will also open up new opportunities in emerging sectors such as healthcare, agriculture, and logistics, leading the way to more resilient, sustainable, and human-centered systems.

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