Advanced Engineering Informatics 62 (2024) 102592

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Review article

A review of digital twin capabilities, technologies, and applications based on the maturity model

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ARTICLE INFO

Keywords:
Digital twin
DT
Maturity model
Digital twin capabilities
Technologies and applications

ABSTRACT

The advanced stage of Industry 4.0 is characterized by the integration and interaction between physical and virtual spaces, and Digital Twin (DT) technology, congruent with this vision, has garnered extensive attention and has undergone large-scale implementation. Yet, in the practical implementation of Digital Twin projects, several issues persist: ① How to formulate reasonable task objectives and action plans before project implementation? ② how to determine and assess the development level of the digital twin during project implementation? ③ How to evaluate the effectiveness of digital twin after project completion and how to enhance improvement in the next steps? Consequently, a methodological model is urgently needed to evaluate the development process of Digital Twins, offering a benchmark for their design, development, and appraisal. To address these issues, this paper introduces a five-level Digital Twin Maturity Model (DTMM), which systematically aligns DT capabilities, phased objectives, and technical requirements within a unified framework, creating a theoretical system capable of assessing DT's developmental level and specifying its construction trajectory. Further, this paper catalogs supporting tools aligned with the technical specifications stipulated in DTMM's functional capabilities, aiding developers in devising implementation strategies. Additionally, it scrutinizes the application status across six DT vertical sectors, conducts maturity evaluations, and confirms the efficacy of the proposed model. The conclusion can be drawn that DT is still in its embryonic phase. This work aspires to assist project managers and public policymakers gain a more objective understanding of Digital Twin, offering references to facilitate their positive development and broader implementation.

1. Introduction

As Industry 4.0 swiftly proliferates, digital transformation and intelligent enhancement emerge as pivotal tools for unleashing productivity, a viewpoint now universally acknowledged by nations in contemplation of their future growth. Viewed from a particular standpoint, the incremental advance of Industry 4.0 resides in enhancing the interplay and amalgamation between virtual and physical realms, building upon the foundation of the digital revolution. The concept of Digital Twin (DT), aligning with this vision, has consequently attracted extensive interest from both academic and industrial sectors. An examination of Fig. 1 reveals a marked escalation, commencing in 2017, in the volume of publications related to DT. Concurrently, Gartner, an eminent global IT research and advisory firm, has consistently positioned the DT as one of the top ten strategic technologies for three years running, beginning in 2017[1–3]. Lockheed Martin[4]and The Intelligent Manufacturing Alliance of CAST Member Societies[5] have identified DT as among the most promising digital technologies in their published research reports. The predilection for DT in academic and industrial circles chiefly stems from its intuitiveness relative to constructs like cyber-physical systems and asset management shells, enhancing its comprehensibility among professionals across various disciplines and thus promoting broader market acceptance and dissemination. Simultaneously, the advancement of big data analysis, cloud computing, IoT, and AI furnishes substantial technical backing and bolsters market confidence for DT's efficacious deployment.

However, alongside the extensive practical application of DT across various industrial sectors, there are still common issues as follows:

- Before initiating a project, what strategies can be employed to devise a viable DT implementation plan and an actionable roadmap?

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https://doi.org/10.1016/j.aei.2024.102592
Received 26 December 2023; Received in revised form 15 April 2024; Accepted 6 May 2024
Available online 10 May 2024
1474-0346/

- Throughout the project's execution, what methods can be utilized to identify and evaluate the developmental stage and proficiency of DT, both in one's realm and in other sectors?
- Following the project's completion, how can the efficacy of the DT project be ascertained, and the direction for future improvements be determined?

The challenges mentioned above can primarily be ascribed to the absence of comprehensive, methodical approaches for characterizing and appraising the functionalities, capabilities, and evolutionary phases of DT. Consequently, entities such as government departments and business organizations, being key stakeholders in DT, find it challenging to accurately identify the current developmental stage of DT technology and the actual progression status across different industries. They face difficulties in assessing whether existing DT solutions align with their business requirements and in evaluating the competencies, investment returns, implementation timelines, and construction results of DT. Furthermore, the diverse technological paths and varied product configurations provided by DT suppliers necessitate the evaluation of methods for grading and certifying the proficiency of DT projects, which can efficiently foster product distinction and facilitate the assimilation of insights as well as the advancement of development paradigms.

