*Review*

# Digital Twins Enabling Intelligent Manufacturing: From Methodology to Application

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**ABSTRACT:** Digital twin technology develops virtual models of objects digitally, simulating their real-world behavior based on data. It aims to reduce product development cycles and costs through feedback between the virtual and real worlds, data fusion analysis, and iterative decision-making optimization. Traditional manufacturing processes often face challenges such as poor real-time monitoring and interaction during machining, difficulties in diagnosing equipment failures, and significant errors in machining. Digital twin technology offers a powerful solution to these issues. Initially, a comprehensive review of the research literature was conducted to assess the current research scope and trends. This was followed by an explanation of the basic concepts of digital twins and the technical pathway for integrating digital twins into intelligent manufacturing including outlining the essential technologies for creating a system of interaction between the virtual and real worlds, enabling multimodel fusion, data sensing, algorithm-based prediction, and intelligent decision-making. Moreover, the application of digital twins in intelligent manufacturing throughout the product life cycle was detailed, covering product design, manufacturing, and service stages. Specifically, in the manufacturing phase, a model based on heat conduction theory and visualization was used to construct a time-varying error model for the motion axis, leading to experiments predicting the time-varying error in the hole spacing of a workpiece. These experiments achieved a minimum prediction error of only 0.2 μm compared to the actual error. By compensating for time-varying errors in real time, the variability in the hole spacing error decreased by 69.19%. This paper concludes by summarizing the current state of digital twins in intelligent manufacturing and projecting future trends in key technologies, application areas, and data use, providing a basis for further research.

**Keywords:** Digital twin; Intelligent Manufacturing; Machining; Sustainable manufacturing

## 1. Introduction

There has been a growing need to transform the traditional manufacturing industry due to the rising demand for digital, networked, and intelligent development. This increasing complexity in disciplines related to mechanical product upgrading, manufacturing, and operation and maintenance necessitates close collaboration [1–3]. Different countries, such as Germany's "Industry 4.0," the United States' "Industrial Internet," and China's "Made in China 2025," have proposed advanced manufacturing development strategies. Currently, the focal point of transformation and upgrading in the machinery manufacturing industry is the digitalization and intelligence of the mechanical process system [4].

In the context of Industry 1.0 and Industry 2.0, the research and development phase relies on drawings, and traditional manufacturing systems use raw materials, parts, and components that are produced through various processes such as

machining and assembly. To ensure accuracy in terms of structure, ergonomics, and performance, physical prototypes are assembled to validate the virtual model. However, the cost of this validation process is prohibitively high [5].

In Industry 3.0, software providers have introduced concepts such as virtual prototyping, digital prototyping, and active prototyping [6]. Digital prototyping replaces physical prototypes by using information modeling, providing a preview of the product [7]. Among the various digital prototyping concepts, digital modeling, which emphasizes complex mapping and contextual relationships between 3D model simulations, is widely used. The use of digital prototypes significantly reduces the need for physical prototypes, minimizing failure rates. Virtual simulations based on physical manufacturing processes enable early assessment of intelligent manufacturing system (IMS) performance, leading to a reduction in reconfiguration costs/losses during physical prototyping of IMS. The incorporation of virtual reality greatly enhances the ease and efficiency of IMS design [8]. Furthermore, the transfer of information in digital prototypes ensures consistency, thereby streamlining manufacturing system design [9–11].

Industry 4.0 has propelled intelligent manufacturing as the future direction for the global manufacturing industry [12]. The adoption of new national advanced manufacturing strategies worldwide has resulted in an increased demand for the design of new IMS [13–16]. An IMS is a multidomain physical system comprising intelligent machines, materials, products, and complex couplings between various components [17–21]. In the digital design process, an IMS can be broken down into digital models at various levels of granularity in a digital space, while physical products and manufacturing processes exist in a separate physical space [22]. The design process of IMS relies heavily on high-fidelity network models that bridge the gap between the design and operational domains [23–25].

## 1.1. Necessity of Digital Twins

There are several challenges in the traditional machining process, including difficulties in collecting dynamic data during processing, limited methods for monitoring the process, and poor interactivity. The complex equipment structure also leads to troubleshooting difficulties, while the debugging cycle is lengthy and costly. Additionally, predicting multifactorial machining errors and determining optimal machining parameters are hindered by the reliance on artificial experience and the randomness and uncertainty of the process. Furthermore, finding optimal machining parameters consumes a large amount of material and is inefficient. These issues have been recognized [26–30].

In response to these challenges, digital transformation based on mechanical process systems has shown early success. For example, algorithms have been developed to monitor machining states, diagnose machinery faults, predict machinery life, forecast machining errors, and optimize machining parameters [31–33]. However, there are still several limitations, such as poor interactivity and visualization of the machining process, the reliance on various algorithms with individual weaknesses, and the complexity and ambiguity of the optimization process. Multimodel fusion is also not well adapted, and most algorithm training is based on historical and empirical data, resulting in limited real-time utilization of data.

As a solution to these limitations, digital twin (DT) technology has emerged. This technology maps physical entities to the digital realm, enabling real-time feedback on processing states and facilitating interaction between virtual and real mechanical process systems [34,35]. By employing artificial intelligence algorithms and multimodel fusion applications, DT technology can predict processing states, forecast equipment failures, and optimize process parameters. It achieves these goals through data perception, analysis, prediction, and intelligent decision-making, ultimately optimizing product quality and processing resource allocation [36,37].

The increasing popularity of DT reflects the inevitable trend of virtual and physical worlds becoming more interconnected and integrated. Grieves' concept of "virtual, digital physical products" and the utilization of DT by NASA and the Air Force Research Laboratory mark significant breakthroughs in overcoming limitations [8]. Siemens applied DT to Industry 4.0 in 2016, leading to exponential growth in related publications as more researchers dedicated themselves to DT [38]. Tao et al. [39] proposed the concept of a DT workshop, providing theoretical support for manufacturing applications by discussing its characteristics, composition, operation mechanism, and key technologies. To further promote the application of DTs in various domains, Tao et al. [40] extended the existing three-dimensional DT model to propose a five-dimensional DT model. Figure 1 illustrates some milestones in DT development.
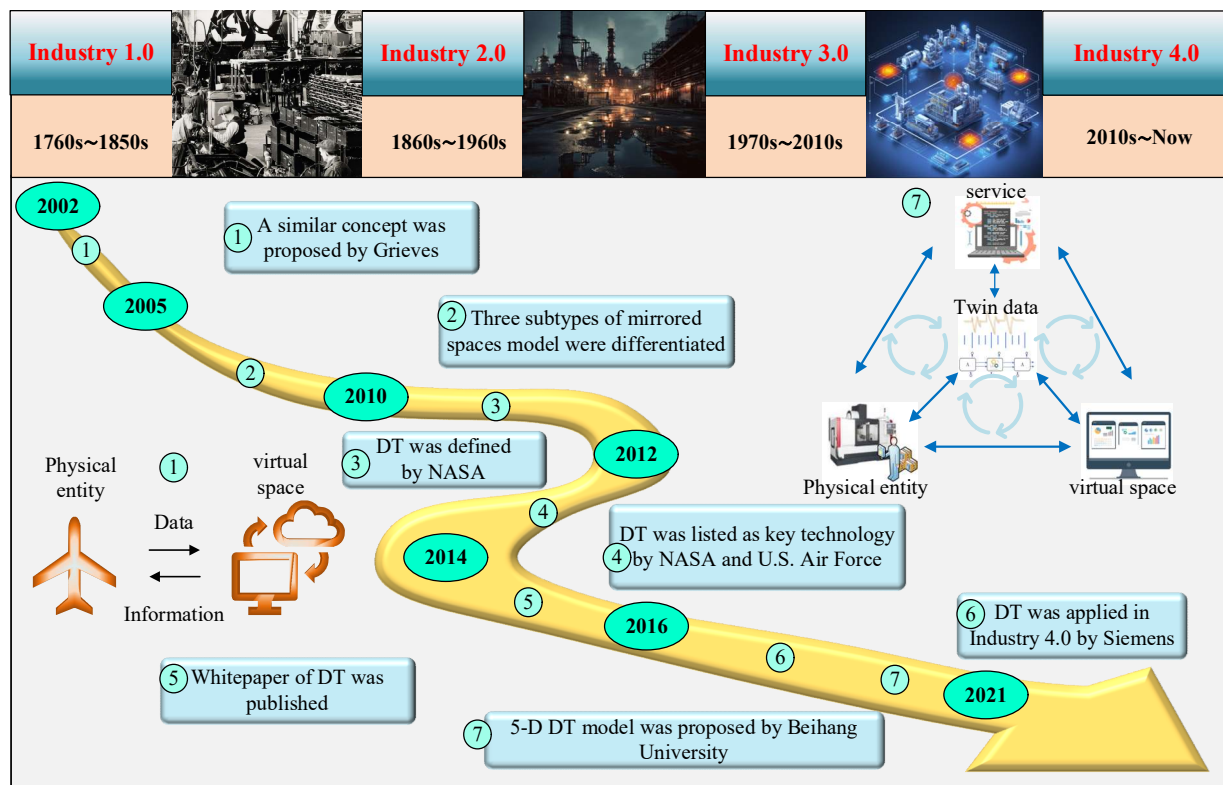
**Figure 1.** The milestones of DT development.

This article focuses on DT-enabled intelligent manufacturing as the research subject. First, a qualitative and quantitative survey of the literature is conducted, and bibliometric analysis of publication sources, annual publication volumes, main publication regions, keyword frequency, and highly cited papers is performed. This analysis identifies the current scope and trends of related research. Second, the concept and connotation of DTs are introduced, and the knowledge graph and application framework of DT-enabled intelligent manufacturing are mapped out. Both the technological paths and core technologies of the key technologies are analyzed, with a particular focus on summarizing the technological architecture and hierarchical systems. This article elaborates on the development and application of related technologies such as virtual system development, DT model construction, data perception and analysis, decision-making, and intelligent decision-making. Furthermore, it summarizes the applications of DT-enabled intelligent manufacturing throughout the product lifecycle, including product planning, virtual commissioning, processing monitoring, predictive equipment maintenance, and processing technology evaluation. Finally, it concludes and provides prospects for the current status and future development directions of DT-enabled intelligent manufacturing, aiming to serve as a reference for subsequent development.

## 2. Methodology

To gain a deeper understanding of the research trends and progress in DT-enabled intelligent manufacturing, this section utilizes two research methods: bibliometric analysis and rooted theory analysis. Bibliometric analysis allows for a systematic examination and measurement of thematic structure, hotspots, trends, and other pertinent information from multiple perspectives. By utilizing bibliometric theory, this section provides an in-depth analysis of DT-enabled intelligent manufacturing by examining the number and trends of publications, research frontiers and hotspots, and research evolution lineages. Additionally, this section incorporates the idea of rooting and constructs a theoretical framework for DT-enabled intelligent manufacturing research by extracting, categorizing, and integrating keywords, abstracts, and research content from relevant literature.

