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A systematic review of digital twin about physical entities, virtual models, twin data, and applications

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ABSTRACT

The digital twin is a crucial technology for realizing smart manufacturing and industrial digital transformation, which has received extensive attention and research from industry and academia. After 20 years of development, the application area of digital twins has been pervasive. Due to the diversity of application areas, various reference models and research methods have been presented for the components of the digital twin. Therefore, this paper provides systematic research of current studies on the basic components of the digital twin. This paper analyzed 117 articles from 2017 to 2022. By clarifying the relationship between the digital twin and the cyber-physical system, it first clarified the definition, characteristics, and application areas of the digital twin. On this basis, the research methodology of the core components of the digital twin (physical entities, virtual models, and twin data) is analyzed. At the same time, the application areas of digital twins are analyzed and delineated, and the application potential of the digital twin is explored. Finally, the research results and future research recommendations are presented.

1. Introduction

Digital transformation and intelligent upgrading have become vital factors in releasing tremendous development momentum and have become a consensus among countries regarding future global development [1]. Taking the manufacturing industry as an example, the United States, Germany, the United Kingdom and other countries have put forward their own national manufacturing development strategies, and the most basic technology drivers are digitalization and intelligence [2]. As a multidisciplinary technology that fully uses models, data, machines, and computers, digital twins can provide real-time, efficient, and intelligent services in multiple areas of smart manufacturing and can also serve as a bridge between the physical world and the information world [3,4]. The concept of a digital twin dates back to a 2002 report by the University of Michigan to industry for the establishment of the Center for Product Lifecycle Management [5]. Limited by the immaturity of data acquisition technology, computer performance and algorithms at the time, the early concepts proposed by Professor Michael Grieves did not receive widespread attention at the time and were not called digital twins. In 2010, the "digital twin" was first proposed in writing by NASA and further developed [6]. In 2012, NASA and the Air Force Research Laboratory collaborated to propose digital twin examples of future aircraft to address the need for future aircraft to be highly loaded, lightweight, and serve longer in extreme environments [7]. In 2014, Professor Michael Grieves published a white paper on digital twins, formally defining the 3 main parts of a digital twin: physical entities in real space, virtual models in virtual space, and data that connects physical entities and virtual models together [8]. In order to study the development trend of digital twins, papers related to digital twins from 2012 to September 2022 were counted. The search keyword was digital twins and the database were Scopus, Web of Science, IEEE Xplore, and Google Scholar. Finally, an annual graph of the number of digital twins is obtained, as shown in Fig. 1. It can be seen from the graph that the number of documents has soared every year since 2017, with the number of papers exceeding 800 in 2021. From the growth trend in the figure, it is speculated that the number of papers in 2022 is expected to exceed 1000.

Physical entities, virtual models, and twin data are the three

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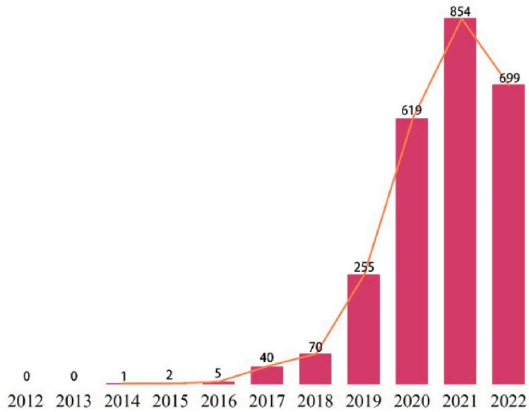

Fig. 1. Number of digital twin papers published per year.

foundational components of the digital twin [9]. Physical entities are the foundation of the digital twin, a single device, or an extensive system like a shop-floor. Physical entities are objectively present and can perform at least one task independently. Monitoring the working process of physical entities through different kinds of sensors to obtain data on the operating status of physical entities is the focus of physical entities' research. The virtual model is the key to differentiating digital twin technology from other technologies and is also the basis for the realization of virtual-real interaction. A virtual model is a copy of a physical entity that can characterize and describe physical entities from multiple temporal and multi-spatial dimensions [10]. The geometric dimensions, material properties, and other parameters of the physical entity are given to the virtual model, and historical working data drive the simulation of the virtual model to realize the control, optimization, and prediction of the actual working state of the physical entity [11]. Twin data is the driver of digital twins, which generally includes physical, virtual, knowledge, and derivative data [12]. Twin data contains different types that can better monitor physical entities' working status and drive virtual models' operation.

Digital twins can be used for the prediction of the remaining lifetime of spacecraft [13], for the digital design of roll-shops [14], and for healthcare for the elderly [15]. Digital twins have excellent performance in design simulation optimization, operation monitoring, predictive maintenance, etc., and have been widely used in industrial production, smart cities, smart medical and other fields [16]. It has gradually become an essential driving force for digital transformation and development in various areas. Different domains have different research approaches to the perception of the working state of physical entities, the construction of virtual models, and the management of twin data. Therefore, it is urgent to divide the application fields according to the characteristics of digital twin models and to summarize the general research methods applicable to different areas.

In this paper, we will systematically review digital twins' current research status and achievements, mainly from the three core components mentioned above and the application areas of digital twins.

1.1. Related review works

Since 2017 digital twins have been developing rapidly. Numerous review articles on digital twin definitions [17,18], reference models [19], key technologies [18,20], and application areas have been published [16,18,21–25]. In this paper, 8 review articles are selected for brief introduction, and the key points of this research are proposed through analysis.

Many articles have studied in detail the definition, connotation, development history, key technologies, and reference models of the digital twin. B. R. Barricelli et al. [26] analyzed 75 articles. The literature concludes that the digital twin must be equipped with network devices to ensure seamless connectivity and data exchange through direct physical or indirect cloud-based connectivity. Lu et al. [27] proposed a reference model for the digital twin, including an information model for abstract physical object specification, a data communication mechanism, and a data processing module. Semeraro et al. [28] answer the question of what a digital twin is, when it can be developed and why it should be used by analyzing the concept of a digital twin, its life cycle stages, and its primary functions at different stages. Tao et al. [9] conducted a systematic study of the current state of research on digital twin modeling, giving a comprehensive and insightful analysis of digital twin models in terms of application areas, levels, disciplines, dimensions, universality, and functionality.

Several articles have also investigated the application areas of the digital twin. Zheng et al. [29] conducted a systematic study on the application of digital twins. They proposed a digital twin application framework consisting of physical space, virtual space, and information processing layers for product lifecycle management. Tao et al. [30] analyzed 50 papers and 8 patents. This article provides an overview of key technologies for data processing, interactive collaboration, and services. The current state of research on digital twins in product design, production, prediction, and health management is discussed. Due to the significant differences in their composition, usage conditions, and application scenarios, the research objects in different industries have different characteristics regarding modeling strategies. Therefore, Fang et al. [31] outlined the focus of digital twin modeling in various industries and summarized the related supporting technologies and methods. There are also scholars who focus on the current application of digital twins in a certain field. Opoku et al. [25] studied the application of digital twin technology in the construction industry. The study analyzes in detail application scenarios such as construction process information modeling, equipment management and energy simulation.

Table 1 shows a summary of these review papers. From these review papers, it can be seen that there is a lot of research on the concept, technology and application field of digital twin. However, the current study does not emphasize the respective approaches to physical entities, virtual models, and twin data. In addition, most of the reviews on digital twin applications focus on areas such as industry and manufacturing, and there is a lack of reviews of promising but less researched areas.

1.2. Purpose of this paper

The digital twin is an essential technology for smart manufacturing and Industry 4.0. Its importance has been recognized by academia and industry, so with a detailed and insightful review, this paper aims to:

1) Analyze and compare the similarities and differences between the digital twin and cyber-physical system technologies.
2) Provides a comprehensive summary and analysis of physical entities, virtual models, and twin data.
3) Summarize and divide the popular application areas of the digital twin, and summarize some potential application neighborhoods.
4) Propose possible future research directions and research methods.

The rest of this paper is organized as follows. Section 2 describes the literature review methodology. Section 3 clarifies the differences between the digital twin and cyber-physical system. Section 4 reviews the research methods for physical entities, virtual models, and twin data. Section 5 analyzes the application areas of the digital twin. Section 6 presents some observations and future developments of digital twins. Section 7 summarizes the whole text.

2. Research method

2.1. Classification criteria

The primary literature classification criteria for this study are based

Table 1
Comparison of digital twin review articles.

Ref.	Timeframe	Number of papers reviewed	Object of the overview	Key findings
[26]	1990–2019.07	75	• To explore the definition of digital twin.	• Definition: A computer-based model that simulates, emulates, mirrors, or “combines” the life of a physical entity. • Features: Both physical and digital twins must be equipped with network devices.
[27]	2004–2019.07	85	• To explore the characteristics of the digital twin.	• Application scenarios: manufacturing, aviation and healthcare. • Digital twin reference model: information model for abstracting physical object specifications, communication mechanism for transmitting data in both virtual and real directions, and data processing module. • Most used scenarios: healthcare, maritime and shipping, manufacturing, urban management, aerospace
[28]	2002–2020	115	• To explore the application areas of the digital twin.	• Research challenge: Need to develop digital twins that can interact with humans. Need to explore modular approach to build flexible DT solutions. • Current research on digital twin modeling rests mainly on model construction, and modeling integrity is a pressing issue. • Established a digital twin application framework for product lifecycle management (consisting of three parts: physical space, virtual space and information processing layer) • Key Theories: Modeling, Data Fusion, Interaction and Collaboration, and Services.
[9]	2014–2021.12.31	160	• Exploring frameworks and development methods for implementing the digital twin in manufacturing.	• Industrial applications: Design, Production, PHM.
[29]	2012–2018	27	• To explore the methods, application areas and implementation challenges of designing and implementing the digital twin.	• Key implementation technologies for digital twin:
[30]	2003.01–2018.04	50 & 8 patents	• To explore the modeling approach of digital twin.	• Basic technology: IoT, Sensor, Visualization, Data transmission, Data management, Data storage.
[31]	2005–2021.10	144	• Research and build the application framework of digital twin. • Definition of the digital twin, application areas, key technologies and challenges of implementation.	• Core technology: Data fusion, FEM, Data drive, Physical model, State model, Agent model. • Advanced technology: AI, Big data analytics, Mobile internet, Blockchain, Cloud computing. • The development of digital twins in the construction industry is still in its infancy.
			• To explore the digital twin application scenarios, and the modeling approaches in different scenarios.	• The current focus on the application of digital twins in architecture is focused on the design and engineering phase, while the demolition and restoration phases are neglected.
[25]	2010–2020	22	• To examine the application of digital twin in respective lifecycle phases of a construction project.	