Consequently, addressing the previously mentioned challenges, this article presents the Digital Twin Maturity Model (DTMM), segmenting DT maturity into five distinct levels. The DTMM systematically describes the conceptual domain, capabilities, and developmental progression of DT. It integrates the objectives and tasks of each level with the capability demands and associated enabling technologies. This facilitates a comprehensive assessment of the present capability level and developmental stage of DT. It offers guidance to project managers for appraising project risks, delineating work objectives, and comprehending technical challenges. Thus aiding pertinent stakeholders in gaining an objective comprehension of DT and in bridging the cognitive divide between the actual product and the envisaged vision. The aspiration is that this work will furnish a reference for activities like communication, evaluation, and optimization in DT implementation, thereby facilitating the high-quality progression of the DT.

The remaining sections of this research are structured as follows: Section 2 delineates the study's methodology, reviewing and analyzing extant comprehensive works on DT; Section 3 explicates the detailed development process of the proposed DTMM; Section 4, aligns with the capability and technical requirements of DTMM's levels, enumerates DT's enabling technologies, frameworks, and tools; Section 5 assesses the stages and levels of development in various vertical application areas via DTMM; Section 6 summarizes the current challenges faced by DT and potential future research directions; The final section presents conclusions. Table 1 provides a list of abbreviations used in this article.

2. Research methodology and related works

2.1. Methodology

In this study, the paper primarily employs a Systematic Literature Review (SLR) methodology, focused on identifying the core research themes, evolutionary context, pertinent authors, and publications in the current realm of DT, while also collating application scenarios and associated enabling technologies across various sectors. To facilitate an efficient search of literature and publications, a search strategy was developed, as detailed in Table 2:

Table 1
List of Acronyms.

Acronym	Description	Acronym	Description
DT	Digital Twin	SoS	System of Systems
DTMM	Digital Twin Maturity Model	AFRL	Air Force Research Laboratory
SLR	System Literature Review	IDT	Implicit Digital Twin Model
DES	Discrete Event Simulation	DestinE	Destination Earth
ABM	Agent-based Modeling	IDEAS	Integrated Digital Earth Analysis Systems
HMI	Human-machine Interaction	CDT	Cognitive Digital Twin
AR	Augmented Reality	LLM	Large Language Model
VR	Virtual Reality	ISO	International Organization for Standardization
DTW	Digital Twin Workshop	IEC	International Electrotechnical Commission
UWB	Ultra-Wideband	NIST	National Institute of Standards and Technology