### 2.1. Literature Search

The aim of this work is to explore DT-enabled intelligent manufacturing. Despite previous in-depth investigations and related applications conducted by numerous scholars, the concept of DTs in the machining process remains vague. Therefore, a literature search on DT-enabled intelligent manufacturing was conducted to organize the related work. The methodology is as follows:

(1) Bibliometric analysis was performed by identifying papers based on titles, abstracts, and keywords from the Web of Science (WOS) core database.

(2) Recent developments in the literature were reviewed based on the most important keywords. Key themes such as the origin, development, key technologies, and implementation architectures of DTs were identified. The chronological order was determined, and common definitions and characterization principles were qualitatively assessed for similarity.

(3) Keyword frequencies were listed, common key techniques were evaluated, and examples were reviewed for further comprehension.

(4) By analyzing the information provided by highly cited literature, a macrolevel understanding of the overall evolution of DT-related research can be obtained.

## 2.2. Bibliometric Analysis

Bibliometric analysis assesses current trends in the research literature, offering a comprehensive overview and structure of the field and providing insights and motivations for future research [41–43]. The analytical process of bibliometrics consists of four main steps: search query, dataset identification, data analysis, and data visualization. Using the WOS core database and the keywords {"digital twin" AND "manufacturing"} AND {"cutting OR machining"}, it was discovered that DT-enabled intelligent manufacturing has been emerging since approximately 2010 and has experienced steady growth, particularly in the last 10 years. Since articles from 2024 are still in the publication process, the search publication years were set from 2013-1-1 to 2023-12-31. A total of 681 papers related to DTs were obtained.

### 2.2.1. Number of Annual Publications

The initial conceptual model of DTs was first explicitly proposed in 2002. Since then, both foreign and domestic academics have conducted extensive research on DTs covering various topics. An analysis of the literature and trends in foreign and domestic DT-driven machining research literature after 2013 is illustrated in Figure 2. As shown in Figure 2, there has been a consistent increase in the overall literature on foreign and domestic DT-driven machining research, with a rising trend every year. This indicates a growing interest in domestic and foreign research on DTs in recent years.
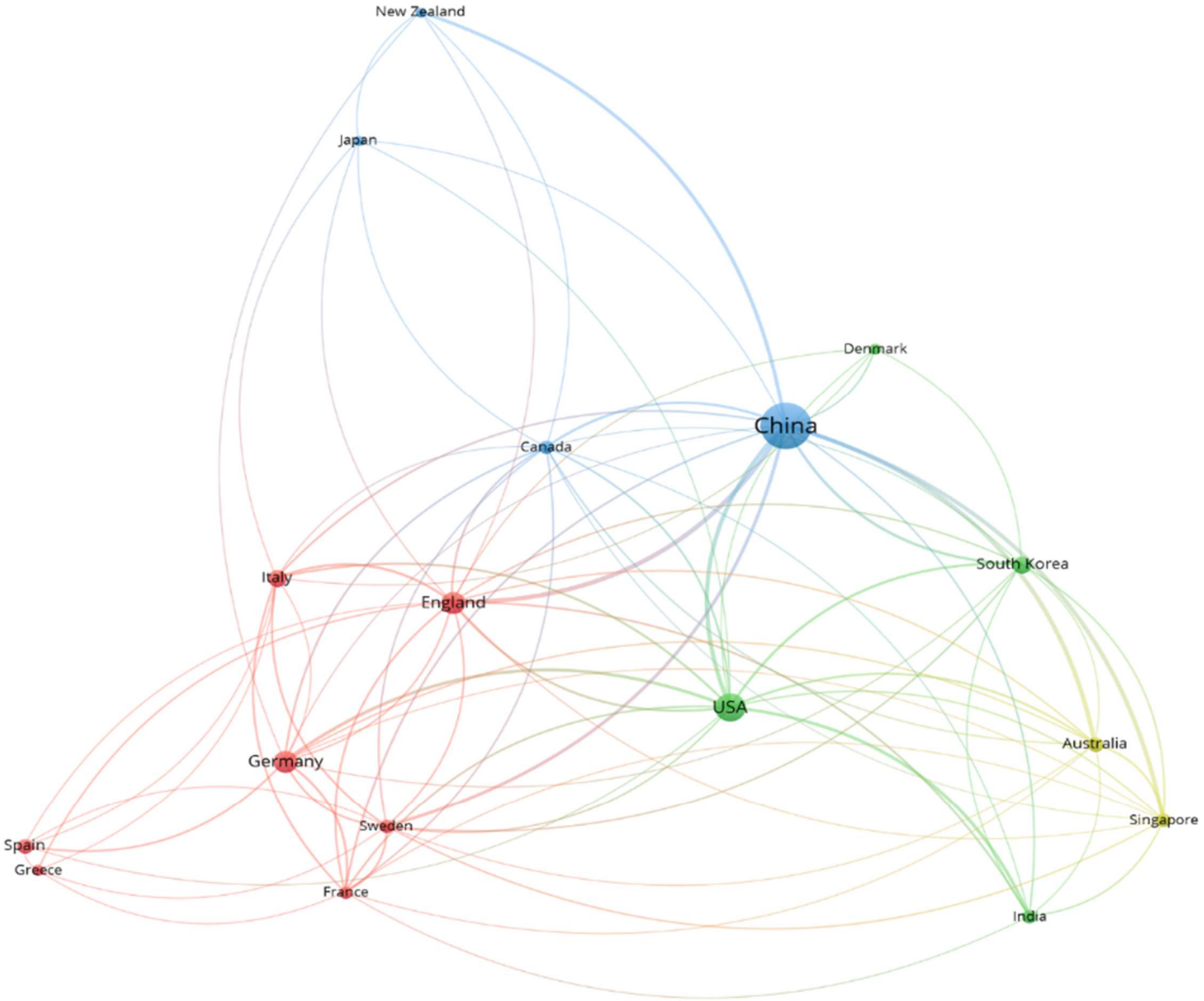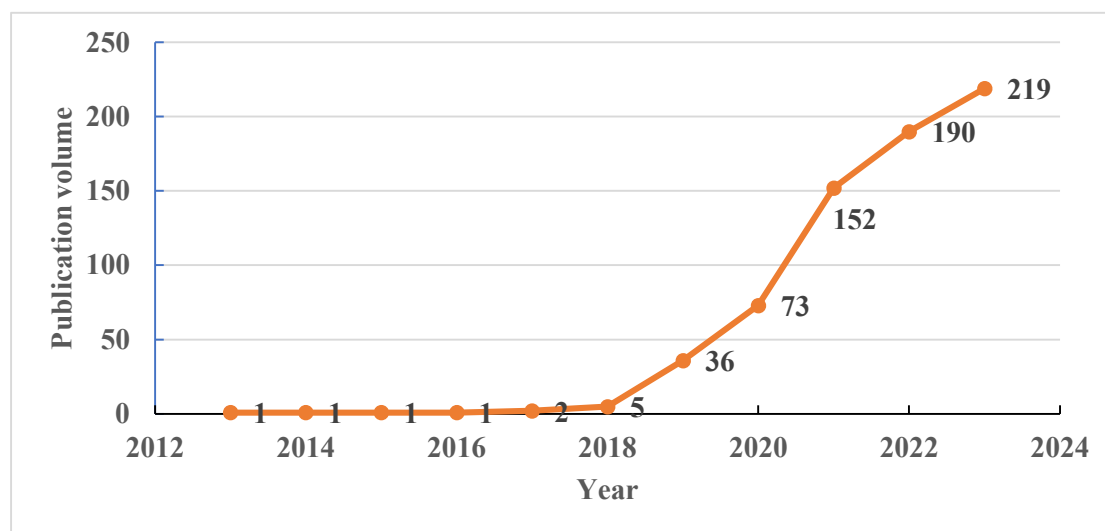


**Figure 2.** Publishes articles per year.

### 2.2.2. Distribution of Relevant Literature

Through a literature analysis, we filtered out the top 20 countries/regions with the greatest number of publications since 2013. These findings are presented in Table 1. China has the largest number of publications, totaling 259 papers related to DT-enabled intelligent manufacturing. The United States is in second place with 96 papers, followed by Germany with 61 papers. Notably, these three countries accounted for 61.1% of the total publications. It should be noted that China, the United States, and Germany have placed significant emphasis on DT-enabled intelligent manufacturing as part of their national manufacturing programs or initiatives. The United Kingdom, Italy, and South Korea occupy the 4th, 5th, and 6th positions, respectively.

**Table 1.** Major countries/regions that publish DTs in the WoS database.

| Country/Region | Ranking | Count |
|---|---|---|
| China | 1 | 259 |
| USA | 2 | 96 |
| Germany | 3 | 61 |
| England | 4 | 61 |
| Italy | 5 | 40 |
| South Korea | 6 | 35 |
| Spain | 7 | 27 |
| Australia | 8 | 26 |
| Canada | 9 | 23 |
| Singapore | 10 | 23 |
| Sweden | 11 | 23 |
| India | 12 | 22 |
| France | 13 | 20 |
| Greece | 14 | 16 |
| Denmark | 15 | 15 |
| New Zealand | 16 | 14 |
| Japan | 17 | 13 |
| Portugal | 18 | 9 |
| Pakistan | 19 | 8 |
| Austria | 20 | 8 |

To analyze the cooperation between publishing countries/regions, we utilized the information visualization tool VOSviewer. Figure 3 presents the country/region interconnection diagram, with the radius of the circular coordinate points indicating the number of published papers and the thickness of the connecting lines representing the level of cooperation. For clarity, only countries/regions with more than 10 published papers were considered in this analysis. The results reveal that China, the United States, the United Kingdom, and South Korea have the most collaborations in the field of DT-enabled intelligent manufacturing.

**Figure 3.** Country/region correlation map of research related to DT-enabled intelligent manufacturing.

### 2.2.3. Primary Journal Sources

A survey of the WoS database identified the main sources of DT-driven machining publications, as shown in Table 2. Sensors has emerged as the journal with the greatest number of publications on DT-driven machining, closely followed by IEEE Access and Applied Sciences-Basel. The top eight journals all published 30 or more articles on DT-enabled intelligent manufacturing. In terms of the journal impact factor, the Journal of Manufacturing Systems is among the top 15 journals, with a factor of 12.1.