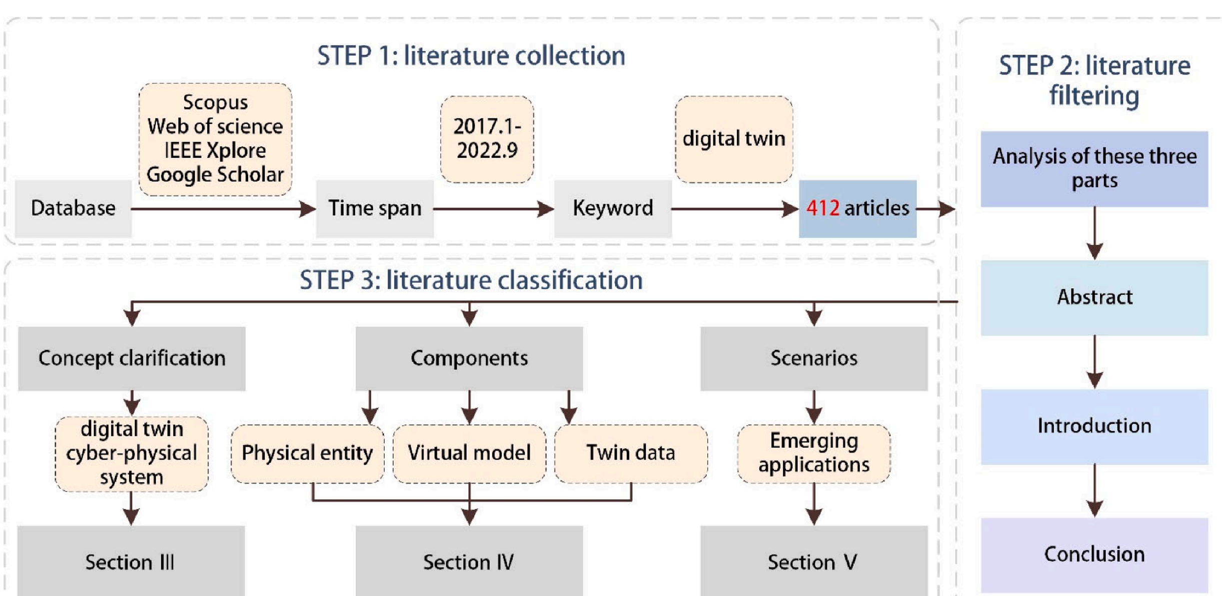

Fig. 2. Literature review methodology.

on the digital twin research approach. The research methodology of the digital twin is deconstructed, classified, and summarized in terms of physical entities, virtual models, and twin data. On this foundation, the different application areas are dissected and classified based on the application characteristics of digital twins, and the general research methodology of digital twins is summarized.

2.2. Literature review methodology

The literature review method is divided into three steps: literature collection, literature screening, and literature classification, as shown in Fig. 2.

STEP 1: literature collection. As seen in Fig. 1, the number of papers on digital twins has proliferated since 2017. Therefore, the time span of the literature collection is from January 2017 to September 2022. Select the databases as Scopus, Web of Science, IEEE Xplore, and Google Scholar. The methods of literature collection are shown in Table 2. Search for keywords to see if the digital twin is included in the titles and abstracts of the documents obtained. After screening, 412 articles containing keywords were preliminarily retained, of which the number of articles from 2017 to 2022 was 6, 11, 57, 128, 156 and 54, respectively. It can be seen that the number of digital twin articles published every year is increasing year by year.

STEP 2: literature filtering. The screening method for papers is to read the abstract, introduction, and conclusion of all documents. If these three parts of the articles contain one of the digital twin definitions, digital twin applications, physical entities, virtual models, and data, the paper is left for review, otherwise deleted. In this way, 117 documents related to the content of this article were finally screened.

STEP 3: literature classification. Classify the screened literature, read each type of paper intensively and summarize commonalities and claims.

2.3. Status analysis of digital twin research

After eliminating the irrelevant literature, 117 papers were finally obtained. To demonstrate the current status of the development of digital twins, we counted the countries and published journals of the 412 documents obtained by filtering in STEP 1, as shown in Fig. 3 and Fig. 4, respectively.

The five countries with the highest number of these papers published were China, the United States, the United Kingdom, Italy, and Germany. Among them, China issued the most articles, accounting for 30.83 %. These countries have a high level of science and technology and a specific foundation of information technology, which can provide a supportive environment for digital twins' research, development, and application. Although digital twins originated in the United States, research on digital twins in other countries shows signs of catching up. The attention on digital twin by these world powers reflects the huge stir digital twin has caused in the industry.

From the analysis of publications, the five journals that published the most digital twins among these papers are shown in Fig. 4. The *Journal of manufacturing systems* published the most articles, accounting for 11.65 %. The analysis of the publications shows that digital twins' current research and application are mainly focused on the manufacturing field. At the same time, these journals are top journals with an international reputation, which reflects that the current papers on digital twin research are not only in large quantity but also in high quality [32].

Table 2
Literature collection methods.

Searching Index	Corresponding Content
Time span	January 2017 - September 2022
Database	Scopus, Web of Science, IEEE Xplore, Google Scholar
Keyword	digital twin
Article Type	Journal papers that have been published

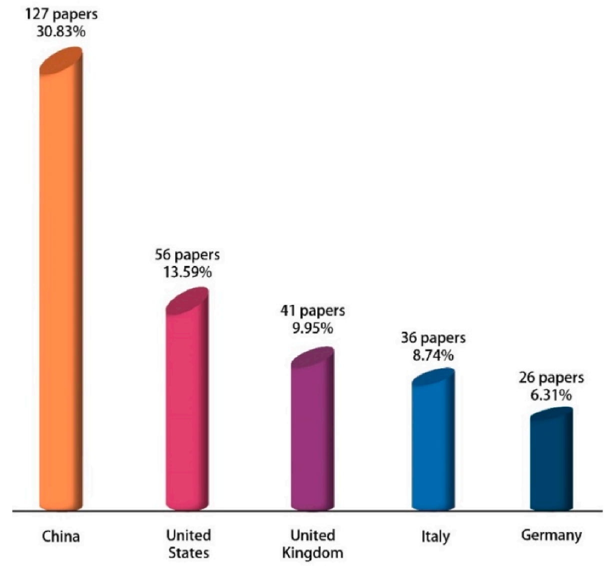

Fig. 3. Top five countries in the number of articles.

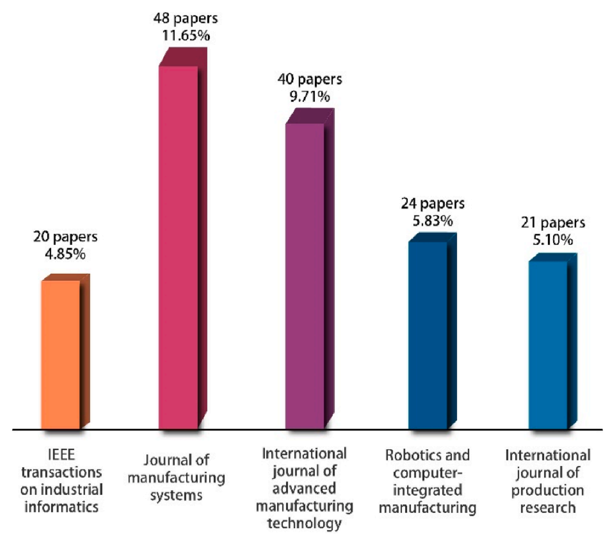

Fig. 4. Top five journals in the number of articles.

3. Concept clarification

Modern technologies such as artificial intelligence (AI), cloud computing (CC), big data analytics (BDA), cyber-physical systems, and the Internet of Things (IoT) have extensively promoted the development of intelligent manufacturing. Among these technologies, cyber-physical systems are similar to digital twin concepts and are easily confused [33].

Cyber-physical systems and digital twins have received much attention from academia, industry, and government [34]. Some scholars believe that the digital twin is a tool to implement the virtual-real interaction of cyber-physical system, and study the digital twin as part of cyber-physical systems. Zheng et al. [35] believe that digital twin technology is one of the core technologies for implementing cyber-physical systems. It is an accurate virtual copy of a physical object or system, including its properties and environment. Son et al. [36] consider that the digital twin is a virtual factory that mimics a manufacturing site, synchronizes its information and operations, and promotes the cyber-physical system's functionality by predicting the manufacturing site's future state using various analytical results. Park et al. [37] suggested a digital twin-based CPPS (cyber-physical production system) architectural framework that overcomes the performance hurdle. A digital twin-driven design and control cyber-physical system was introduced in [38] to lessen the difficulties of RCL (roller conveyor line) construction and remove faults between design and control. However, according to the definitions of digital twin and cyber physical system, they both have the ability to achieve virtual-real interaction themselves. Therefore, this section compares the definition, mapping mode, and application scenario to distinguish the relationship between the digital twin and cyber-physical system.