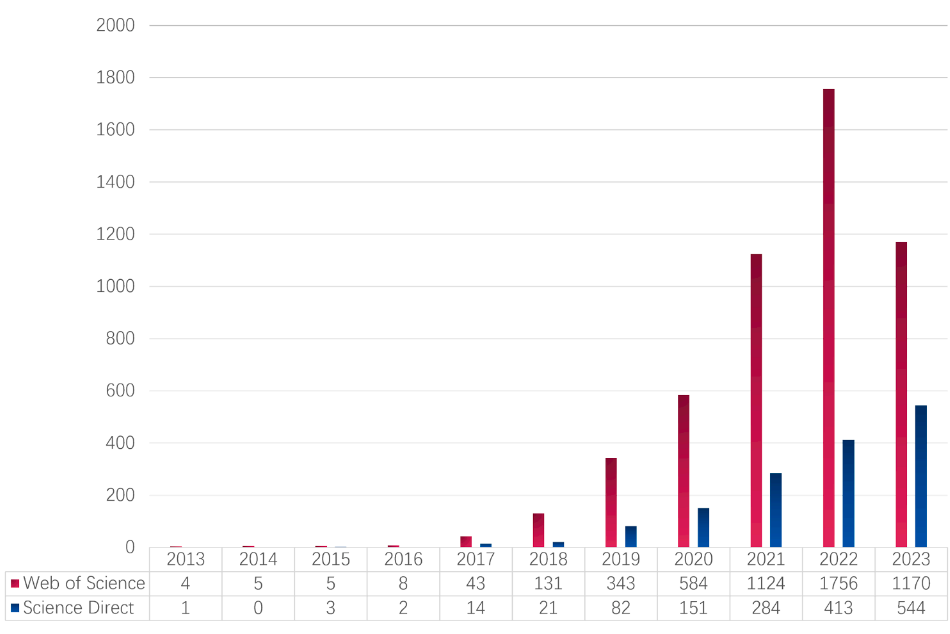

Fig. 1. Number of papers published per year during the digital twin growth stage.

Table 2
Retrieval index of the literature review.

Search index	Contents
Search string	("digital twin" OR "DT" OR "DTs") AND ("definitions" OR "characteristic" OR "capability" OR "technologies" OR" applications") AND ("maturity" OR "classification" OR "levels")
Time span	January 2018- August 2023
Database	ScienceDirect, Web of Science, IEEE Xplore
Literature type	Scientific article

The methodology for the literature review in this paper encompasses three stages: collection of literature, screening of literature, and categorization of literature, illustrated in Fig. 2.

First Step: Literature Collection. Illustrated in Fig. 2, the quantity of papers concerning DT has exhibited a remarkable surge since 2018. Consequently, the timeframe for literature collection spans from January 2018 to August 2023. Databases such as Web of Science, IEEE Xplore, and ScienceDirect have been chosen. Subsequently, guided by the retrieval strategy, searches are conducted utilizing predefined keywords to ascertain the presence of "DT" in the titles and abstracts of the acquired literature. Following meticulous screening, an initial corpus of 396 articles containing relevant keywords has been preserved, with the distribution of articles from 2018 to 2023 being 11, 18, 57, 118, 156, and 36 respectively. Notably, it is discernible that, excluding 2023, the quantity of DT-related articles published annually is progressively escalating.

Second Step: Literature Filter. The methodology for paper selection involves scrutinizing the abstracts, introductions, and conclusions of all collected papers. Papers are retained for review if any of these sections encompass discussions on DT definitions and characteristics, DT applications and case studies, DT enabling technologies and supporting tools, or DT models and descriptions; otherwise, they are discarded. Consequently, a total of 119 papers relevant to the subject matter were ultimately screened.

Third Step: Literature Categorization. Thoroughly peruse papers of each typology, synthesize commonalities, core research themes, and propositions, and classify the screened literature accordingly.

Following the exclusion of irrelevant literature, a final set of 119 papers was obtained. To gain deeper insights into the current landscape and prospective trends in the industry of DT, this study conducted a comprehensive statistical analysis of the collected literature samples.

2.1.1. Keywords analysis

To further understand the current state and future trends of industry research on DT, this paper conducted statistical analysis on the collected literature samples. Keywords serve as condensed representations of the main content of the literature and can reveal the current frontiers and trends of DT-based research. For each paper in the collected sample, keywords were extracted and the quantities of each keyword were tallied. Semantic similar and duplicate keywords were merged. As shown in Fig. 3, the top 15 keywords (excluding "Digital Twin") are displayed. From the Fig. 3, it can be seen that the background of DT-related research is largely aimed at responding to Industry 4.0 and digital transformation. In terms of application areas, research outcomes and implementation cases in smart manufacturing and smart cities are predominant. Regarding enabling technologies, research focuses on modeling and simulation of DT, with many researchers utilizing technologies such as artificial intelligence, the Internet of Things, big data, cloud computing, and visualization to construct DT. From the perspective of DT functionality, optimization, prediction, maintenance, decision support, and remote control are focal points for many industries and organizations. Additionally, many papers discuss the value of DT in realizing cyber-physical systems, as it has the potential to revolutionize traditional manufacturing paradigms.