A survey of the core databases of WoS reveals the main sources of publications on DT-enabled intelligent manufacturing, as displayed in Table 2. The International Journal of Advanced Manufacturing Technology leads the pack with the highest number of publications, closely followed by the Journal of Manufacturing Systems and Applied Sciences-Basel. The top six journals all have over 30 publications on DT-enabled intelligent manufacturing. In terms of the journal impact factor, the IEEE Transactions on Industrial Informatics tops the list among the top 15 journals, with a factor of 12.3.

**Table 2.** Statistics on DT-driven machining publications.

| Journal | Ranking | Count |
|---|---|---|
| *International Journal of Advanced Manufacturing Technology* | 1 | 59 |
| *Journal of Manufacturing Systems* | 2 | 52 |
| *Applied Sciences-Basel* | 3 | 33 |
| *Journal of Intelligent Manufacturing* | 4 | 33 |
| *Robotics and Computer-Integrated Manufacturing* | 5 | 33 |
| *Sensors* | 6 | 31 |
| *IEEE Access* | 7 | 24 |
| *CIRP Annals-Manufacturing Technology* | 8 | 19 |
| *International Journal of Computer Integrated Manufacturing* | 9 | 18 |
| *International Journal of Production Research* | 10 | 18 |
| *Advanced Engineering Informatics* | 11 | 17 |
| *Computers in Industry* | 12 | 16 |
| *Processes* | 13 | 11 |
| *Machines* | 14 | 10 |
| *IEEE Transactions on Industrial Informatics* | 15 | 7 |

### 2.2.4. Analysis of Highly Cited Papers

The frequency of citations a paper receives reflects its scientific value and research significance. Table 3 presents the top 15 cited papers related to DT-enabled intelligent manufacturing from 2013 to 2023. The most cited paper is Tao et al.'s [38] paper titled "DT in Industry: State-of-the-Art," published in 2019 in the IEEE Transactions on Industrial Informatics. This paper provides a comprehensive overview of DT research in the context of intelligent manufacturing, examining key components, development status, main applications, current challenges, and future directions. Other highly cited papers are listed in Table 3. From the table, it is evident that highly cited papers on DTs mostly focus on intelligent manufacturing and are increasingly recognized as crucial drivers for achieving intelligent manufacturing in the future.

### 2.2.5. Keyword Analysis

Research hotspots are crucial for understanding the development trends within a particular field. By importing relevant data from the WoS core database into the visualization tool VOSviewer, high-frequency keywords can be analyzed to identify research hotspots. Figure 4 presents a co-occurrence map of high-frequency keywords related to DT-enabled intelligent manufacturing research. Only terms appearing more than 10 times were considered to ensure network clarity.

From the perspective of keyword distribution, this research primarily focuses on machine learning, models, frameworks, and related topics. By examining the correlation between these keywords, it is found that keywords such as machine learning, system, model, framework, design, prediction, and data analytics frequently appear in the context of DTs. The frequency of keyword usage reflects the common concepts or technologies in DTs. Section 3 reviews and discusses the common concepts of DT-enabled intelligent manufacturing, frequently mentioned frameworks, and the key enabling technologies for DTs. The keyword analysis highlights the use of DT as a crucial enabling technology for intelligent manufacturing. As research progresses, DT will not be limited to technology alone but will include the entire lifecycle of the enterprise, involving aspects such as management, manufacturing, sales, and services.
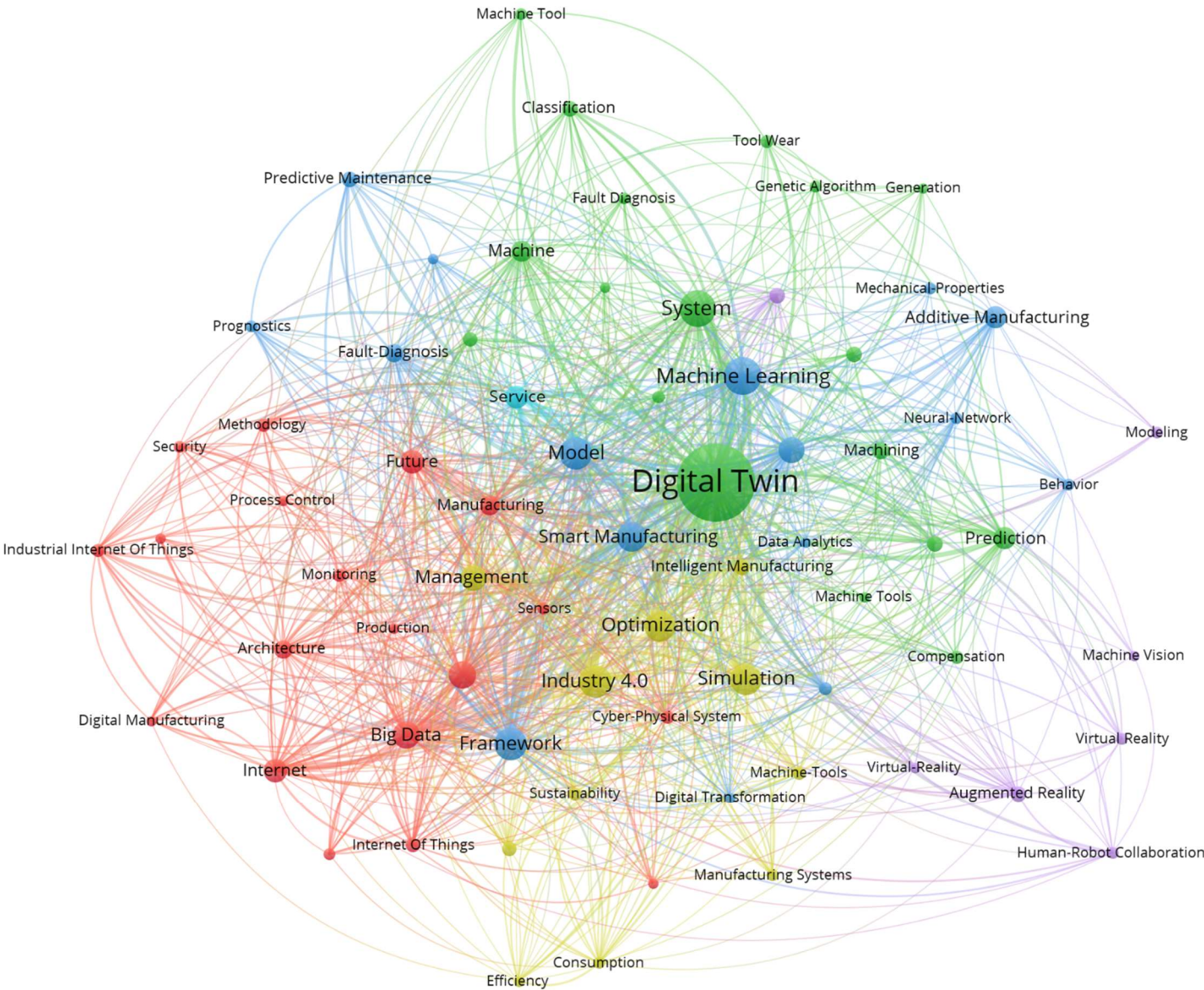
**Figure 4.** DT-enabled intelligent manufacturing keyword contribution mapping.

**Table 3.** Statistics of highly cited papers on DT-driven machining.

| Rank | Author | Title | Journal | Citations | Year |
|---|---|---|---|---|---|
| 1 | Tao et al. [38] | Digital Twin in Industry: State-of-the-Art | *IEEE Transactions on Industrial Informatics* | 1189 | 2019 |
| 2 | Fuller et al. [44] | Digital Twin: Enabling Technologies, Challenges and Open Research | *IEEE Access* | 541 | 2020 |
| 3 | Alcacer et al. [45] | Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing Systems | *Engineering Science and Technology-an International Journal-Jestech* | 479 | 2019 |
| 4 | Qi et al. [46] | Enabling technologies and tools for digital twin | *Journal of Manufacturing Systems* | 440 | 2021 |
| 5 | Maddikunta et al. [47] | Industry 5.0: A survey on enabling technologies and potential applications | *Journal of Industrial Information Integration* | 394 | 2022 |
| 6 | Barricelli et al. [48] | A Survey on Digital Twin: Definitions, Characteristics, Applications, and Design Implications | *IEEE Access* | 389 | 2019 |
| 7 | Jin et al. [49] | Triboelectric nanogenerator sensors for soft robotics aiming at digital twin applications | *Nature Communications* | 312 | 2020 |
| 8 | Cimino et al. [50] | Review of digital twin applications in manufacturing | *Computers in Industry* | 309 | 2019 |
| 9 | Lim et al. [51] | A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives | *Journal of Intelligent Manufacturing* | 262 | 2020 |
| 10 | Wei et al. [52] | Mechanistic models for additive manufacturing of metallic components | *Progress in Materials Science* | 259 | 2021 |
| 11 | Zhang et al. [53] | Review of job shop scheduling research and its new perspectives under Industry 4.0 | *Journal of Intelligent Manufacturing* | 257 | 2019 |
| 12 | Liu et al. [54] | Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system | *International Journal of Production Research* | 228 | 2019 |
| 13 | Minerva et al. [55] | Digital Twin in the IoT Context: A Survey on Technical Features, Scenarios, and Architectural Models | *Proceedings of the IEEE* | 205 | 2020 |
| 14 | Leng et al. [5] | Digital twins-based smart manufacturing system design in Industry 4.0: A review | *Journal of Manufacturing Systems* | 204 | 2021 |
| 15 | Luo et al. [56] | A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin | *Robotics and Computer-Integrated Manufacturing* | 203 | 2020 |

## 3. Overview of Digital Twins in Intelligent Manufacturing

DT technology combines the physical world with the digital world, using real-time and historical data to model, simulate, and analyze physical objects. Its objective is to optimize performance, improve reliability, and reduce maintenance costs. This section first examines the history of the DT concept and then analyzes its five-level architecture in DT-enabled intelligent manufacturing. Finally, the key enabling technologies for DT-enabled intelligent manufacturing are introduced.

### 3.1. Definition of Digital Twins

In recent years, DT has increasingly been recognized as a crucial innovative technology for intelligent manufacturing, driving its development [57]. A DT is a virtual representation that creates and simulates a physical entity, process, or system within an information technology platform. By utilizing DTs, the state of physical entities can be understood on the information technology platform, and predefined interface components within the physical entity can be controlled [58–60]. The concept of DTs was first proposed by Professor Grieves in the United States in 2002. In approximately 2010, the U.S. aerospace industry adopted DT technology, building upon model-based systems engineering and the advancement of the Internet of Things (IoT). Currently, DTs are recognized as excellent solutions for intelligent manufacturing, and extensive research has been conducted by scholars globally. DT technology has also made significant breakthroughs in engineering applications, making it a vital technical pillar for realizing intelligent manufacturing and industry 4.0.