3.1. Definition

The concept of a digital twin was first proposed by Michael Grieves in 2003 in a product lifecycle management class at the University of Michigan [5]. The concept of cyber-physical systems originated in 2006 by Helen Gill of the National Science Foundation to describe increasingly complex systems [39]. Although digital twins were proposed earlier than cyber-physical systems, it was cyber-physical systems that received attention first, and digital twins have only developed in recent years. Tables 3 and 4 are some definitions of digital twins and cyber-physical systems in recent years. It can be seen from the definitions of both that although digital twins and cyber-physical systems have the function of interacting with the virtual world and the physical world, they are implemented in different ways. Digital twin optimizes the working state of physical entities through the simulation of virtual models [40]. In contrast, cyber-physical systems control the operation of physical equipment by analyzing the raw data collected by sensors and issuing instructions by computers. At the same time, the essential components of the digital twin are physical entities, virtual models, and twin data, while the basic elements of cyber-physical systems are the perception layer, the network layer, and the control layer. The most significant difference is that the digital twin must build a virtual model, while the cyber-physical system does not need to.

3.2. Core elements

The core elements of digital twins and cyber-physical systems are different. Cyber-physical systems enable precise control of physical processes, remote collaboration, and self-management [41]. Data is the foundation on which cyber-physical systems manage physical processes. Therefore, data acquisition equipment is extremely important for cyber-physical systems. Large-scale data acquisition with multiple sensors distributed across physical devices and environments. The collected data is analyzed and processed by a computer, and control commands are generated according to defined rules [42]. Actuators operate according to control commands in response to changes in physical processes. Therefore, sensors and controllers are the core elements of cyber-physical systems. The core purpose of the digital twin is to control, optimize and predict the working state of the physical entity through a virtual model. Digital twins use many functional models to describe physical entities, such as geometric models, physical models, and so on [43]. Digitalization and visualization of production processes through the combination of different functional models. The working data generated by the physical entity and the simulation data obtained from the virtual model together form the twin data [30]. Based on twin data, virtual models can be used to guide, control, optimize, and predict the working state of physical entities. Therefore, models and data are core elements of a digital twin.

Table 3
Digital Twin definition.

Ref.	Publication time	Definitions
[46]	2019.11	"Digital twins can be defined as (physical and/or virtual) machines or computer-based models simulating, emulating, mirroring, or "twinning" the life of a physical entity."
[47]	2020.6	"Digital Twins (DT) are defined as simulation models that are both getting data from the field and triggering actions on the physical equipment."
[15]	2020.8	"A digital twin is a digital representation of a physical asset reproducing its data model, behavior, and communication with other physical assets."
[48]	2021.7	"A digital twin is a virtual model of a physical entity, with dynamic, bi-directional links between the physical entity and its corresponding twin in the digital domain."

Table 4
Cyber-Physical System definition.

Ref.	Publication time	Definitions
[41]	2017	"Cyber-physical system is a new trend in Internet-of-Thing-related research works, where physical systems act as the sensors to collect real-world information and communicate them to the computation modules to the corresponding physical systems through a feedback loop."
[49]	2018.1	"Cyber-physical systems are physical facilities with embedded sensors, processors, and actuators controlled or monitored by computers."
[33]	2019.8	"Cyber-physical systems are multidimensional and complex systems that integrate the cyber and dynamic physical worlds."
[36]	2021.5	"A cyber-physical system is an engineering system that seeks to enhance the performance of manufacturing systems, aggregates the information of heterogeneous manufacturing elements and applications, and uses it to predict future conditions in manufacturing plants wherein abnormal scenarios occur."

3.3. Virtual reality mapping method

The matching method between physical and virtual is different. Digital twin emphasizes the one-to-one correspondence between the physical entity and the virtual model. The virtual model must have the exact structural dimensions, physical properties, assembly relationships, etc., as the physical entity. In cyber-physical systems, the computer at the network layer controls the physical devices at the sensing layer. The data obtained at the sensing layer is sent to the network layer, which analyzes it and sends control commands to the sensing layer. Therefore, the virtual-real mapping method of the information-physical system is one-to-many.

3.4. Application scenario

Both digital twin and cyber-physical systems can be applied to large industrial systems, such as aerospace and shop-floor, and realize virtual-real interaction through their respective mapping methods. However, digital twin also has applications in other areas, such as smart healthcare and smart cities. Liu et al. [44] proposed a digital twin-based cloud medical system framework that enables monitoring, diagnosis, and prediction of users' health status. Youngjib et al. [45] propose a new framework for building digital twin cities that can better understand spatiotemporal information about physical vulnerabilities for effective risk-informed decision-making. The digital twin generally has more application scenarios than cyber-physical systems.

Digital twin emphasizes the correspondence between a physical entity and its virtual model, optimizing the performance of physical entities through virtual and real data interaction. Cyber-physical systems consider biological systems composed of multiple physical devices and carry out data acquisition and processing operations from the system. Therefore, digital twins and cyber-physical systems are different technologies with different application purposes and implementation methods, and there is no inclusion relationship between them. Digital twins or cyber-physical systems should be selected according to the specific needs when applying.

4. Current development of digital twin components

The three core components of digital twins are the physical entity, virtual model, and twin data [30,50], so this section reviews the current research methods in these three sections.

4.1. Physical entities

Through the intensive reading of 117 documents, we first determine whether there is research content in the literature on one of the three parts of physical entities, virtual models and twin data. Ignoring the literature without these three parts, 88 documents were obtained. Secondly, according to the research focus, the corresponding number of documents studying physical entities, virtual models and twin data is obtained, as shown in Fig. 5. As can be seen from the figure, the most research on virtual models accounted for 45.45 %, and the slightest research on physical entities accounted for 21.59 %. This may be due to the fact that physical entities, as objects of study, are machines or devices that already exist, which leads to the neglect of the study of physical entities. However, physical entities are the basis for virtual model construction and are the source of twin data. It is essential to conduct research on physical entities.

4.1.1. Definition of physical entities

Physical entities refer to the study object ontologies and their ancillary resources. Bevilacqua et al. [51] proposed a digital twin reference model, and the physical entities consist of physical industry resources such as products, personnel, equipment, material, process, environment, and facility. Zhang et al. [52] proposed an implementation framework for the digital twin shop-floor. The physical factory they defined includes material resources, such as equipment resources, industrial robots, AGV cars, intelligent production lines, and information infrastructures, such as computer network systems, data centers, and information interaction systems. Zhang et al. [53] believe that the workshop entity refers to the physical elements that are indispensable for daily production and processing in the production workshop, including processing equipment, material transportation systems, operators, and production environments. Physical entities in a physical assembly space are defined by Sun et al. [54] as peoples, devices, components, and products. Therefore, physical entities refer not only to themselves but also to the ancillary resources such as workers, environment, and materials associated with the physical entities.

4.1.2. Selection of physical entities

Classifying the components of a physical entity facilitates the construction of accurate virtual models. When studying the physical entity ontology, it is reasonable if the products, workers, etc., associated with it are taken into account and built into virtual models, but this method may increase the difficulty of building virtual models, and at the same time, the complexity of the model will also increase. Therefore, classifying and packaging the components of physical entities is conducive to achieving accurate match modeling between physical entities and virtual models. Duan et al. [55] divided the physical entities into two parts, the equipment layer, and the test layer. The components that make up each device can be regarded as the equipment layer, such as blades, bearings, motors, etc. The test layer includes static tests and dynamic tests of the system. Dividing physical entities into multiple modules facilitates the modular modeling of virtual models and the accurate matching of virtual models to physical entities.

The usefulness analysis of the components of the physical entity is conducive to improving the modeling speed. The complexity of physical entities varies in different fields, and the elements of physical entities are analyzed to screen out parts that do not affect the model's functionality. For example, the shop-floor includes many components, not all of which need to appear in the virtual model. Only a few core components need to be modeled, and the rest can be ignored. In this way, the modeling speed is accelerated, and the complexity of the model is reduced without affecting the functionality of the virtual model.

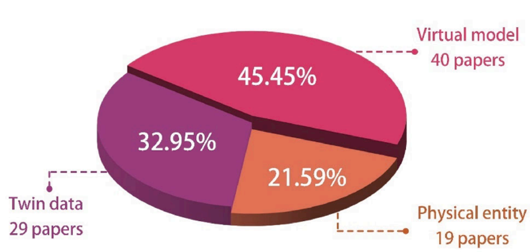

Fig. 5. Distribution of the three parts.

4.1.3. Perception of physical information

The acquisition of physical information is the focus of physical entity research, and information collection is inseparable from sensors. The acquisition of biological information importantly includes the sensing of environmental information, the sensing of worker operation information, and the acquisition of equipment working data, as shown in Fig. 6. Sensors distributed throughout the manufacturing process could enable twins to capture operational and environmental data relevant to physical processes in the real world [56].

Selection of the sensor type. Different types of sensors are used for various data acquisitions. For example, position/angle encoders for obtaining position information, current and voltage sensors for obtaining current and voltage data, and torque sensors for obtaining force information. There are also devices for sensing working conditions: vibration accelerometers, vibration displacement sensors, thermometers, microphones, acoustic emission sensors, RFID readers for code identification, energy sockets, and industrial cameras, etc., which can be used to collect the data people need to build digital twin [57].

Perception of physical environment information. Choi et al. [58] used two RGB-D sensors to reconstruct and track the working environment. A sensor scans an area of the physical environment through 3D point cloud data. The other also scans another area of the environment, tracking the user's 3D bone information.

Perception of operator information. Nikolakis et al. [59] proposed a way to identify the natural actions of operators in manufacturing systems. The Kinect v2 depth camera and an electronic glove are used to identify the operator's movements and motion constraints. The corresponding data is generated in the physical environment and then sent to the virtual model so that the virtual model can simulate the behavior of the actual operator in the virtual environment.

Perception of work data. Aivaliotis et al. [60] used the digital twin to calculate the service life of a six-axis robot. When collecting signals, in addition to the real sensors, 3 virtual sensors were constructed, because in the digital twin model simulation process, data that could not be reached by real machines was generated. Virtual sensors could monitor and collect data from various virtual parts of the device. Three virtual sensors acquire position, velocity, and acceleration signals.

4.2. Virtual model

A virtual model is a digital mirror image of a physical entity and an essential part of enabling digital twins [22]. Therefore, establishing a virtual model with a high degree of match with physical entities is the key to achieving digital twin technology. There is currently a lot of research on virtual model modeling methods, and many methods for constructing virtual models have been proposed.