2.1.2. Major journals analysis

This paper analyzes the types of publications in the literature sample, revealing that journals account for 61.2 %, conferences for 30.1 %, and books, reports, and electronic resources for 8.7 %. Furthermore, the publication volume of major journals with a significant number of DT publications is depicted in Fig. 4. It is evident that research and applications of DT are primarily concentrated in the manufacturing industry, with a substantial number of publications also in the fields of computer science and information technology. At the same time, these journals and conferences are all internationally renowned top-tier publications and conferences, reflecting the fact that current research papers related to DT are not only numerous but also of high quality.

2.2. Related works

This paper investigates existing survey articles on DT, uncovering

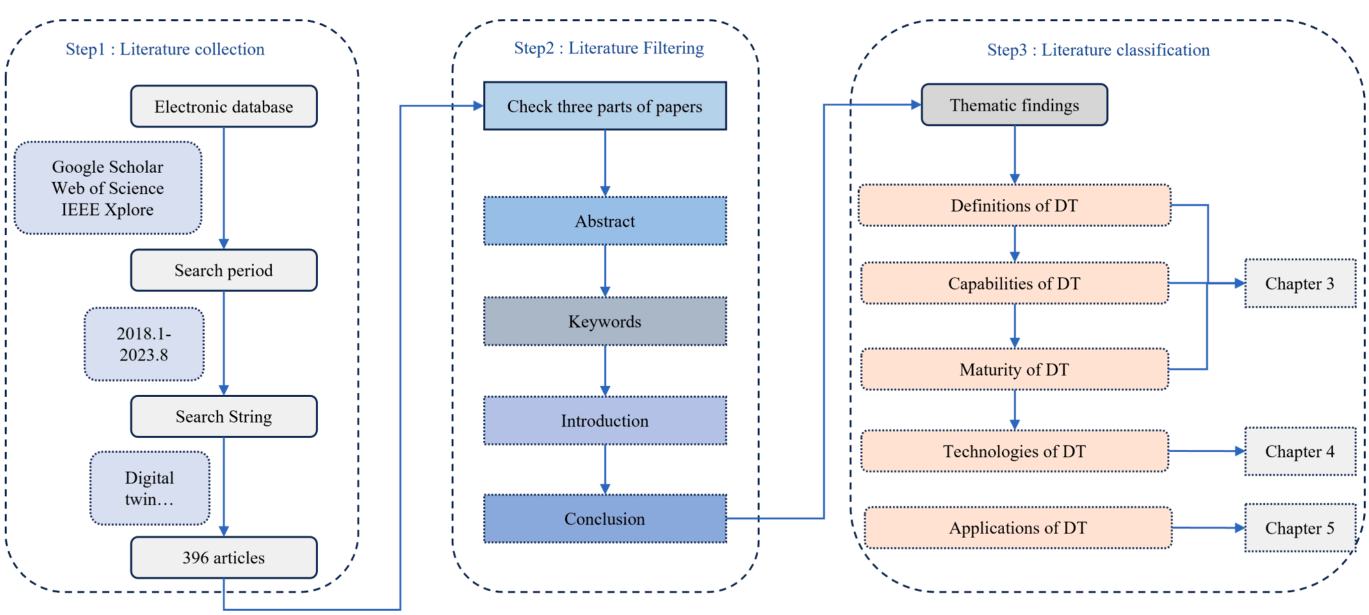

Fig. 2. Literature review strategy.