Since the advent of DTs, scholars have attempted to define DTs in the context of product design, manufacturing, and total lifecycle management. However, due to the diverse range of physical objects involved in manufacturing systems, it is challenging to provide a specific definition. Different DT models must be tailored to specific physical objects, such as workpieces, manufacturing equipment, factories, and employees, based on their unique structures, functional requirements, and modeling strategies. Table 4 presents relevant definitions of DTs in both academia and industry.

**Table 4.** Definition of DTs.

| Definition | Refs. |
| --- | --- |
| DTs are digital copies of biological or non-biological physical entities. By connecting the physical and virtual worlds, data can be transferred seamlessly, allowing virtual entities to coexist with physical entities. | Abdulmotaleb et al. [61] |
| DTs use physical data, virtual data, and the interaction between them to map all components of the product lifecycle. | Tao et al. [62] |
| By integrating design/simulation, manufacturing and usage, the Product DT is able to visualize the entire product business process, plan details, avoid problems, close loops and optimize the entire system. | Zhuang et al. [63] |
| A coupled model of real machines running on a cloud platform that uses a combination of data-driven analysis algorithms and other available physics knowledge to simulate health conditions. | Lee et al. [64] |
| Real-time optimization using digital copies of physical systems. | Söderberg et al. [65] |
| DTs are virtual information structures that comprehensively describe potential production or actual manufactured products from the micro-atomic level to macro-geometry. | Grieve et al. [66] |
| DT is a comprehensive digital representation of a single product, a model that simulates its actual behavior in a real environment through models and data. | Haag et al. [67] |
| DT is a technology that adds or extends new capabilities to physical entities through virtual-real interaction feedback, data fusion analysis, and iterative decision optimization. | Li et al. [68] |

### 3.2. Digital Twin Framework

The DT framework utilizes extensive data from the machining process as a foundation. Using virtual simulation, artificial intelligence, and other technologies in the virtual space, a DT of the mechanical process system is constructed. This enables mapping, prediction, optimization, and other functionalities related to the physical entity [69]. This section explores the intelligent manufacturing hierarchy enabled by DTs, with a focus on its architecture.

DT technology is a crucial tool for integrating virtual and real interactions, thereby advancing the development of the manufacturing industry. For instance, applying DTs to the process planning of aviation parts involves constructing a data- and mechanism-driven process planning framework. This framework includes four key enabling technologies: a mechanism-data fusion DT model, a dynamic process knowledge base, process decision-making and evaluation, process quality prediction, and process feedback optimization. The framework is validated through an example of overall impeller process planning for a miniature turbojet engine [70]. Another example is the application of DT

technology in the development of aero-engines. This involves unifying the data storage and management platform to overcome information silos and enhance data utilization. Additionally, it accelerates the iteration-verification speed, reducing the test time and enhancing the efficiency. Moreover, it breaks down the barriers of traditional simulation through multidisciplinary fusion, effectively improving accuracy [71]. Building on these cases, this section describes the capabilities of visual presentation, analysis and diagnosis, learning and prediction, and intelligent decision-making in mechanical product processing. This is achieved through data acquisition, storage, processing, virtual system construction, and algorithmic modeling of the mechanical process system. Importantly, these applications span the entire product lifecycle [72]. In this section, an architecture for the DT-enabled intelligent manufacturing hierarchy is constructed, comprising the physical layer, data layer, model layer, functional layer, and application layer, as illustrated in Figure 5.

The physical layer includes various components of the production process, which can be summarized as the human–machine-object-environment relationship. These factors include the operator, machine tools, data sensing devices, processing environments, internal logical relationships of equipment, information flow, and other relevant factors. The physical layer provides technical support for the data layer. The data layer primarily focuses on data perception, storage, and processing. Data perception involves real-time data, mechanism data, process data, historical data, etc. Data storage is achieved through the establishment of processing databases and DT model databases. Data processing encompasses twin model construction, parameter optimization, and other functions. The data layer supports the model layer by providing the necessary data [73].

The model layer is the central layer of the DT and is divided into mechanism models and data-driven models. Its key components include model construction, calibration, fusion, and optimization. The model layer provides support for the functional layer [74–76].

The functional layer refers to the implementation of intelligent manufacturing enabled by DTs. It achieves process system visualization, analysis and diagnosis, learning and prediction, intelligent decision-making, and other functionalities through single or multimodel coupling. The functional layer provides system support for the application layer.

The application layer involves the full life cycle management of products and relies on the functional layer for related support. It covers various aspects, such as product design, manufacturing, and service phases. This includes technology management, product design definition, equipment maintenance, and end-of-life/recycling.
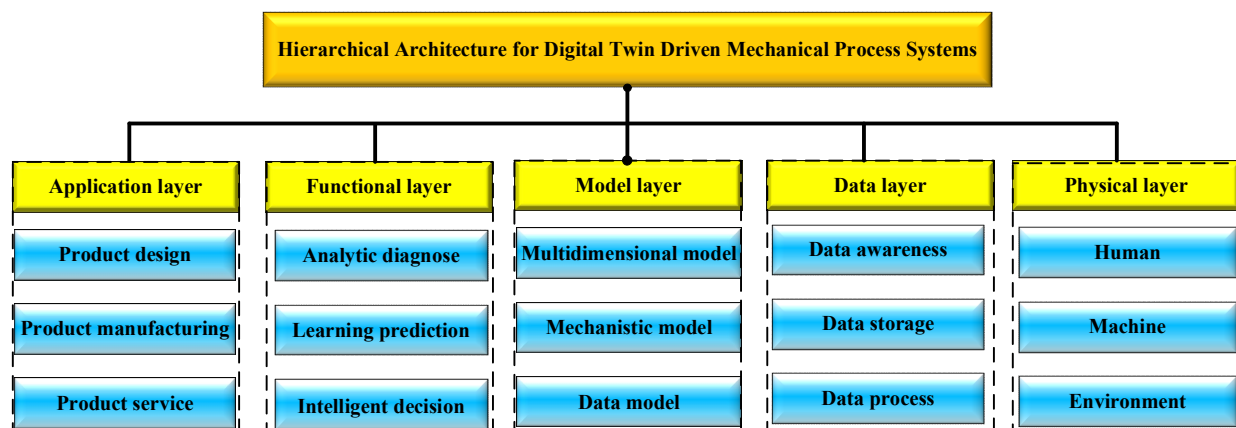


**Figure 5.** Hierarchical architecture of DT-enabled intelligent manufacturing.

## 3.3. Key Enabling Technologies

The core technologies of DT-enabled intelligent manufacturing include data sensing and processing technology, high-fidelity modeling technology, and model-based simulation technology [77,78]. This section examines the development and application of virtual systems based on DTs, model construction, data perception, analysis and prediction, intelligent decision-making, and other technologies, as shown in Figure 6. Among these technologies, the development of a virtual system provides a necessary foundation for the establishment of a DT model. The construction and application of the model, on the other hand, provides theoretical support for virtual system construction. Additionally, data perception, analysis and prediction, and intelligent decision-making contribute to the static attributes of the physical system and related parameters, such as machine tool parameters, workpiece parameters, cutting tool parameters, and fixture parameters. Furthermore, these technologies provide data support for model training, including empirical data and historical data, of the mechanical process system.
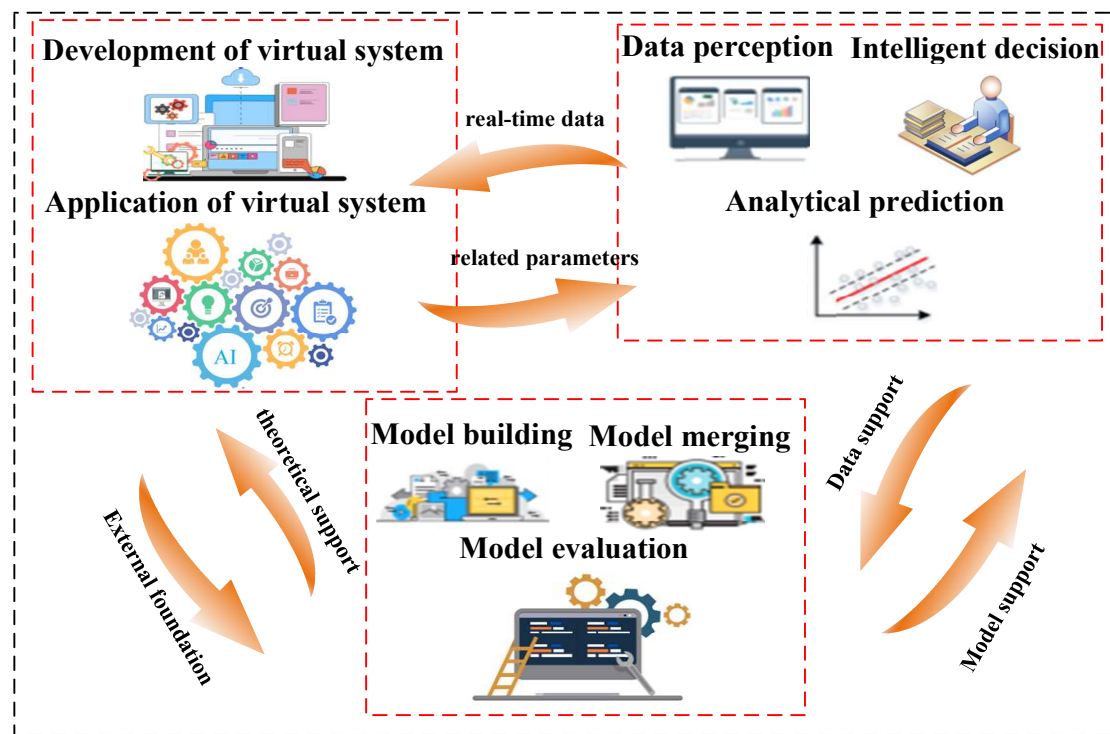
**Figure 6.** Core technology framework of DT-enabled intelligent manufacturing.

## 3.3.1. Virtual System Development and Application

Three-dimensional visualization serves as the basis for achieving the "virtual integration, to virtual reflection of the real" of DTs. The key to achieving three-dimensional visualization lies in the development and application of the DT virtual system. The development of a DT virtual system typically involves steps such as virtual scene development, simulation system development, and application.