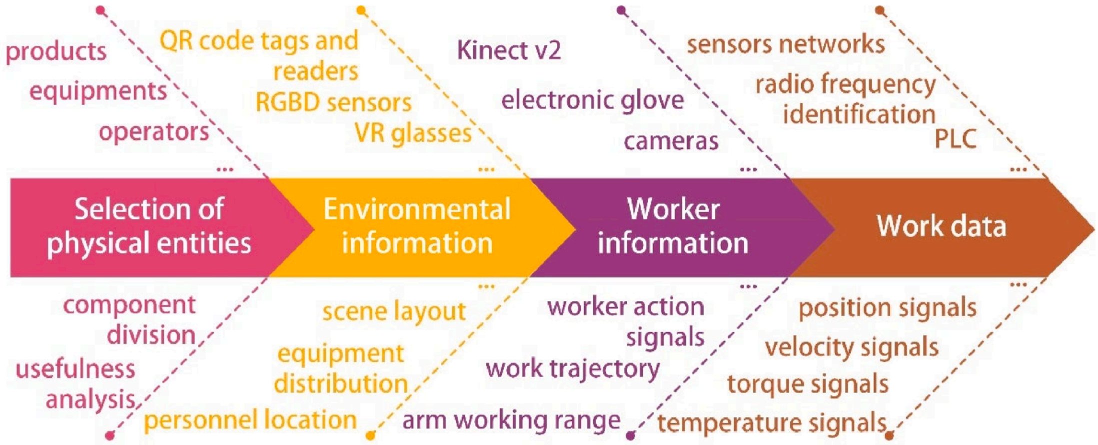

Fig. 6. Physical information perception method.

4.2.1. Modeling method paradigm

Tao et al. [50] proposed that a complete digital twin should include five parts: the physical entity, the virtual entity, the data, the service, and the connection. Professor Tao Fei proposed the digital twin five-dimensional model, which defines the components of the virtual model, namely the geometric model, the physical model, the behavior model, and the rule model, as shown in Fig. 7. This provides a research paradigm for virtual models. Most of the digital twin virtual models in research are built on these four parts.

These four parts can describe and characterize physical entities from multi-time scales and degree-space scales. Geometric models describe the geometric parameters of physical entities, and standard tools are SolidWorks, 3D MAX, CATIA, etc. The physical model adds the physical properties of the physical entity and constraints based on the geometric model, and tools such as ANSYS and ABAQUS are usually available. The behavior model describes the evolutionary behavior, real-time response behavior, performance degradation behavior, etc., of the virtual model. The behavioral models can usually be constructed using Markov chains, neural networks, and other methods. The rule model describes the laws of change in historical data and the standards and guidelines in related fields.

These four models depict physical entities from the perspective of structural dimensions, physical properties, rules, and evolutionary development, which is very comprehensive. Dividing the different properties of physical entities is conducive to accurate modeling of virtual models.

4.2.2. Modeling method variants

On the basis of the geometric model, physical model, behavior model, and rule model, some new methods for virtual model modeling are proposed.

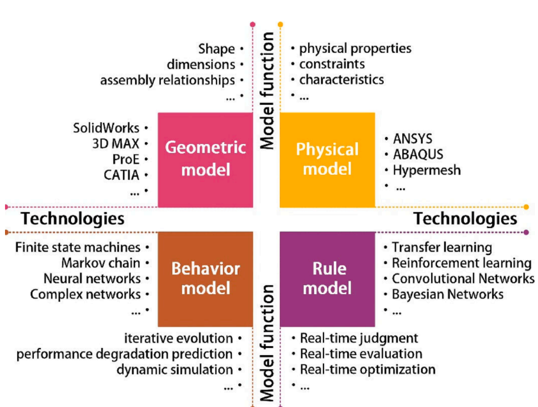

Fig. 7. Virtual model component paradigms.

Wu et al. [61] proposed a multidimensional digital twin conceptual modeling method, which describes the digital twin's composition, behavior, and rules in detail. It introduces the TRIZ function model into the five-dimensional framework and improves its system construction process. Zhang et al. [43] proposed a five-dimensional fusion model, including a geometric model (GM), a physical model (PM), a capability model (CM), a behavioral model (BM), and a rules model (RM). This five-dimensional fusion model adds an ability model to the five-dimensional model, which describes the capabilities of each entity in the physical layer, including what it can do, what it can do, what it is doing, and what it is doing. The purpose of adding a capability model is to understand the capabilities and roles of various manufacturing resources in the manufacturing system and infer them into relevant knowledge to support outcome prediction, performance evaluation, plan optimization, etc., to achieve automatic reconstruction of the manufacturing system. Liu et al. [62] proposed a biological mimicry-inspired digital twin modeling method. The proposed digital twin simulation model simulates the physical process from three aspects: geometry, behavior, and environment. In addition, the digital twin simulation model has adaptive variation characteristics that enable the synchronization of workpiece changes during machining. A six-layer digital twin model is proposed, conceptually classifying digital twin components according to their responsibilities and collaborative ways [63]. These six layers are the consumption layer, the service layer, the reasoning layer, the persistence layer, the ingestion layer, and the physical layer. Data signals are generated by the physical layer, absorbed by the ingestion layer, stored in the persistence layer, computed at the inference layer, provided by the service layer as a data service, and consumed at the consumer layer, ultimately providing the user with insights.

4.2.3. Domain-specific modeling methods

The modeling methods mentioned above refer to the general techniques of virtual model modeling and are applicable in different fields. Many scholars have focused on applying digital twins in a particular area, proposing virtual model construction methods suitable for that field.

Modeling methods in human-robot collaborative manufacturing systems. Fan et al. [64] discussed digital twin modeling of the life cycle of human-cyber-physical manufacturing systems (HCPS) and proposed a digital twin concept of "Geometry-Object-Snapshot-Topology" (GHOST). The main elements in GHOST include Geometric information (GDT), Historical samples (HDT), Object collection (ODT), Snapshot collection (SDT), and Topological constraint (TDT). GDT refers to the geometric information of a physical asset. HDT refers to historical example information about the service processes of a production system.

ODT describes the relevant properties and information of the operating objects in the manufacturing system. SDT refers to the collection of physical data and virtual data. TDT comprises the system hierarchy and relation tree of each object in a manufacturing system. This article presents GHOST as a universal reference method for the digital twin model construction of flexible manufacturing systems.

Modeling methods in CNC machine tools. Luo et al. [65] proposed a multi-field unified modeling method for CNC machine tools (CNCMT) based on digital twins, which include a sensing system, digital space, and a mapping model. In the digital space, the digital twin of the CNC machine tool (DTMT) consists of DTMT descriptive model and the DTMT algorithm model. The primary function of the description model is to describe the geometric, physical, and electrical properties of the CNCMT. The DTMT algorithm model stores and analyzes the operational state data and then uses machine learning algorithms to make decisions on the running state adjustment of the CNCMT. Due to the excellent encapsulation ability of CNCMT objects, the object-oriented modeling method is adopted for the description and algorithm models. The modeling language used is Modelica, a multi-domain unified modeling language with object-oriented characteristics. This paper establishes a multi-domain unified digital twin modeling method and explores the mapping strategy of physical space and digital space. The established digital twin model effectively reduces the probability of sudden failure of CNCMT and improves stability.

Modeling methods in product manufacturing. Zhang et al. [66] first explored the Product Manufacturing Digital Twin (PMDT), which focuses on the production phase of the intelligent shop-floor. The PMDT consists of five models: Product Definition Model (PDM), Geometry Model (GSM), Manufacturing Attribute Model (MAM), Behavioral Rule Model (BRM), and Data Fusion Model (DFM). PDM refers to product design and manufacturing information such as bill of materials, and surface roughness. GDM refers to the geometry and shape of intelligent workshop components, such as the machine tool's the length/height/width. MAM describes the non-geometric properties of smart shop-floor elements, such as energy consumption, product quality, processing methods, etc. BRM describes the behavior and rules of intelligent shop-floor elements. Behavior includes the operation activities of workers and the work activities of machinery and equipment, and the rules have material energy consumption constraints, work process constraints, etc. Add rule knowledge to modeling to promote the decision analysis capabilities of behavioral models. DFM refers to the data storage and association method of individual elements of the smart shop-floor. Compared with the digital twin five-dimensional model, this paper divides the composition of the digital twin model more accurately, and the proposed PMDT modeling method pays more attention to the description of complex element attributes and correlation relationships in the workshop, which is more in line with the needs of each element in the workshop modeling.

The analysis of the above-mentioned virtual model modeling approaches in different domains shows that although the modeling approaches in different domains are different, they are all based on the virtual model paradigm, i.e., geometric model, physical model, behavioral model, and rules model. Therefore, this paper summarizes the general steps when constructing the virtual model, as shown in Fig. 8. Firstly, the analysis is performed to determine the functions the virtual model should have. Secondly, determine whether the virtual model paradigm meets the required model functions. If it cannot be satisfied, the corresponding functional model is added. If the functionality of some models of the paradigm is useless, the paradigm model is modified, or the model is deleted. For example, in the modeling of human–machine collaborative manufacturing systems, the function of Topological constraint (TDT) is added to the model to reflect the system hierarchy and relationships between different objects in the manufacturing system.

4.2.4. Dynamic update of virtual models

The working state of physical entities is constantly changing. In order to make predictions about the operational state of physical entities, the virtual model must have the ability to update the model parameters continuously. From the literature, it is found that using Bayesian networks to give virtual models the ability to update dynamically is a more applied method.

Dynamic Bayesian networks have shown good application in fault diagnosis and prediction, which can track and correct the evolution of time-varying variables and predict the probability of future failures. Ye et al. [13] proposed a digital twin framework for spacecraft structural life tracking. The proposed framework consists of two parts: the offline phase and the online phase. Under this framework, the crack propagation model with uncertain parameters is integrated with the observed crack data using the dynamic Bayesian network. The model parameters and crack length predictions are updated. Li et al. [67] used the dynamic Bayesian network to establish a probabilistic model for aircraft wing fault diagnosis and realized the accurate diagnosis and prediction of cracks. Yu et al. [68] proposed a digital twin model based on a nonparametric Bayesian network to represent the dynamic degradation process of health conditions and the propagation of cognitive uncertainty. A real-time model update technique is provided, which improves the model's flexibility by using enhanced mixed models of Gaussian particles and Dirichlet processes.