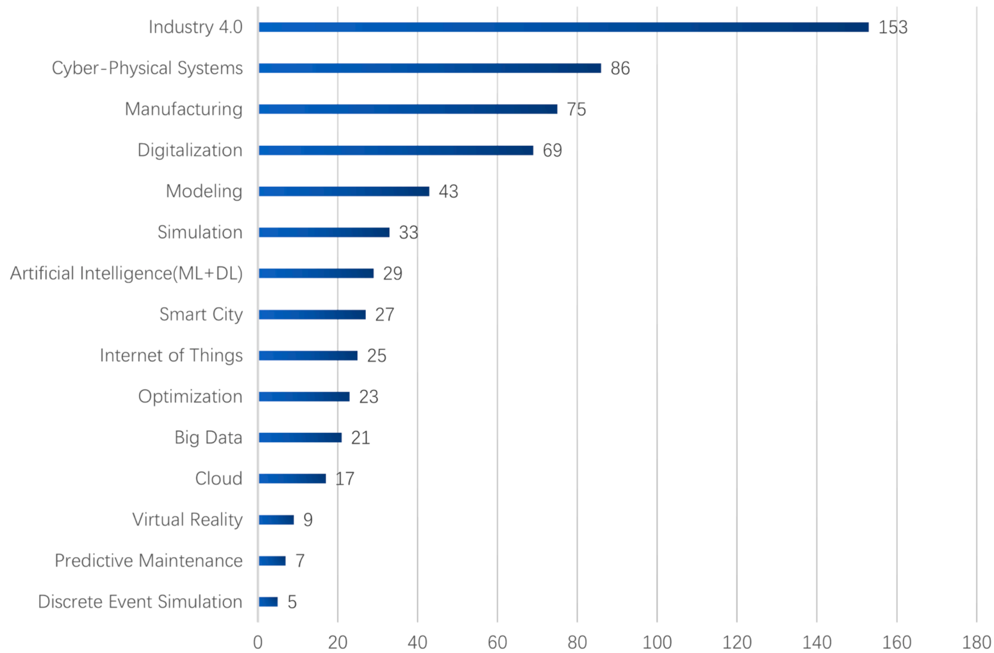

Fig. 3. The number of mentions of keywords by publication authors (excluding digital twin).

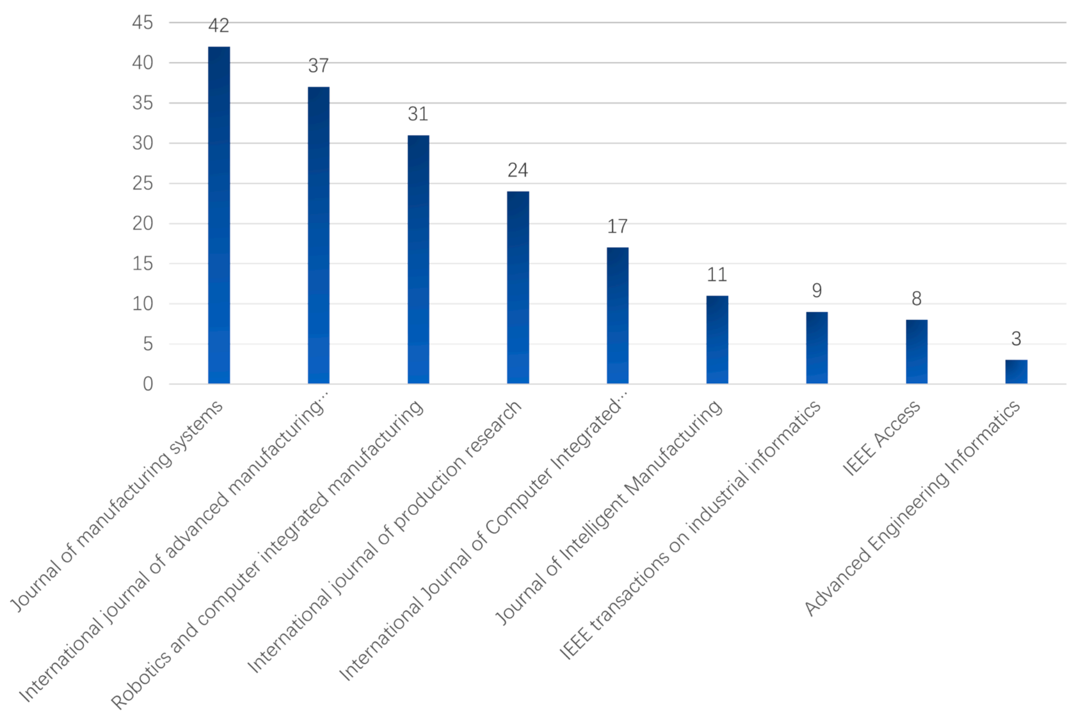

Fig. 4. Distribution of publications among the main journals in the sample.