Virtual scenarios and simulation systems have been developed using different approaches. Li et al. [79] developed a computer numerical control (CNC) milling DT simulation system for tool wear. They used SolidWorks 3D modeling, the 3D Max rendering model, the Unity 3D design system interface, program interaction, and the TCP/IP protocol for real-time data transmission. Zhang et al. [80] used the Adaptable Planning Simulation Platform Software (VE²) to visualize and present DTs in IMSs. They verified the effectiveness of their proposed contour error suppression method by characterizing the DT of a small 3-axis CNC machine tool. Jiang et al. [81] perceived the machining environment through vision sensors and reconstructed the machining scene using machine vision. They achieved collision detection of the machine tool by perceiving the machining elements and simulating virtual machine tool operations. Duan et al. [82] addressed the issues of poor real-time monitoring and interaction effects in existing CNC machine tools. They constructed a blade-rotor DT system for monitoring the blade-rotor test bench in real time, enabling dynamic testing and visualization monitoring of the equipment. Refer to Figure 7 for visualization. Sun et al. [83] developed a DT for a supercombustion ramjet engine. Their approach allowed hierarchical parameter portrayal of the engine and design of real-virtual interactions in multiple environments.



**Figure 7.** Application examples of virtual system.

Although the development of DT virtual systems is diverse, it highlights the lack of a unified standard method for connecting different devices. Therefore, the establishment of a unified standard method is currently in the exploratory stage and represents a crucial breakthrough point for the future development of DT virtual systems.

### 3.3.2. Model Construction

The DT model serves as the core and foundation of the DT system. A multitude of studies are model-driven and complemented by the development of virtual systems [84–88]. Research on DT-driven modeling of mechanical process systems can be summarized as the resolution of the underlying problem, the requirements of the modeling methodology, and the evaluation of the model [89]. The primary challenges associated with DT models include the absence of suitable modeling tools for complex mechanical products, the handling of extensive data in the machining process, and synchronization issues regarding the dynamic mapping evolution information of mechanical product DTs throughout their life cycles [90]. Consequently, a hierarchical modeling method for DT models of mechanical products based on graph databases has emerged. This approach involves creating product subassemblies or component nodes, establishing node relationships in a predefined graph database, storing feature information in the nodes, and conducting postprocessing on the established DT models [91–93]. Additionally, a dynamic data modeling method based on time-sequence databases is proposed. Leveraging the structure, attributes, and scale characteristics of product dynamic data, this method significantly enhances the performance of data importation, storage, and analysis [94]. Finally, a collaborative evolutionary approach for DT ontology modeling of mechanical products is presented. This approach utilizes blockchain technology to address the context of multisource heterogeneous evolutionary content and variable collaboration based on trust. By employing distributed storage and ensuring the interoperability and interconnection of all modeling operations, this method supports conflict identification and lightweight publishing, yielding favorable results [95].

The modeling approach for DTs in the context of engine health monitoring and machining processes requires the ability to adaptively integrate multidisciplinary and multilevel information. This is essential for constructing high-fidelity, multiscale, and multidimensional processing models and for facilitating real-time model updates.

For instance, Sun et al. [96] demonstrated the application of DT technology in the health monitoring of rotating turbine components in an aeroengine. They integrated a multifactor model of the engine's system performance with thermal and structural factors to enable cumulative damage monitoring and prediction of the remaining life under various influences. Hu et al. [97] proposed the concept of a Wasserstein generative DT model. They utilized the Wasserstein generative adversarial network to model health physical samples accurately, ensuring that the adaptive requirements were met. This approach facilitated health monitoring, fault detection, and degradation tracking of rotating machinery without the need for prior knowledge, historical data, or fault samples. In a similar vein, Liang et al. [98] proposed a multidynamic process modeling model using the DT framework. They established a system-oriented correlation and interaction mechanism to optimize cutting parameters, visualize process variables, and assess machining stability. This integration of data models, kinetic theories, positional variables, and cutting excitation variables enabled comprehensive process optimization. Yu et al. [99] developed a nonparametric Bayesian network DT model to monitor the health state of complex systems. They also proposed a model update strategy that exhibited strong self-learning capabilities and excellent real-time performance, as demonstrated through experiments. Inspired by biomimicry, Liu et al. [100] proposed a knowledge-driven DT mimetic modeling method based on the principles of bionics. This method effectively integrates geometric, behavioral, and process models, allowing for mutual interactions. It facilitated real-time feedback on the machining process and provided assistance in decision-making, as evidenced by the validation conducted on an aerospace part. Building upon this work, Liu et al. [101] further elaborated on the adaptive evolution mechanism of decision-making models for DT processing systems. They focused on both incremental learning and migration learning. Shen et al. [102] proposed an adaptive migration method for DT models to facilitate their migration under complex working conditions. By using drilling machining as an example, they verified the effectiveness of model migration, with a prediction error of less than 1.5%. Although various DT modeling methods are available, they all revolve around the objectives of adaptability, high fidelity, and multifactor fusion. Consideration must be given to the construction of relevant models and the realization of multimodel fusion to accommodate different processing conditions [103].

The evaluation of DT models is crucial for quantifying factors such as their quality, performance, applicability, and value. To address this issue, Wei et al. [104] proposed a comprehensive DT model evaluation index system, as depicted in Figure 8. This system outlines the evaluation criteria for DT models and provides a specific quantitative calculation reference method, thereby aiding decision-making at all stages of the product's life cycle in a DT-enabled intelligent manufacturing setting. Evaluating DT models in this manner enables a reference guideline for the modeling process, allowing for easier updates and improvements to the models.
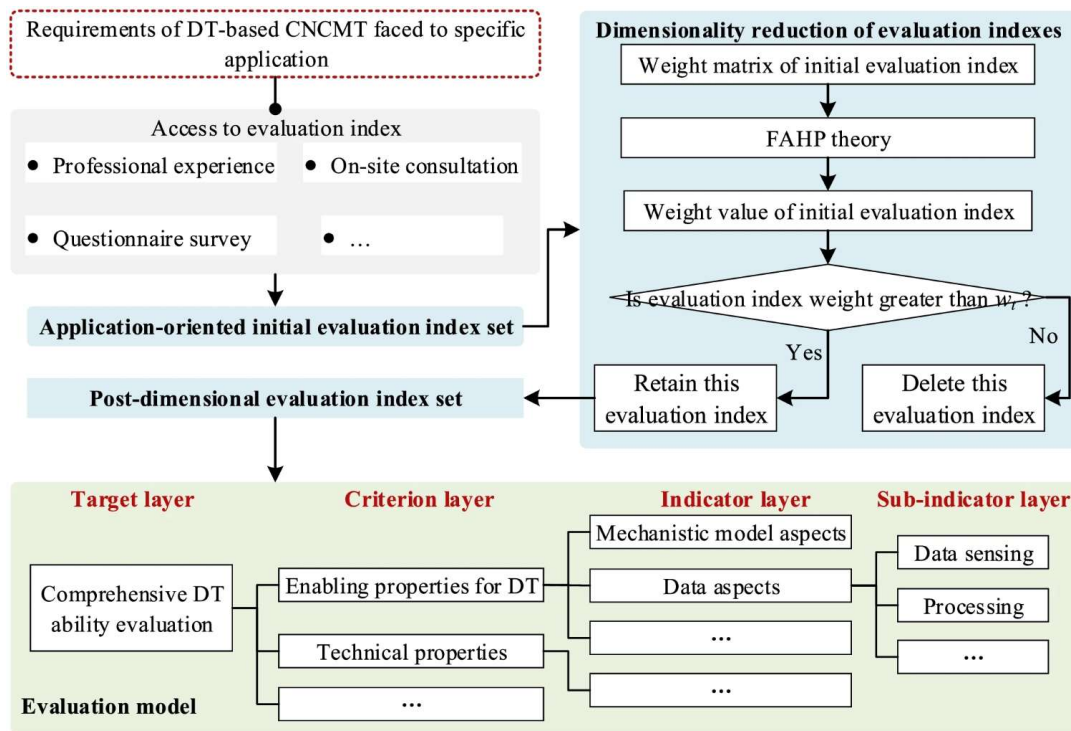
**Figure 8.** DT technology applicability evaluation index of CNC machine tools.

### 3.3.3. Data Perception, Analysis and Prediction, Intelligent Decision-making

Data perception, analysis, prediction, and intelligent decision-making technology constitute a key aspect of DT application. This technology leverages data perception, analysis, and prediction to enable intelligent decision-making for mechanical process systems, thereby guiding their development from digitalization to intelligence [105]. In the context of DT-enabled intelligent manufacturing, the primary principle involves collecting vast amounts of data generated by the processing process. This includes empirical, historical, and real-time data related to the process. With the aid of algorithms and models [106–108], the goals of monitoring and predicting the processing state, performing predictive maintenance on processing equipment, and optimizing and evaluating the machining and manufacturing process are achieved. Additionally, Kaewunruen et al. [109] constructed and analyzed a 6D building information model (BIM) for lifecycle management of railroad turnout systems. This modeling approach facilitates the application of data and supports the implementation of DT technology. Hence, the ability to perceive and process heterogeneous data from multiple sources originating from mechanical process systems is a prerequisite for the application of DT-enabled intelligent manufacturing.

Analysis and prediction are the fundamental components of intelligent manufacturing applications enabled by DT technology. By utilizing the vast amount of data generated by mechanical process systems, algorithms and model training can accurately predict the machining state and equipment performance, thereby enhancing the predictability of the overall machining process [110–112]. Zhao et al. [113] proposed a novel combination of virtual and real DT techniques for the full life cycle management of rolling bearings. They employed an improved CycleGAN model with the Wasserstein distance to map simulation data in virtual space to actual measurements in physical space, effectively minimizing the error between the two datasets. Subsequently, they utilized the simulation data in an advanced remaining service life prediction method, achieving highly accurate predictions for rolling bearings. Similarly, Feng et al. [114] presented a DT-driven intelligent health management method aimed at monitoring and evaluating the degradation of gear surfaces. This approach successfully predicts the remaining service life of gears and has been validated through two durability tests involving different major degradation mechanisms. In addition, Zheng et al. [115] developed a DT-driven intelligent algorithm that combines two different force models to identify milling parameters during milling processes. Through milling experiments, the proposed algorithm was found to enhance machining quality and efficiency. Finally, Liu et al. [100] proposed a DT modeling approach based on bionic principles, constructing multiple DT models, including geometric, behavioral, and process models. The feasibility of this method for monitoring and controlling the air rudder machining process was experimentally demonstrated.