4.3. Twin data

The sources and categories of twin data are diverse and can generally be divided into physical and virtual data [69]. Physical data refers to the data generated during the work of a physical entity, which is collected by different sensors. Virtual data is generated during the operation of a virtual model. Because physical and virtual data are different formats, it is essential to study data exchange protocols that link physical and

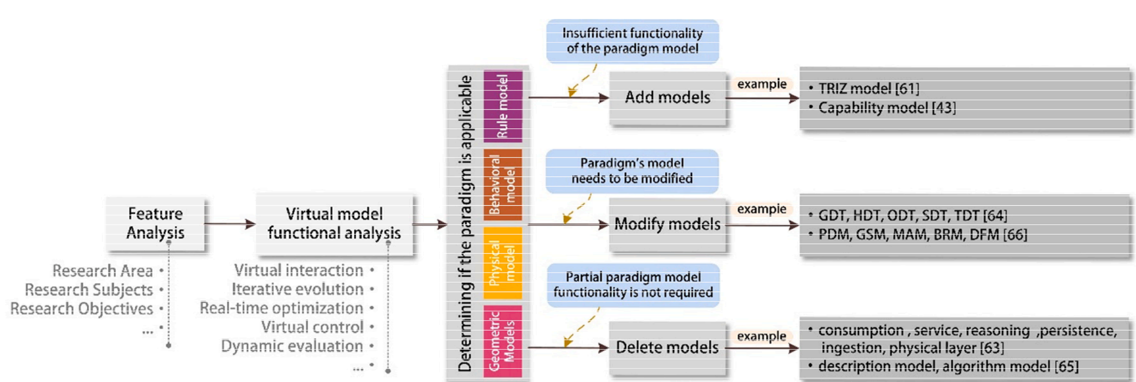

Fig. 8. General steps of virtual model construction.

virtual data. At the same time, the data acquisition method and processing process are also the difficulties of twin data research. This section provides an overview of data acquisition methods and data exchange protocols.

4.3.1. Data acquisition methods

This section summarizes several methods of collecting twin data obtained through literature reading.

Sensors are the most commonly used to collect data. Kong et al. [70] proposed a data construction method that provides stable and efficient data support for applying digital twin systems. The shop-floor digital twin data construction framework consists of four parts: the data representation, the data collection, the data organization, and the data management, as shown in Fig. 9. The data representation module refers to the hierarchical representation of manufacturing data and the character representation of the application. The data organization module contains data customized processing and Data pre-processing. The data management module consists of a database and the corresponding storage and retrieval policies. First, the raw data is collected by the sensor, DAQ (data acquisition), and RFID (radio frequency identification) under the guidance of the data representation module. After that, the data is processed in the data management module, and the cleaned data is stored in the database. Finally, the appropriate information is sent to the top-level application through data customization processing.

Blockchain can be used for digital twin data acquisition. Huang et al. [71] proposed a method for obtaining data for product digital twins based on blockchain technology. The product life cycle data is recorded on the blockchain, and the digital twin data at a specific time can be queried on the blockchain. In addition, a shared network is built where each participant can send data directly over the network to the requestor, which improves the efficiency of data sharing.

Programmable Logic Control (PLC) could receive and send data from the machine. Wang et al. [72] detailed how to obtain the data of conventional devices, as shown in Fig. 10. The operational data is read in real-time by PLC and displayed on the human–machine interface (HMI). The PLC and the human–machine interface are connected via CN1 cable. The digital dashboard receives data from the HMI, and the HMI supports Ethernet to exchange data with the digital dashboard. The communication protocol between the digital dashboard and the human–machine interface is Modbus TCP/IP, which uses the Ethernet protocol for data exchange to meet real-time and reliability requirements. The data on the machine dashboard can be stored in the database in real-time, while the data stored in the database can also be accessed and displayed on the digital dashboard.

4.3.2. Data exchange protocol

The operational data of physical entities collected by sensors cannot be used directly in the virtual environment due to different data formats [73,74]. At the same time, the virtual data produced by the virtual model cannot be transferred directly to the physical entity. The data exchange protocol is the key to realizing virtual and real data interaction, and a proper data interaction protocol must be chosen [75]. Currently, the leading transmission technologies include mainstream industrial bus protocols: Industrial Internet, Profinet, Profibus, Ethernet, EtherCAT, etc. In addition, the general wireless transmission method can be divided into WIFI, Bluetooth, Zigbee, and so on [76]. Table 5 summarizes the data conversion protocols in these papers, and several are analyzed.

TCP/IP protocol is a connection-oriented, reliable, byte-stream-based transport layer communication protocol that can accommodate hierarchical hierarchies that support multi-network applications. Bai et al. [83] proposed a data transmission principle. The sensor signal is collected by the data collection card and sent to the computer via the USB port. The computer/other network devices then send the data to the cloud server via the TCP protocol, which saves the data as a data file. Finally, the data are read, updated, analyzed, and calculated in real-time by MATLAB to realize the information interaction between the physical entity and virtual model, and the principle is shown in Fig. 11.

OPC UA is an open standard for horizontal communication from machine to machine and vertical communication from device to the cloud, which provides a beneficial basis for digitalization. Luo et al. [65] proposed a multi-domain unified modeling method of a digital twin for the CNC machine tool, which includes a sensing system, digital space, and a mapping model. The mapping method was designed according to the OPC UA standards in this research. The mapping model server consists of four layers, as shown in Fig. 12. The physical interface layer implements the compatibility of different interfaces such as RS485, RS232, Wi-Fi, Bluetooth, and Can. The protocol driver layer provides a standardized read-and-write technique for various interfaces. The data parsing layer is responsible for data processing for various

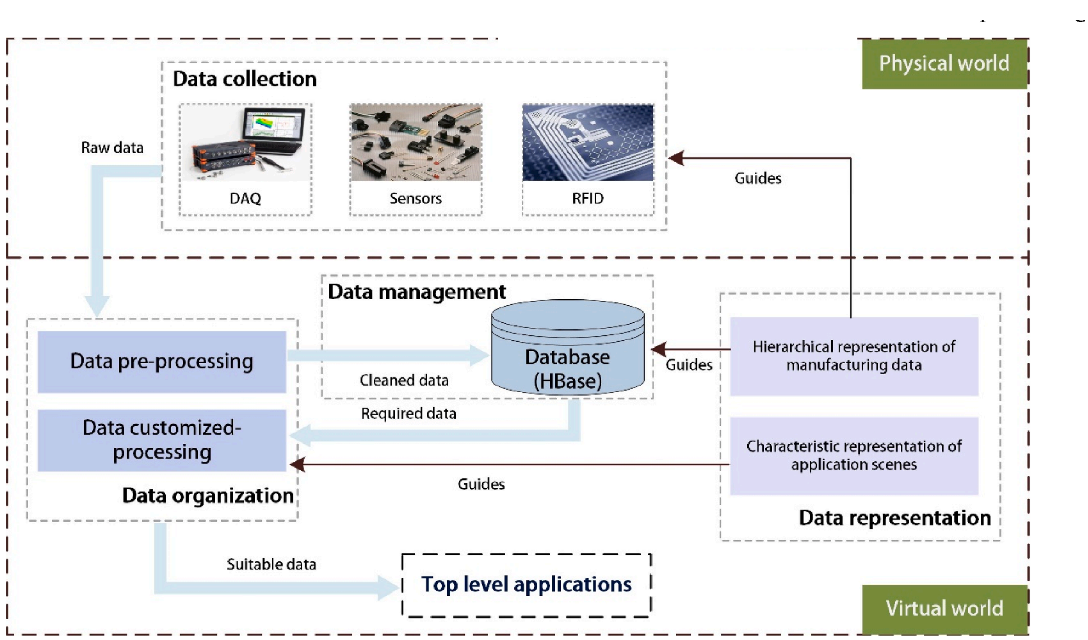

Fig. 9. Framework of data construction method for workshop digital twin [70].

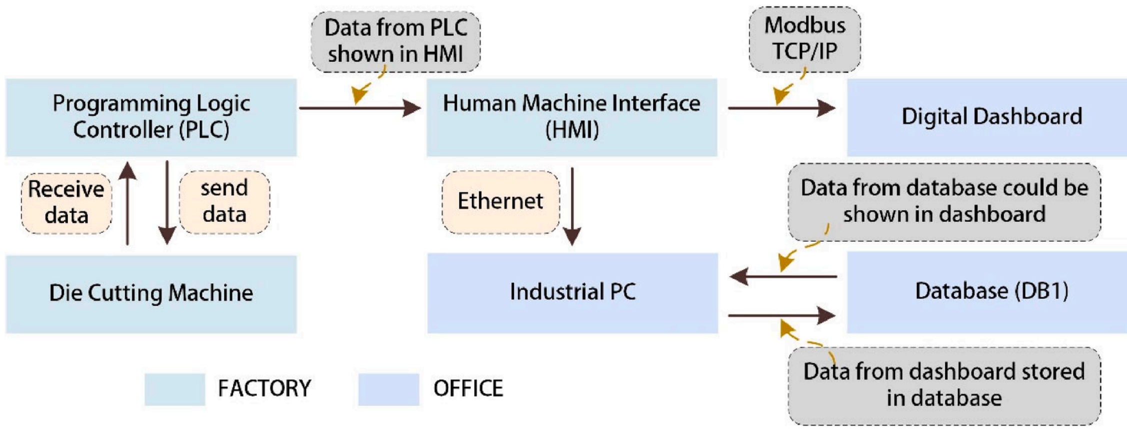

Fig. 10. Data acquisition process.

Table 5
Partial data exchange protocol.