that these primarily delve into DT's fundamental concepts, inherent attributes, application contexts, and developmental prospects. The findings can generally be classified into three categories: the first category encompasses the consolidation of DT's definition, meaning, core elements, and diverse traits; the second category involves comparisons between DT and similar technologies, like CPS, digital shadow, digital thread, etc.; the third category pertains to the exploration of DT application scenarios across different industries, along with a range of enabling technologies and tools. Furthermore, this paper analyzes and compares the research content of these survey articles, as shown in Table 3.

Table 3 reveals that although numerous studies and explanations exist regarding DT's definition, capabilities, applications, and enabling technologies, these efforts do not amalgamate DT's capabilities, task objectives, technical tools, and developmental status across industries into a unified framework for systematic analysis. This results in developers being unable to effectively ascertain DT's capabilities, construction direction, and the actual developmental state of various industries. It also hinders stakeholders from effectively evaluating project risks, and technical challenges, establishing phased task objectives, and formulating actionable strategies and implementation plans. To rectify this research gap, the paper introduces a five-tier Digital Twin

Table 3
Comparison between this survey paper's contents and other related works.

Ref.	definition	capability	maturity	technology	application	challenge
Barricelli[6]	✓✓	✓✓	×	×	✓	✓
Jones[7]	✓	✓✓	×	×	✓	×
Fuller[8]	✓	×	×	✓	✓	✓✓
Hu[9]	✓	✓	×	✓✓	✓	✓
Singh[10]	✓✓	✓✓	✓	×	✓	✓✓
Qi[11]	✓	✓	×	✓✓	✓	×
Singh[12]	×	×	×	✓	✓✓	×
Botin-Sanabria[13]	✓	✓	✓	✓	✓✓	✓
Liu[14]	✓	✓	×	✓	✓	✓✓
Minerva[15]	✓	✓	×	✓✓	✓	✓
He[16]	✓	×	×	✓	✓	✓
This survey	✓✓	✓✓	✓✓	✓✓	✓✓	✓

(✓✓– in-depth coverage of the subject; ✓– partial coverage of the subject; ×– subject not addressed.).

Maturity Model (DTMM), aiming to assist project decision-makers and public policy designers in gaining a more objective understanding of DT and facilitating its higher-quality proliferation and deployment.

3. Digital twin maturity model

The maturity model represents a stratified methodological paradigm for delineating the evolution of an entity, affording stakeholders within a specific domain a lucid and unequivocal framework for communication, effectively culminating in the establishment of a harmonized value system. DT maturity refers to the relative level of a DT's development at a certain point in time compared to its ideal state. The DTMM is a theoretical model used to assess the relative level between the DT's current state of development and its ideal state. his model systematically describes the conceptual scope, capability requirements, developmental process, stage objectives, and improvement directions of the DT, effectively evaluating its current level of development and capabilities.

The construction process of the DTMM is divided into two steps: (1) Aggregating and synthesizing various definitions and interpretations of DT to extract its components, functional competencies, and characteristics; (2) Drawing upon DT's functional and capability requisites, as well as previous work in maturity, refer to relevant standards and the design experience of maturity models in other disciplines, clearly divide the levels of DTMM, and systematically describe the work objectives, capabilities, and technical requirements that each level should achieve. This forms a structured maturity description framework of progressively advancing twin capabilities.

3.1. Capabilities of digital twin

The DTMM is a framework for the continuous progressive development of twin capabilities, where higher stages offer more functions and stronger capabilities, but also come with increased technical complexity and difficulty. Therefore, the primary task in the design and development of the DTMM is to comprehensively organize and summarize the functions and capabilities of DT. In the definitions of DT, there is generally some interpretation of the connotations, characteristics, functions, capabilities, and goals, thereby allowing the extraction of DT's capabilities from these definitions.