Zhao et al. [116] utilized an intragroup alignment strategy, an intergroup alignment strategy, adversarial learning, and a regression alignment strategy to learn domain invariant features and supervision from multiple sources. The proposed fusion life prediction method successfully addresses the issue of small samples and achieves accurate prediction of bearing health states. Ghosh et al. [73] proposed two computerized systems for building and adapting dDTs. The modular

architecture of the proposed DT construction system (DTCS) and DT adaptation system (DTAS) is described in detail. The efficacy of the DTCS and DTAS is demonstrated using milling torque signals as an example. Luo et al. [117] developed a multidomain unified modeling method for DTs and investigated the mapping strategy between physical and digital space. This method improves the operation mode, reduces the probability of sudden failure, and enhances the stability of CNC milling machines. The predictive analysis of mechanical process systems through algorithmic models and other predictive techniques enables various functions, including fault diagnosis, error suppression, life prediction, and parameter optimization. These functions greatly contribute to improving machining accuracy and efficiency.

Intelligent decision making is a critical aspect of DT-enabled intelligent manufacturing, as it significantly contributes to the resource utilization of machining processes. Liu et al. [118] constructed an adaptive DT decision model that can adjust to different working conditions. Through drilling experiments, it is proven that the decision model effectively reduces burr prediction errors. De Giacomo et al. [119] proposed an approach based on a Markov decision process, inspired by the combination of network services, to automatically assign equipment to manufacturing tasks. This approach overcomes the limitations of traditional planning methods and provides optimal strategies in terms of cost and quality. The strategies are continuously updated to adapt to changing scenarios. The DT decision model achieves machining error suppression and dynamic resource scheduling optimization, leading to improved machining accuracy and efficient scheduling strategies.

The fundamental technologies that enable DT-enabled intelligent manufacturing are complementary in nature. The development of virtual systems serves as the underlying foundation for establishing DT models. The construction of these models accurately reflects the operational status of real systems, while data perception ensures that the models are continuously updated with real-time data. Through analysis and prediction, it becomes possible to forecast the performance and anticipate failure risks of real systems, which aids in early intervention and optimizes decision-making. The integration of artificial intelligence and machine learning technologies in intelligent decision-making assists decision-makers in making more accurate and timely decisions. In summary, the integration of DT into intelligent manufacturing empowers companies to optimize operations, enhance production efficiency, reduce costs, and significantly contribute to product design and services. As technology continues to progress, DT systems will exhibit vast potential in various sectors, thereby becoming a vital tool for driving industrial upgrading and encouraging innovation.

## 4. Applications in Machining

In recent years, the scope of research on DT-driven mechanical process systems has expanded significantly, resulting in a wide range of applications. In this section, we examine the utilization of DT-driven mechanical process systems at various stages of the product life cycle, including product design, manufacturing, and service. We utilized the product full life cycle classification standard as a reference to analyze the incorporation of DT at each stage. We present the specific applications of DT technology at each stage, alongside a comprehensive assessment of its strengths and weaknesses. This analysis is presented in Figure 9.
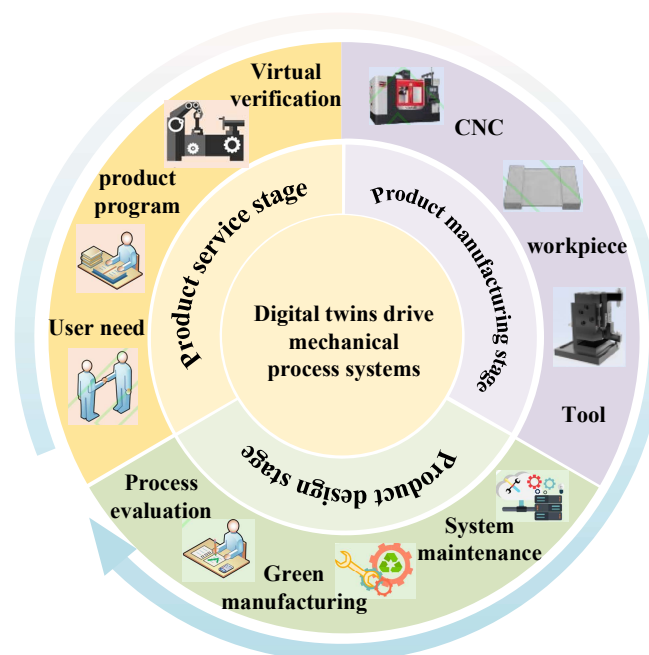


**Figure 9.** Specific application of the DT-driven mechanical process system.

## 4.1. Product Design

In the product design stage, the implementation of DT technology can enhance the intuition and accuracy of the design, incorporating user requirements, iterative optimization, and a focus on human-centered product design and green sustainable design goals. Additional benefits include virtual sample processing, product performance verification, and optimization.

As an illustration, let us consider the design stage of a semi-industrial combustion furnace. By leveraging Kalman filtering, adjustments to the model's predictions can be made, taking into account potential uncertainties. This allows for the realization of predictions regarding combustion chamber performance, reliability assessments, and test program optimization, all of which are pivotal in upgrading processing standards and reducing energy consumption [120]. In a separate study, Friederich et al. [121] proposed the application of DT in product design and presented a framework for DT-driven intelligent product design, focusing on key processes and related technologies. They investigated the conceptual theory of product design and described the DT model configuration process based on conceptual design [122,123]. Furthermore, they proposed a DT-driven product design evaluation process and evaluation algorithm [124]. The authors also investigated the application of a DT-driven green design methodology [125]. By expanding the application of DTs to product design, the authors propose a virtual prototype design for CNC machine tools based on DTs and successfully model the coupling relationship of complex electromechanical systems of machine tools [126]. Moreover, they proposed a lean design process for machine tools based on DTs, which allows for the optimization of machine tool feed system parameters [127,128].

In addition, the application of DT technology in the product design stage provides valuable guidance for determining product solutions, analyzing product parameters, and integrating products with user requirements.

Tao et al. [62] proposed a novel approach to product design based on the DT method. They analyzed the DT-driven product design framework, developed a DT model for design tasks incorporating task analysis and scenario decomposition, and proved through experiments that it enhanced product quality. Huang et al. [129] proposed a DT data management method for products using blockchain technology to improve the efficiency of data sharing among participants. They created a peer-to-peer network and achieved complexity management in the product design process through product design workload prediction and functional change propagation analysis methods. Wu et al. [130] proposed a DT complex product loop design framework that integrates multidisciplinary collaboration across three phases: conceptual design, detailed design, and virtual verification. This framework enables real-time verification and modification of issues arising from multidisciplinary integration, thereby minimizing the number of iterations and costs in the design process. This study lays a theoretical foundation for bridging the gap between the product design and manufacturing phases.

In the product design stage, the application of DTs effectively considers user needs and design goals, making product program development more intuitive and rational. It also provides the design team with additional opportunities for innovation and optimization through virtual machining verification, thus enhancing the efficiency and quality of product design. Moreover, this approach significantly reduces the cost of physical processing verification.

## 4.2. Product Manufacturing

During the product manufacturing stage, the application of DT technology aims to achieve quality data acquisition, processing quality monitoring and analysis, processing quality prediction, and control functions in the mechanical process system. These aspects are crucial for optimizing the product manufacturing process, improving processing quality, and increasing processing efficiency [131–133]. This section explores the specific applications of DT-driven machining processes and analyses their research progress and limitations.

### 4.2.1. Applications in Machining

The traditional mechanical process system includes a machining process involving a machine tool system, a workpiece, a tool, and a fixture. In this section, we will examine the concept of the traditional mechanical process system and discuss the specific application of DT-driven mechanical process systems [134]. We will explore the application of DTs in machine tool systems, workpieces, tools, fixtures, and their respective functions.

(1) DTs for Machine Systems

DT of machine tool systems refers to the application of monitoring the performance status of machine tool systems, including machining parameters, machining errors, modals, and other performance and abnormal fault status processing, based on DT technology. Machine tool condition monitoring is a significant application of the DT of

machine tool systems. Traditional monitoring technologies, such as cameras and sensors, may encounter issues such as image delays, delays, and difficulties in determining the source of errors at the physical end. An approach proposed by Liu et al. [135] addresses the fusion of heterogeneous data from multiple sources and the lack of semantic information through DT modeling of CNC machine tools. It enables comprehensive sensing of the operating status of machine tools, thus achieving condition monitoring services. Another study by Guo et al. [128] focused on an improved Gilbert–Johnson–Keerthi distance algorithm to enhance the detection of collision information between a tool and a machine tool during the simulation and monitoring of machine tool motion. This enhancement results in a more realistic display of the workpiece shape. The usability and efficiency of the system are verified through an example of machining a typical shaft part with a CNC machine tool. This remote interactive simulation of the machine tool demonstrates the benefits of the improved algorithm.

Overall, the DT modeling of CNC machine tools addresses the challenges of fusing multisource heterogeneous data and addressing insufficient semantic information. It enables effective condition monitoring services by comprehensively sensing the operating status of machine tools and enhances the detection and display of collision information during the simulation and monitoring of machine tool motion.

Realizing the prediction process for abnormal states in machine tool systems is another crucial application of machine tool DTs. This includes predicting machine tool performance and component wear degradation. Lv et al. [136] confirmed the effectiveness of a self-built, self-assessed, and self-optimized maintenance system based on a bioinspired DT machine tool. Through bearing fault diagnosis experiments, this system achieved unmanned maintenance of bearings. Yang et al. [137] established a hybrid prediction method for a performance degradation model by constructing a meta-motion DT model, analyzing wear theory, and applying algorithms. This method inherits the advantages of both data-based prediction and model-based prediction, accurately predicting machine tool transmission units. liu et al. [138] proposed a DT approach for motion axes, incorporating a time-varying error model based on heat transfer theory and vision modeling. This method predicts and compensates for time-varying errors, reducing error fluctuations by 69.19%, as demonstrated by experiments on real-time errors in hole spacing.

The application of DTs for machine tool systems enables condition monitoring and the prediction of abnormal conditions in machine tools. This significantly promotes the safe and efficient machining of mechanical process systems. Parameter optimization plays a crucial role in optimizing the machining process. Traditional parameter optimization methods rely on manual experience and often involve high levels of uncertainty. The machining process DT facilitates error suppression and optimization of machining parameters, thereby laying the foundation for achieving high-quality and high-level machining.

(2) Workpiece DT

The term "workpiece DT" refers to the application of DT technology in predicting and optimizing various machining parameters, machining accuracy, surface roughness, and other characteristics of workpieces during the machining process [139]. Ghosh et al. [140] developed a DT structure based on a hidden Markov model to predict the surface roughness generated by continuous grinding operations. This DT structure was then implemented to accurately predict the surface roughness during continuous grinding operations. Zhu et al. [141] proposed a DT-driven manufacturing framework for thin-walled parts. This framework collects and updates DTs of workpieces in different states, providing machine tool operators with real-virtual interaction opportunities. The aim is to make the start-up phase faster and more accurate. The feasibility of this framework was demonstrated in a case study involving leaf disc machining.