Ref.	Protocol name	Description
[72]	TCP/IP	A transmission control/network protocol, also known as a network communication protocol. It is the most basic communication protocol in the use of the network.
[77]	MQTT (Message Queue Telemetry Transport)	A "lightweight" communication protocol based on the publish/subscribe model, built on the TCP/IP protocol. The biggest advantage of MQTT is that it can provide real-time and reliable messaging services for connecting remote devices with very little code and limited bandwidth.
[78]	AMQP (Advanced Message Queuing Protocol)	An application-tier standard advanced message queuing protocol that provides Unified Messaging services, is an open standard for application-layer protocols designed for message-oriented middleware.
[65]	OPC UA (OPC Unified Architecture)	OPC UA is an OPC unified architecture that can better realize factory-level data acquisition and management, historical data access, and interactive communication of complex data.
[79]	oneM2M	A set of specifications for machines-to-machines in the Internet of Things that enable all devices to communicate with M2M application servers by creating a common M2M service layer.
[80]	XMPP (Extensible Messaging and Present Protocol)	An xml-based instant messaging transport protocol
[81]	MTConnect	A data transmission protocol for CNC machine tools
[82]	Automation ML (Automation Markup Language)	An XML-based automated description language designed to interconnect various engineering tools

communication protocols. The information model layer uses a data mapping dictionary to turn various types of data into information. The data mapping dictionary contains precise information regarding CNCMT data, such as standard data element definitions, meanings, and allowable values.

MTConnect is an interconnection communication protocol between CNC equipment and is specifically used for the interconnection of machine tools. Tong et al. [84] proposed a framework diagram of the data transformation based on the MTConnect protocol for the CNC system. The framework is shown in Fig. 13. After retrieving the data, the data is cleaned and pre-processed. The adapter converts the data into a standard format and sends it to the MTConnect agent. the MTConnect adapter can be designed separately in the sensor or CNC system, providing different sets of interfaces for different data transfers. Based on the information model created by the agent, the data is interpreted and converted, and the converted information is integrated into the terminal or database for the customer's use.

5. Digital twin application scenarios

With intelligent manufacturing, all walks of life are developing in the direction of intelligence, digitalization, and visualization, and digital twin technology is the key technology to achieve this goal. After 20 years of development, the concept and technology of digital twins have gradually improved, and the application fields have extended from manufacturing to the service industry, agriculture, commerce, etc. In order to analyze the application of digital twins in various fields, 412 articles were first screened according to whether the research content was related to digital twin applications, and 193 articles were obtained. Secondly, since there are only 1 or 2 documents in some fields, 193 documents are divided with 3 documents as the threshold, and 16 application areas are finally obtained. It is shop-floor, city, product design, predictive operations, robotics, monitoring, fault diagnosis, manufacturing systems, logistics transportation, medical, assembly management, aerospace, power plant, scheduling systems, CNC machine tools, and quality control. The number of articles in these 16 areas is shown in Fig. 14.

5.1. *Application classification of digital twin*

As can be seen from Fig. 14, the number of articles published in workshop, city, and product design is relatively large, with 25, 22, and 20 articles, respectively, which is a hot area of digital twin research at present. In order to find the characteristics of the digital twin in different application areas and to obtain general rules, this section analyzes and compares the application purposes and model characteristics in different areas. And finally divides digital twin application into three phases, i.e., the design phase, the operation process phase, and the dynamic interaction phase, as shown in Fig. 15. Firstly, the digital twin is used in the design phase to simulate and verify the design results. Secondly, real-time optimization and interaction are performed during operation, such as fault diagnosis and energy consumption optimization. Finally, visualization and dynamic interaction of the working results are realized to facilitate people's work.

5.1.1. *Design phase*

Application purpose: The design phase refers to using digital twin virtual models to simulate and verify product design results or to redesign and optimize the structure of critical components of physical entities to improve efficiency of physical entities. The main application areas are product design [55,85–88], structural design [89–92].

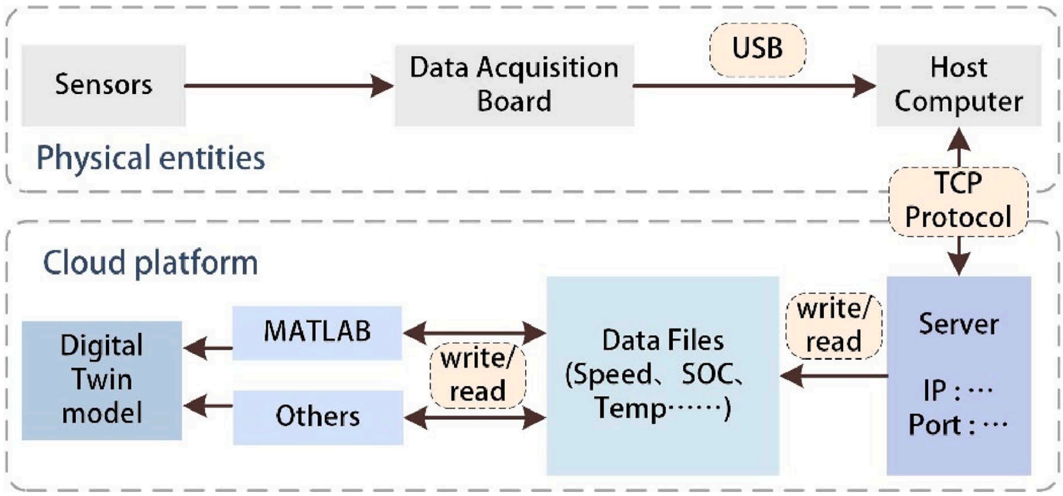

Fig. 11. Cloud platform data transmission principle.

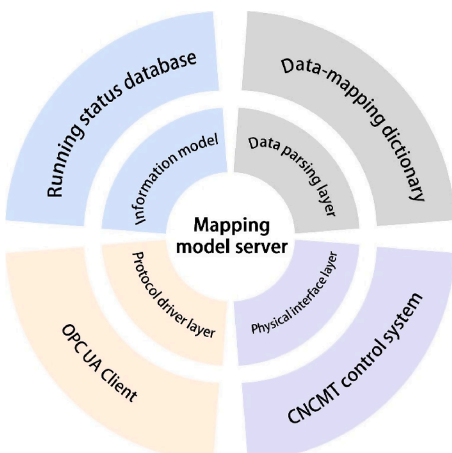

Fig. 12. DTMT mapping strategy.

The model features: The digital twin model constructed during the design phase should be able to describe the physical entity or system accurately and in detail. At the same time, the structural dimensions need to be identical between the virtual model and the physical entity in real-time. Therefore, the digital twin model should have the characteristics of accuracy and dynamic consistency. Accurate models can reduce the accumulation of model errors, thus effectively avoiding the severe problems caused by iterative amplification of model errors in structural refinement design.

5.1.2. Operation process phase

Application purpose: The operation process phase refers to the use of the iterative evolution ability of digital twin models to predict the future working state of physical entities. The representative application areas are fault diagnosis [93–98], predictive operations [99–105], medical [48,106–110], quality control [111–113], and other fields.

The model features: The digital twin model in the operational process phase should be able to be updated iteratively based on physical data to improve the decision-making and evaluation capabilities of the model continuously. Therefore, the digital twin model in the behavioral domain should have evolvable and reconfigurable features.

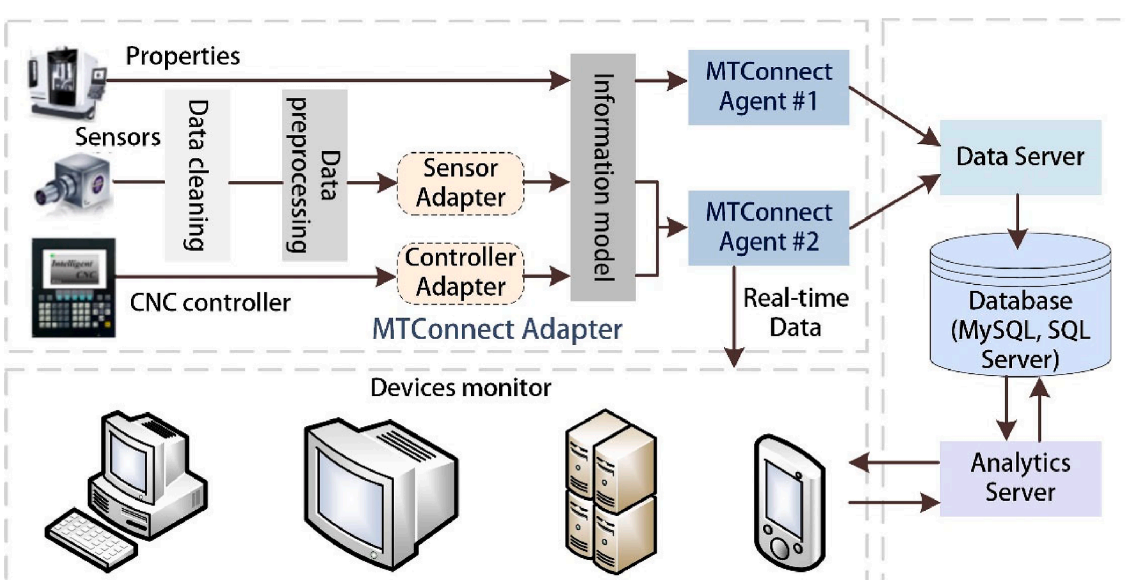

Fig. 13. Data transformation under the MTConnect protocol [84].

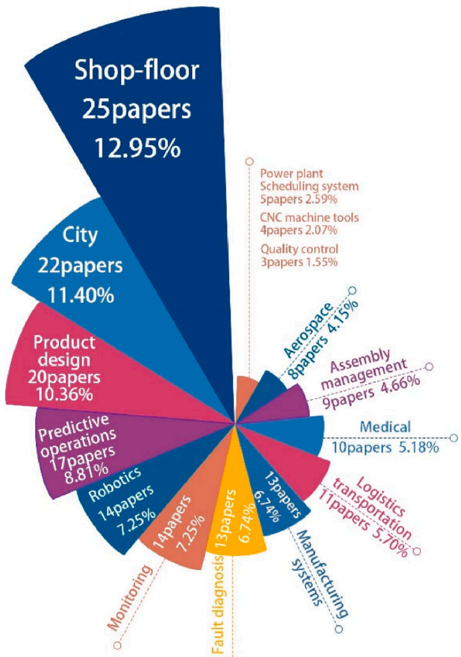

Fig. 14. The number of articles published in different areas.