Wang et al. [142] proposed a DT-driven clamping force control method to improve the machining accuracy of thin-walled parts. By establishing a full-factor information model of the clamping system and incorporating dynamic information from the clamping process, a virtual space model was constructed using finite element simulation and deep neural network algorithms. This method was verified and found to be effective through arithmetic examples. Dai et al. [143] proposed an ontology-based information modeling method for prefabricated parts. This method enables the association and integration of machined part feature information in the process of virtual-real interaction. This study also provides a theoretical foundation for optimizing machining parameters and predicting machining quality.

Zhang et al. [144] investigated the interaction between machine tools and milling processes from a system perspective. They developed an integrated model of the ball screw feeding system and the milling process, which enabled multiphysics field simulation of the entire system considering multisource harmonics. This approach is highly significant for studying machine tools and milling processes as a coupled whole. Li et al. [145] presented an aeroengine assembly quality assessment method based on cumulative block information modeling and a process-oriented assembly twin. They established an analytical DT platform that integrates modules for measurement, a digital design model, a

geometric deviation analysis model, an information model, and a database. This platform enables quality analysis at the assembly operation stage and lays the foundation for machining key aeroengine components.

Wang et al. [146] proposed a novel method for rapidly calculating engine blade strains, aiming to overcome the technical challenges of real-time calculations in DTs and achieve simultaneous mapping of engine blade health states. The accuracy and effectiveness of this method were verified through engine blade strain measurement experiments and numerical simulations. The results demonstrated a significant improvement in real-time performance, with a speed increase of approximately 1444 times compared to that of conventional finite element methods. The minimum run time achieved was 0.91 seconds. Furthermore, the minimum relative error was 0.11%, and the average relative error was less than 0.76%. The application of workpiece DTs facilitates the optimization of machining parameters, the prediction of surface roughness, and the optimization of machining decisions. These functions have a significant impact on the machining of special workpieces, such as aerospace thin-walled parts, aero-engine blades, and case parts.

(3) Tool DT

Tool DT refers to the application of DT technology in researching and analyzing tool wear monitoring and prediction, selection decisions, and tool service in the machining process [147–149]. First, monitoring and predicting tool wear can effectively reduce machining errors and improve efficiency [150]. Qiao et al. [151] proposed a data-driven DT model and a hybrid model prediction method based on deep learning, which demonstrated the accuracy of tool wear prediction through the study of vibration data from a milling machine. In addition, Natarajan et al. [152] proposed a technique that utilizes DTs to construct a balanced virtual instrumentation framework that is perfectly matched to the physical system to achieve exceptional accuracy in inspecting and predicting tool conditions. The tool condition monitoring system deploys the DT model to predict different tool conditions based on sensory data. Deebak et al. [153] presented a deep migration learning-based DT-assisted troubleshooting method for analyzing the operating conditions of machining tools. Furthermore, the system develops an intelligent toolholder that integrates a type K thermocouple and a cloud data acquisition system on a WiFi module. Analytical studies confirm that this intelligent tool holder provides higher accuracy and enables the optimization of milling and drilling operations of cutting tools. Finally, Zhuang et al. [154] proposed a DT-based approach that realizes the physical-virtual symmetry of the DT model by constructing a symmetric virtual tooling system that exactly matches the actual tooling system. This approach accurately maps the real-time state of tool wear.

Zhang et al. [155] proposed a framework for model updating based on DTs, which is used to obtain an accurate tool wear model for predicting and managing machining processes. Xia et al. [156] presented a kinematic model and trajectory planning method for the UR10 robot by establishing a DT unit in the inspection system. The authors utilized Unity3D software to create the DT environment for the inspection system. Through socket communication, a synchronous mapping function is established between the robot's digital model and the physical entity, enabling complex tool edge image acquisition trajectory planning, precise teaching of the virtual scene, digital monitoring of the inspection process, and optimization of the system model. The stability and effectiveness of robot kinematics, trajectory planning, and interactive communication in the tool wear image inspection environment are verified. Chen et al. [157] utilized a bionic digital brain as the intelligent core of the DT double-cutting machining framework, which includes monitoring, prediction, optimization, and control. They demonstrated the powerful information processing capabilities of DTs and presented real-time precision intelligent machining results. Liu et al. [158] proposed a DT-driven method for predicting surface roughness and adaptively optimizing process parameters. When the predicted surface roughness based on real-time data does not meet the machining requirements, the DT system issues a warning and adaptively optimizes the cutting parameters based on the current tool wear prediction. The effectiveness and advancement of the proposed method are verified through the development of a DT system for process optimization and a large number of cutting tests. This approach combines real-time monitoring, accurate prediction, and optimization decision-making in the machining process, resolving the issues of inconsistent quality and efficiency. Song et al. [159] addressed the problem of tool wear-induced vibration and deformation in the milling of thin-walled parts. They proposed a DT tool wear state recognition method using feature vector extraction, hyperparameter optimization, and support vector machine algorithms. The experimental results show a recognition rate of over 90% for the system. However, due to limitations in the support vector machine algorithm itself, the method exhibits weak generalizability and is not applicable to large sample sizes. Additionally, Zhang et al. [160] incorporated a deep migration learning strategy and edge distribution rule into the DT tool model to achieve target domain training with small samples. This approach improves the accuracy and appropriateness of the model and resolves the issue of small samples under variable working conditions.

Second, in terms of tooling services, DT-based tooling services enable the efficient utilization of tooling. Xie et al. [161] established a tool DT model consisting of five stages: tool market investigation, research and development, production planning, manufacturing, customer use and service. This model allows real-time status monitoring of cutting tools, visualization of tool information, parameter optimization, maintenance strategies, and virtual maintenance. The application of tool DTs is one of the most widely used and extensively researched applications of DT-driven mechanical process systems. The achievement of tool wear state monitoring and prediction plays a crucial role in reducing machining errors. Research on DT-based tool services, tool selection strategies, and tool change speeds has entered the exploration stage.

(4)  Fixture DT

Fixture DT refers to the application of DT-based technology to the control of the fixture itself and the clamping force control during machining. Wang et al. [142] designed a DT dual-drive clamping force control method by integrating a neural network and finite element simulation to address the problem of machining deformation caused by inadequate fixture clamping in traditional machining processes. Through experiments considering the full-factor information of the clamping system, they proved the effectiveness of the method. Weckx et al. [162] proposed a cloud-based DT for monitoring high-performance composite machining adaptive clamping devices by incorporating computer vision-related technology. This implementation achieved functions such as tool wear monitoring based on the clamping force and the evaluation of clamping device operation. Additionally, they innovatively developed the function of automatically triggering monitoring algorithms for the transmission of machining signals to the cloud.

The application of fixture DTs allows for the optimization of clamping parameters, the prediction of clamping stability, and the control of clamping force during machining. These capabilities contribute to improving the stability of clamping and enhancing machining accuracy. By leveraging key technologies such as analysis and prediction, decision-making optimization, and fault processing, the application of fixture DTs significantly improves the efficiency and accuracy of machining. Implementing error prediction in the machining process is an essential step to avoid downtime risks and ensure machining efficiency. Anomaly detection based on DT technology provides a guarantee for improving efficiency and accuracy. The integration of DTs in the machining process enables the suppression of machining errors, effectively improving machining accuracy and ensuring machining safety.

### 4.2.2. Deficiencies

In the product manufacturing stage, the implementation of DT technology has greatly facilitated the transformation and upgrading of mechanical process systems. However, there are still certain limitations that need to be addressed. First, research on DT-driven mechanical process systems requires a substantial amount of data. The existing research predominantly relies on a single method of data monitoring, which incurs high acquisition costs, low accuracy, poor real-time performance, and a limited amount of data [154]. Second, the research on DT-driven mechanical process systems is often limited to specific research objects, processes, working conditions, and machining scenarios, rendering it inapplicable in a universal context [163]. Finally, while there is a significant amount of research on condition monitoring and virtual simulation in DT-driven mechanical process systems, there is a lack of research on algorithms, models, and mechanism analysis. Consequently, the application of algorithms is often constrained by their inherent limitations, which restrict the conditions under which they can be implemented [164]. Therefore, there is a crucial need for improvements in the application of DT-driven mechanical process systems.

### *4.3. Product Service*

From the previous discussion on the specific application of DT-driven mechanical process systems and the analysis of DT application in machining processes, it is evident that DT technology enables functions such as machining status monitoring, prediction, and process optimization. Building on this, this section will explore the application of DTs in the product service stage, focusing on fault detection and predictive maintenance of mechanical process systems, machining process evaluation and optimization, and product sustainable manufacturing and operation and maintenance.

### 4.3.1. Fault Diagnosis and Predictive Maintenance

Traditional preventive maintenance, with its high cost and low efficiency [165,166], is being challenged by the emergence of predictive equipment maintenance. This approach, based on DT technology, allows for the prediction of maintenance risks and effectively reduces the chances of equipment failure. By improving maintenance efficiency, it is

clear that predictive maintenance is the future trend for mechanical process system maintenance [167–169]. To optimize equipment failure monitoring, prediction, and maintenance decisions, He et al. [170] proposed a complex equipment health management approach. A hybrid framework based on DT modeling and DT data, as presented by Luo et al. [56] further enhances this optimization. Building on this framework, a hybrid predictive maintenance algorithm was proposed, and its effectiveness was verified through examples. In the quest for effective DT-based predictive maintenance systems, Van et al. [171] used domain analysis to model key features and synthesize relevant literature. The result was a DT-based predictive maintenance system that derives three views: a user view, an architecture view, and a deployment view. The analysis demonstrated the potential of creating a reference architecture in the field of DT-based predictive maintenance.

Zhong et al. [168] summarized the growing research interest in predictive maintenance based on DTs in the field of manufacturing. This paper proposes a gap between DT technology and predictive maintenance technology, emphasizing the importance of utilizing DT technology to achieve effective predictive maintenance. Furthermore, a predictive maintenance approach based on DTs is presented, highlighting the differences between this approach and traditional predictive maintenance. To address fault diagnosis in both the development and maintenance phases, Xu et al. [172] proposed a two-stage DT-assisted method based on deep migration learning. This method identifies potential problems that may not have been considered during the design phase and uses deep neural network-based diagnostic models for fault diagnosis. By employing deep migratory learning, previously trained diagnostic models can be migrated from virtual space to physical space for real-time monitoring and predictive maintenance. This ensures diagnostic accuracy and prevents unnecessary delays. Predictive maintenance based on DTs enables an "ex ante" preventive mode for mechanical process systems, effectively reducing machining losses and improving efficiency compared to the traditional "ex post" repair and fix mode.