5.1.3. Dynamic interaction phase

Application purpose: The dynamic interaction phase refers to the digital twin virtual model to visualize the running state of physical entities or to optimize and interact in real-time during operation. The typical areas are workshop [114–121], city [122–127], monitoring [68,128–130], manufacturing systems [131–133], power plants [134–137], etc.

The model features: Digital twin models in the dynamic interaction phase focus on data interaction and storage methods between virtual models and physical entities. At the same time, the operation and interaction process of the virtual model should be observed by the user to facilitate the user's in-depth operation of the model. Therefore, the digital twin model in the dynamic interaction phase should be guaranteed to have the characteristics of interoperability and visualization. The interactive and visualized digital twin model facilitates the visual monitoring of the working conditions of physical entities and the efficient collection and transmission of virtual and real data.

The division of these three application phases provides a reference. It does not mean that a particular field belongs to only a specific stage, which may involve two phases in a certain area, or all three phases are included. Therefore, the division of application phases can help to understand the characteristics of the research field and thus determine the features that the digital twin should have to build the digital twin model according to the steps in Fig. 8.

5.2. The emerging applications of digital twin

In the course of the literature survey, in addition to the application areas shown in Fig. 14, some application areas are currently less studied but are very promising. This section analyzes the current state of research in these promising application areas and summarizes the general characteristics of digital twins in these fields.

5.2.1. Digital twin in food

Food process modeling is becoming more mature with the development of multi-scale, multi-stage, multi-physical methods. The digital twin is used to increase productivity, reduce waste and improve traceability when answering questions related to food security, changing and diverse needs, climate change, sustainability, and consumer demand.

Digital twin enables monitoring, control, and prediction of food quality. The freshness of food is the key to food quality, which is related to the environment in which it is located. Food preserved in low-temperature environments has better freshness and less energy loss. Environmental factors that affect the freshness of food are temperature, humidity, light, etc., which can be monitored by wireless sensors and synchronized with the obtained data in the virtual environment so that the virtual model of food is in the same environment as real food. In order to grasp the decay law of food and predict the decay of food, in addition to environmental impact factors, it is more important to study the biochemical degradation reaction inside the food so that the virtual model of food can simulate the biochemical degradation reaction. Defraeye et al. [138] developed a digital twin of fruit based on mechanical modeling. Based on the measured ambient temperature, a digital twin model of the food was constructed, simulating the thermal behavior of the mango. At the same time, a temperature-sensing device corresponding to the real mango was developed for model verification of pulp temperature. The thermal behavior of the artificial fruit sensor device is very similar to that of natural fruit, and its temperature is distributed within the data range of real fruit. Digital twin mangoes also can iteratively evolve, providing predictions for enzyme-driven, temperature-dependent biochemical degradation reactions.

Digital twin facilitates the control of food processing lines. In the case

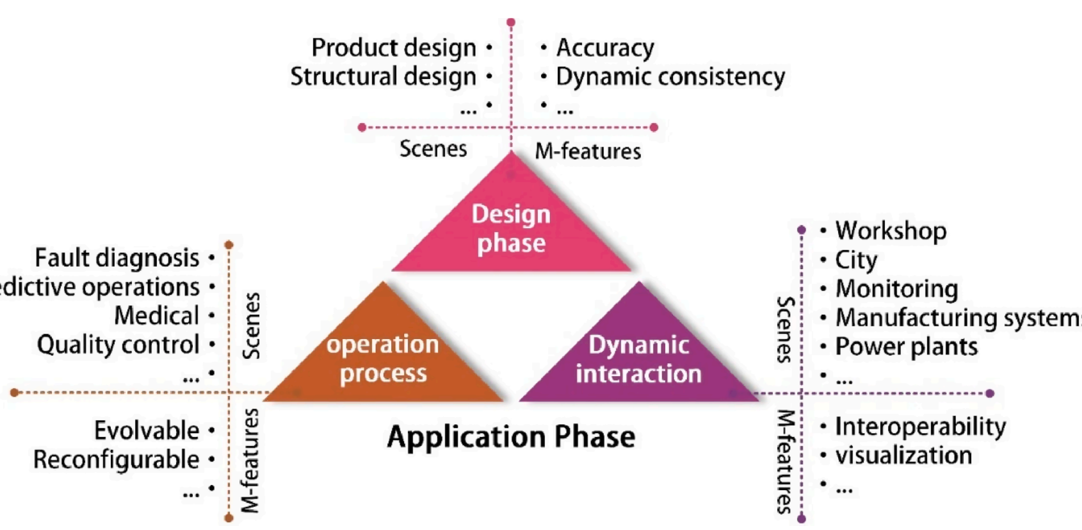

Fig. 15. Application segmentation and model features.

of changing environmental conditions, the digital twin can predict whether the quality loss occurs during food processing and where it occurs. In this case, the digital twin can help reduce food losses, making the food processing process greener. Verboven et al. [139] proposed a food processing process control method based on digital twins. The method includes three main elements: food process operation, virtual replica of food process operation, and IoT platform. IoT platforms provide the necessary framework and tools for integrated sensor communication. The data collected by the sensors during food processing is used to drive the operation of the virtual model of the food process operation. Running the virtual model of the food process operation and the actual process provides real-time output for process control related to the production process and operation.

5.2.2. Digital twin in agriculture

Agriculture is a complex and uncertain field. The production process is dynamic because crops are affected by natural conditions such as weather, soil, etc. Farmers must always pay attention to the growth of crops and intervene in emergencies. In addition, farmers need to be responsible for the management and operation of the farm, constantly evaluating production strategies to adapt to changing market conditions.

Digital twin facilitates process management on farms. The use of digital twin to plan, monitor, control, and optimize farm management is currently-one of the directions in which digital twins are presently applied in the agricultural field. Using digital twins as a means of farm management, farmers can remotely manage operations based on digital information without relying on direct observation and on-site manual tasks. This allows farmers to take immediate action when deviations occur and simulate the effects of interventions using virtual farm models based on real-world data. Verdouw et al. [140] proposed a conceptual framework for designing and implementing digital twin agriculture, including a control model based on a common systems approach and an IoT-based implementation model characterized by timeliness, fidelity, integration, intelligence, and complexity. This allows farmers to monitor and simulate the effects of interventions and to control objects remotely via actuators.

Digital twins can be used for the growth process management of crops. In agriculture, the digital twin can be applied not only to farm management but also to control crops' growth process. Establish digital twin crop models, grasp crops' real-time growth, determine whether they are malnourished, and provide guidance on crop harvesting. Kampker et al. [141] implement the digital twin on potato harvesting. When an operator harvests potatoes using a harvester, the operating parameters of the machine are set based on the previous year's data and each operator's "intuition". In this case, the productivity of each device is highly dependent on the operator's experience, there is no standardization at all, and it is easy to damage the potatoes., Kampker et al. built a digital twin model of potatoes, a plastic product that weighs and measures the same as real potatoes and is equipped with sensors to detect collisions and rotations to reduce the amount of damage to potatoes at harvest time. The data is analyzed in real-time on the harvester at harvest time and presented to the machine user. Operators adjust the operating machine in real-time based on the data received to increase the harvester's productivity and ensure the potatoes' integrity.

Digital twin agriculture is still in its infancy, with many difficulties. The environment in which crops are located is dynamic, and how to ensure the integrity of data is crucial to building digital twin farms. At the same time, to achieve digital twin agriculture, good network signal and comprehensive network coverage are necessary, but network coverage in rural areas is limited, so how to achieve real-time synchronization is a problem that needs to be solved.

5.2.3. Digital twin in oil

With the development of digital technology, the oil and gas industry has also combined a series of digital technologies with traditional methods to improve oil and gas production efficiency.

Digital twin plays an essential role in improving oil and gas production efficiency. The oil and gas production process is multi-tasking and complex, involving many disciplines. Establish a digital twin virtual model of the oilfield to participate in all aspects of the entire life cycle, such as early design guidance, monitoring and optimization of the operation process, and fault diagnosis and prediction. Shen et al. [142] established a digital twin model for oil and gas production. The oil and gas production digital twin model includes six parts: physical entity, virtual model, data acquisition, intelligent algorithm, service, and interactive control, and each element is connected and driven by twin data. Case studies show that the efficiency of the oil and gas production model system based on the digital twin has increased by 3 %.

The digital twin can help understand the storage, flow, and unique transport mechanisms of unconventional reservoirs. Zhang et al. [143] designed a digital twin model of an unconventional reservoir. Numerical simulation and analysis of representative mechanisms affecting the production of unconventional reservoirs such as capillary, dynamic adsorption and salinity injection are used by virtual models, and the influence of these mechanisms on the flow phenomenon of oil reservoirs is simulated and illustrated by combined with multi-scale algorithms.

5.3. Other digital twin applications

In addition to applications in food, agriculture, and oil and gas, digital twin technology is also used in some areas, as shown in Fig. 16. Although digital twin research in these areas is not much at present, it is fascinating and contributes to the diversification of digital twin application areas.

The digital twin can be used for indoor safety management. Liu et al. [144] applied digital twins to indoor safety management construction and proposed an indoor safety management system framework. The framework leverages Building Information Modeling (BIM), the Internet of Things (IoT), and the Internet to build a building interior security digital twin. BIM provides safety-related building information and 3D geometric models. Indoor operation information is collected in real-time through IoT sensors, and data is stored on the Internet. SVM automatically classifies and grades indoor hazards through the mining of safety data. The framework provides a good way for indoor safety management to improve the level of intelligence in indoor safety management.