### 4.3.2. Process Evaluation and Optimization

The process evaluation of machining processes is crucial for enhancing process execution and reducing product development cycles [173]. Liu et al. [124] proposed a data-driven machining process evaluation method using DTs by aligning machining process data with process design data. This method successfully evaluated the machining process for key components of marine diesel engines. Pereverzev et al. [174] applied DT technology fused with dynamic programming to test and iteratively optimize the grinding cycle of a CNC machine. This optimization ensured consistent quality of machined parts by designing the optimal feed control cycle. To optimize the CNC machining process, Vishnu et al. [175] simulated, predicted, and optimized the workpiece surface roughness in the process planning and machining stages. They developed a surface roughness prediction model based on DTs, providing theoretical support for the development of optimization technology.

Zhu et al. [141] established a DT model for the workpiece and utilized algorithmic optimization to provide real-time machining information to the machine operator. By optimizing the tool direction and tool path after each work step, they demonstrated the effectiveness of their method through machining examples. Chen et al. [176] proposed a DT-driven method to suppress delamination damage in real time by analyzing the relationship between the thrust increase caused by tool wear and CFRP delamination. Through extensive drilling experiments, they input cutting parameters and thrust signals into the DT model, Gaussian process regression, and mathematical modeling to predict current tool wear and thrust profiles, respectively. The results showed excellent real-time prediction, with maximum errors of 4.1% and 4.2% for tool wear and exit thrust prediction, respectively. Compared to conventional drilling, DT provided closed-loop feedback on the time-varying critical feed rate for each hole, resulting in no delamination mode I and up to 48.4% suppression of delamination mode III. This intelligent virtual-real linkage in the CFRP drilling process offers important theoretical support for the effective suppression of delamination damage in automated production processes.

Optimizing machining processes holds significant value in improving machining performance, accuracy, and efficiency. Utilizing DT technology provides a new approach to mechanical process optimization. Implementing DT-based machining process evaluation and optimization positively impacts reducing machining error rates, formulating optimal machining process routes, and enhancing machining efficiency.

### 4.3.3. Product Sustainable Manufacturing and O&M Management

With the introduction of China's "Carbon Peak Carbon Neutral" initiative and other major strategic decisions, the green and sustainable product manufacturing mode has become the mainstream approach in the machinery manufacturing industry [177–180]. The entire life cycle of sustainable manufacturing is supported by a model that includes product

material selection, sustainable disassembly, end-of-life recycling, and remanufacturing, all based on DT technology. This model provides technical support for achieving a green and sustainable development model through the monitoring and evaluation of energy consumption during the processing process and visualization of green features [181].

Xiang et al. [182] proposed a DT-based approach for selecting sustainable materials optimally, with the aim of achieving sustainable manufacturing over a specific period. This is done through simulating and evaluating the performance of sustainable materials. Li et al. [183] proposed a DT-driven method for evaluating sustainable performance in intelligent manufacturing and confirmed the effectiveness of this approach through testing. Kerin et al. [184] proposed a product DT model that utilizes data from different instances in the product life cycle to optimize remanufacturing plans. This includes predicting residual product life through neural networks and employing techniques such as bee algorithms for decision-making, ultimately achieving optimal product remanufacturing decisions. Sustainable manufacturing plays a crucial role in building an ecological civilization, and the adoption of DTs in the sustainable manufacturing of products promotes the transformation of the manufacturing industry toward sustainability and intelligence. This is achieved through the monitoring and evaluation of energy consumption during the processing process, the characterization of sustainable features, and the establishment of mechanisms for end-of-life recycling, among other technological means.

It is crucial to understand the operation and maintenance of the mechanical process system during the product service stage. The operation and maintenance service system driven by DTs is explained in terms of pattern updating, data application, and system interaction. For instance, this article explores the application of DTs in the operation and maintenance of aviation engines [185], focusing on accurate monitoring, fault diagnosis, performance prediction, control optimization, and other functions. Fu et al. [186] identified the time and cost inefficiencies of traditional design, manufacturing, and maintenance processes as inefficient due to their independent operation and management. To address these inefficiencies, a unified platform is needed for efficient and intelligent design, manufacturing, and maintenance of machinery, equipment, and systems. To achieve this goal, an information-physical combinatorial framework is proposed that enables more accurate design, defect-free manufacturing, smarter maintenance, and advanced sensing technologies.

Chen et al. [187] addressed the problems with the traditional "regular maintenance and fault repair" mode for mechanical equipment, including high costs and low efficiency. An intelligent mode of "predictive maintenance" and "condition maintenance" is proposed to achieve predictive maintenance, life prediction of industrial equipment, and improved virtual-realistic interaction and autonomous accurate service. Huang er al. [188] proposed an operation and maintenance service system that included virtual-real space interaction, data-driven knowledge updating, and real-time product diagnosis and maintenance. The effectiveness of this system is verified through a machine tool performance analysis test.

It is highlighted that operation and maintenance management based on DTs is significant for mechanical process systems. The establishment of a digital operation and maintenance system reduces the impact of unpredictable factors, such as the aging and wear of equipment and structural deviations. This enables more accurate and efficient operation and maintenance compared to traditional manual experience-based systems [189].

Throughout the product life cycle, the application of DT technology can achieve collaborative optimization of product design and manufacturing, improve production efficiency and product quality, and continuously create value through digital services to meet customer needs and enhance competitiveness. With the continuous development and popularization of digital DT-enabled intelligent manufacturing, its application in the product field is expected to become more extensive, offering greater innovation and development opportunities for enterprises.

## 5. Conclusions

The research significance and current status, key technologies, and specific applications of DT-enabled machining are analyzed in the context of the development process of DT-enabled intelligent manufacturing. With the rapid integration of information technology and operational technology in the industrial field, significant progress has been made in manufacturing intelligence. DT-driven applications, as a core element of future manufacturing, will challenge and transform the foundation of manufacturing systems and operations. The convergence of the digital and physical worlds enables informed decision-making in all aspects of manufacturing operations, resulting in a data-driven intelligent manufacturing environment. The conclusions of this paper are as follows:

(1) The development history of DT-enabled intelligent manufacturing can be examined through the analysis of the volume and trend of publications over time. By analyzing the research frontiers and hotspots, we can highlight the concerns of practical applications related to DT-enabled intelligent manufacturing research. Bibliometric analysis revealed a surge in the number of articles on DT-enabled intelligent manufacturing since 2019, generating significant interest in the industry. This analysis provides clues and support for further exploration and research.

(2) DTs play a vital role in enabling intelligent manufacturing by facilitating interactions between the physical and virtual worlds of mechanical process systems. It promotes the digital transformation of mechanical process systems and paves the way for cyber-physical integration. The theoretical framework of the key enabling technologies of DT-enabled intelligent manufacturing revolves around the architecture of the five major layers: physical, data, model, function, and application. These key enabling technologies are mutually complementary. The basic research route includes data-driven approaches, model simulation, algorithm analysis, intelligent decision-making, and experimental verification. As technology continues to advance, DT systems will exhibit significant potential in various fields, becoming a crucial tool for promoting industrial upgrading and innovation. However, there is currently a lack of common definitions and methods for the core technologies of DTs, including data types, virtual system construction, and the integration and selection of models and algorithms.

(3) The application of DT-driven mechanical process systems has yielded significant results, enabling various functions such as mechanical product design, processing status monitoring, processing error suppression, equipment predictive maintenance, processing process evaluation, and processing parameter optimization. Throughout the entire product life cycle, the use of DT technology enables the collaborative optimization of product design, manufacturing, and service, resulting in improved production efficiency, product quality, and customer satisfaction. During the product manufacturing stage, a time-varying error model of the motion axis is constructed based on heat conduction theory and a visualization model. Through experimental predictions of the time-varying error in the hole distance of workpieces, it has been found that the lowest discrepancy between the predicted and actual errors is only 0.2 μm. By compensating for real-time time-varying errors, the fluctuation range of the hole distance errors is reduced by 69.19%.

(4) The development of DT-driven mechanical process systems continues to play a pivotal role in the digital transformation of the manufacturing industry. The "DT + emerging technologies" model holds the potential for even greater possibilities. However, the current stage is marked by a paradox wherein the demand for more advanced levels of technology, methodology, system integration, and skilled professional clashes with the limited availability of industrial software and hardware infrastructure. This bottleneck poses a challenge to the rapid advancement of DTs.

## 6. Prospects

The application of DTs remains a critical technology for intelligent manufacturing. To address the challenges related to DT empowerment in intelligent manufacturing, it is necessary to examine existing accomplishments, assess the technical framework, and evaluate the current application status. The future development directions are as follows:

(1) As the manufacturing industry undergoes transformation and upgrades, the importance of intelligent manufacturing continues to grow. Intelligent manufacturing, combined with DT and its intelligent sensing and simulation capabilities, enhances the efficiency and intelligence of product production. The rapid advancement of enabling technologies such as cloud computing, big data, artificial intelligence, the Internet of Things, hypernetworks, blockchain, and 5G has led to the diverse development of DT-enabled intelligent manufacturing. The fusion of DTs with emerging technologies holds tremendous potential for further advancements in intelligent manufacturing.

(2) The efficient utilization of data is a crucial objective of DT-enabled intelligent manufacturing. The collection, processing, and storage of heterogeneous data from various sources play a vital role in achieving this goal. The widespread adoption of systematic DT-enabled intelligent manufacturing applications is expected. The limited functionality of localized DT applications can be overcome by advancing DTs from the component level to the machine level, production line level, and even the DT ecosystem level. This evolution will positively impact the digital transformation of the manufacturing industry.

(3) The concept of sustainability has gained significant importance, and integrating it with intelligent manufacturing to achieve sustainable intelligent manufacturing has become a priority in future research. As a sustainable technology, DT helps reduce emissions throughout a product's life cycle. This aligns with the requirements of intelligent manufacturing and comprehensive sustainable development, taking into account environmental, economic, and social perspectives.

(4) Intelligent manufacturing is widely recognized as a crucial area for future research and applications. By applying cutting-edge technologies to traditional products in manufacturing and services, intelligent manufacturing adds value to a broad range of products and systems. Its potential can be further maximized by integrating it with other technologies such as intelligent transportation, intelligent energy/grid, intelligent buildings, intelligent healthcare, intelligent cities, and intelligent societies.

## Author Contributions

Conceptualization, S.H. and C.L.; Methodology, S.H.; Software, B.L.; Validation, M.Y., X.W., T.G. and W.X.; Investigation, S.H.; Data Curation, C.L.; Writing – Original Draft Preparation, S.H.; Writing – Review & Editing, C.L.; Supervision, Y.D., Z.Z. and P.X.; Funding Acquisition, C.L.

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