The digital twin can be used to help understand a person's personality. Sun et al. [145]focus on the digital twin issue to predict users' personalities. In this study, a person's personality is understood through the representation of a virtual person, which refers to the content and liking behavior of users on social networks. A method for predicting

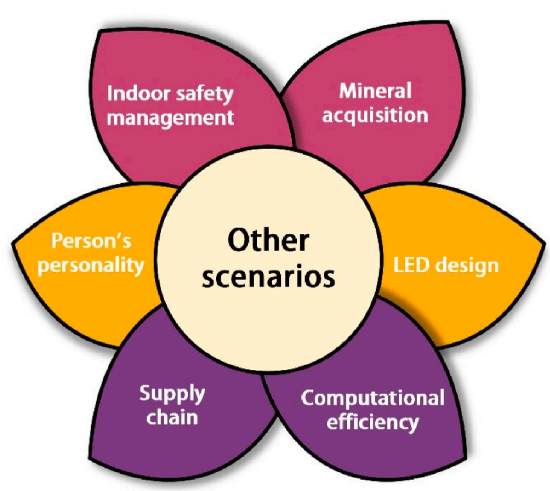

Fig. 16. Other application areas for digital twins.

individual personality traits based on deep learning is proposed. Predict the user's big five personalities by the state content and liking behavior posted by the user. This work integrates different types of data through digital twins, providing a reference for identifying human personality traits.

The digital twin can be used for the supply chain management. Saucedo et al. [146] applied digital twins in the supply chain. This study describes a supply chain decision-making tool based on the digital twin concept. The goal is to share information among supply chain stakeholders to increase visibility into products and processes. The tool integrates facility siting models, linear mixed integer optimization models, and dynamic simulation techniques for hypothetical multi-scenario analysis.

The digital twin can be used for computational efficiency offloading. Dai et al. [147] applied digital twins to the Industrial Internet of Things (IIoT), proposing a digital twin network that leverages the real-time status of monitoring devices and base stations to create a virtual model of the IIoT. A random computational offloading and resource allocation problem with the optimization goal of long-term energy efficiency minimization is established through a virtual model, which effectively improves the data processing efficiency of IIoT devices.

The digital twin can be used for LED design. Schans et al. [148] applied the digital twin technique to the LED process and constructed an LED digital twin model. The results show that using digital twins can significantly reduce the design time while maintaining the required accuracy.

The digital twin can be used for mineral resource acquisition. Maksim et al. [149] proposed a digital twin-based approach for phosphorus production and processing, using the digital twin's virtual simulation function to optimize resource consumption during phosphorus production and processing.

It can be seen from the areas mentioned above that digital twins have powerful application capabilities. We can infer from this that digital twins may be applied to various industries in the future. The reason is that in the digital era, the concept and capability of virtual-real interaction are needed in any industry.

6. Observations and recommendations

By analyzing the current research status of the definition, modeling methods, and applications of the digital twin, some observations were obtained, and some suggestions were made.

6.1. Digital twin Concept: Gradual diversification

The digital twin and the cyber-physical system are different technologies. With the development of the digital twin, the difference between the digital twin and the cyber-physical system is becoming more and more evident. At the same time, with the increase of digital twin application fields, digital twin definitions have shown diversified development. For example, Hubert et al. [150] proposed a Digital geo-Twin - a virtual, semantic 3D replica of all elements and objects of the city. The authors chose to add the prefix geo to the digital twins to emphasize the author's concerns about geodetic and geometric aspects when creating semantic geographic objects for the digital twins. The concept of digital twins is an aspect that deserves to be explored in depth. Physical entities, virtual models, and data are fundamental components of the digital twin. On this basis, researchers in different industries have given a new definition of the digital twin according to the needs of industrial applications, that is, a variant of the digital twin. While this is conducive to increasing the diversity of digital twin concepts, most of the proposed definitions of digital twin are not universal. Therefore, in future research, whether it is possible to obtain a more detailed and general digital twin definition according to the classification of digital twin application scenarios to guide the construction of digital twin models is a direction worth thinking.

6.2. Virtual Model: The core of modeling

Virtual models are the most studied, followed by data and the slightest physical entities. The construction of virtual models is the core of the digital twin, and the research on virtual models mainly focuses on the division of its components and the definition of the functions of each part.

The composition of virtual model is generally composed of functional models that reflect the relevant properties of physical entities and the functions that the author expects the virtual model to achieve. Standard functional models are geometric models, physical models, behavioral models, and rule models. Geometry models describe the geometric dimensions of physical entities, and the definition of the virtual model composition includes geometric models in most articles. Physical models refer to the physical properties of physical entities, and some articles combine physical models with geometric models into one model, while others do not. Behavioral models generally embody the predictive capabilities of virtual models. The rule model represents some evolutionary laws, expert knowledge, etc. These two models do not have a high appearance rate of geometric and physical models, and researchers will modify them according to the application needs of their field. For example, change the rule model to Historical samples [64], or discard the behavioral model and the rule model and add an algorithmic model [65].

In addition to considering virtual models and data, physical entities are also areas that should be focused on in digital twin modeling. Should there be a criterion for the selection of physical entities? Can solid physical components that are not related to the purpose of the study be discarded? These questions can provide a direction for future research on physical entities.

6.3. Digital twin applications: In the conceptual application stage

The application of digital twins in some traditional intelligent manufacturing fields has been very mature, and there is a lot of related research. The emergence of the digital twin has injected vitality into some common industrial areas and promoted the intelligent transformation of the manufacturing industry.

Due to the excellent decision analysis capabilities, the digital twin is also gradually applied to some new fields, such as the food industry, agriculture, and other non-traditional intelligent manufacturing fields. The continuous expansion of digital twin applications reflects the vitality of digital twins. However, although the application field of the digital twin is very extensive, most of the application areas are only the application of digital twin theoretical concepts, and there is still a certain distance to achieve the guidance, optimization, and prediction of the working state of physical entities through virtual models. At the same time, there is a lack of criteria for judging whether a particular field is suitable for digital twin applications. Due to the advanced nature of the digital twin concept, researchers in various fields want to apply digital twin technology to their own areas, creating the illusion that digital twin technology can be used in any field, but this is incorrect. The digital twin is a multidisciplinary technology that integrates machinery, computers, etc. When applied to specific applications, it is necessary to consider the necessity and feasibility of implementing digital twins within a particular field.

The future application areas of digital twins will likely be more extensive after the full implementation of 5G technology. At the same time, the advantages of digital twins will be more obvious.

6.4. Other recommendations

6.4.1. Accelerate modeling and reduce model weight

The current research on digital twin modeling only focuses on the establishment of the digital twin model, and the model's construction speed, the model's lightweight, and the model's accuracy are not taken into account. Speeding up modeling and reducing the model's weight is conducive to saving human and material resources. Consequently, in future research, how to speed up modeling and improve the model's lightweight degree without affecting the model's function is a reference direction for digital twin modeling.

6.4.2. Combination of digital twin and ML/DL

Artificial intelligence harnesses the power of computers and machines that mimic human thinking to solve problems and make decisions. Machine learning (ML) and deep learning (DL) are two enabling technologies for artificial intelligence. Alexopoulos et al. [151] provided a systematic methodology for establishing digital twin-driven ML-based AI applications in manufacturing. This method replaces the work of real-world dataset generation by generating a virtual dataset in a virtual model in digital twins. Virtually created datasets enable efficient ML model development that can further enrich real-world datasets through DT-CPS communication channels. Creating appropriate training datasets through digital twin virtual models and simulating toolchains to automatically tag datasets to accelerate the training phase in ML/DL and thus reduce user engagement during training is worth exploring direction. At the same time, virtual models must use a large amount of data to achieve iterative evolution, and ML/DL is also based on data-training network models. Therefore, it is possible to use ML/DL technology to accomplish the iterative evolution of virtual models.

6.4.3. 3D point clouds facilitate virtual model building

The construction of digital twin virtual models currently adopts the method of 3D modeling. The structural shape of the virtual model is first built on 3D modeling software, such as SolidWorks, 3D MAX, etc. The virtual model created by this method is highly accurate and matches the physical entity well. However, when the physical entity structure changes, the constructed virtual model cannot dynamically update its structural dimensions as the physical entity changes. The virtual model can only be modified manually, which is time-consuming. 3D point clouds are one of the most important representations of 3D data, and point clouds can retain the original geometric information in 3D space. It has been used in three-bit reconstruction, instance segmentation, and three-dimensional object detection. Therefore, whether it is possible to obtain the 3D point cloud data of physical entities through lidar, cameras, and other equipment to achieve the construction of digital twin virtual models is also a direction worth exploring.

7. Conclusion

The digital twin is in a rapid development phase, and various research types are arising. At the same time, the digital twin study is becoming more profound and specific. This article reviews 117 papers related to digital twin concepts, component research methods, and application areas from 2017 to 2022. And some observations and recommendations are made. The main contributions of this work are as follows:

1) It clarifies the digital twin's definition, characteristics, and application scenarios by analyzing the difference between the digital twin and the cyber-physical system.
2) It reviewed the research methods of physical entities, virtual models, and twin data. The types and methods of physical information acquisition are summarized. The general steps of virtual model construction based on the virtual model paradigm are presented. The methods of twin data acquisition and data exchange protocols are summarized.
3) It summarizes the popular application areas of the digital twin. According to the characteristics of digital twins in different fields, the application areas of digital twins are roughly divided into three phases: the design phase, the operation process phase, and the dynamic interaction phase. The application potential of the digital twin is explored through some emerging application areas, which boost the promotion and application of digital twin.

Overall, despite the proliferation of digital twins, research on digital twins is still in the early stages of rapid development. From the literature review, it is clear that due to the diversity of application domains, researchers have proposed a wide variety of digital twin reference frameworks and developed different digital twin components with various implementation tools. This indicates that the current research on digital twins lacks industry consensus and is challenging to conduct systematic research. Therefore, it is urgent to establish a common software platform for multi-domain digital twins that integrates model construction, testing, and implementation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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