Although the standardization efforts related to DT lag behind the market's development, it is heartening to note that ISO released standards on the concepts and terminology of DT towards the end of 2023, namely ISO/IEC 30173–2023[17]. However, to comprehensively summarize the descriptions of DT capabilities, this paper has attempted to compile the definitions and explanations of DT provided in existing literature across various domains as comprehensively as possible, as depicted in Table 4, aiming to derive the foundational capabilities and functionalities of DT.

3.1.1. Differences between DT and traditional digital model

As indicated in Table 4, experts across various domains interpret DT based on their perspectives and business characteristics. Yet, there is a consensus on virtual modeling capabilities, simulation capabilities, and bidirectional communication abilities. These also constitute the "minimal concept" of DT. DTs endowed with these capabilities inherently possess the functional traits of closed-loop feedback control and full lifecycle management.

The most important and fundamental distinction between DT and conventional digital models lies in the dynamic nature of DT. This dynamism manifests as real-time changes in the DT synchronized with the variations occurring in the physical objects it represents, evolving and aging alongside them. This characteristic is referred to as the real-time self-evolution of DT. Additionally, DT entail a more stringent requirement: the aspiration for them to form a closed loop with physical objects. This implies that analyses and decisions made based on the twin should be fed back to the physical object in real-time, thereby influencing its behavior.

Indeed, a consensus among scholars and the wider community posits that DT should possess enhanced intelligence and capabilities for large-scale integration. Constructing a multi-twin integrated platform that crosses domains and systems, on a grand scale such as the coupled twin systems of nature-human-society, to achieve autonomous reasoning, prediction, decision-making, and optimization. Treating natural and human social systems as a unified whole for multi-scenario simulation, deduction, and demonstration, providing more comprehensive and rational decision-making advice for stakeholders. In this context, DT is no longer just a digital technology, but a grand scientific apparatus.

In summary, DT is conceptualized as follows: A DT is a virtual representation of a physical entity, perpetually evolving through iterative data exchanges with its physical counterpart, thereby maintaining congruence throughout its entire lifecycle. Leveraging the virtual model and associated data, DT autonomously engages in analysis, simulation, deduction, forecasting, and diagnostics, channeling the outcomes of these simulations back to the physical entity. Furthermore, multiple DTs can be integrated to perform deductions, scenario validations, and policy decisions on a larger scale. Thus, the physical object, virtual model, and various autonomous activities based on the virtual model, along with the feedback loop, constitute a complete cyber-physical system, As shown in Fig. 5.

3.2. Description of DTMM

Drawing from the aforementioned consolidation of diverse DT definitions, it is inferred that DT encompasses capabilities like virtual modeling, simulation, two-way communication, human–machine interaction, intelligence, and integration, along with functional characteristics of full lifecycle management and closed-loop control. This underpins the robust delineation of capabilities at each level of the DTMM. To enhance the comprehensiveness of DTMM's capability

Table 4
The various definitions of digital twin are found in the literature.

Capability	No.	Definitions
Virtual, replica	1	A digital twin is a computerized model of a physical device or system that represents all functional features and links with the working elements. [18]
	2	A digital twin is a digital representation of a physical item or assembly using integrated simulations and service data.[19]
	3	A dynamic virtual model of a system, process, or service. [20]
	4	PE refers to the physical entity, VE is the virtual equipment, SS stands for services for PE and VE, DD refers to DT data, and CN is the connection among PE, VE, SS, and DD. [21]
Two-way communication	5	Avatar of a real physical system that exists in the computer. While a computer model of a physical system attempts to closely match the behaviors of a physical system, the digital twin also tracks the temporal evolution of the physical system. [22]
	6	A physical manufacturing system can be represented in near real-time in the digital world using feedback from sensors in the system to modify the digital model. [23]
	7	Multi-physical, multi-scale, and probabilistic simulation model of a complex product. It uses updated sensors and physical models to mirror physical life in the digital world and vice versa. [24]
	8	Provides a clear and feasible way to realize the functions of CPS. It is a data and model-based system modeling method that emphasizes the simulation synchronization of the physical world and cyber world. [25]
	9	A digital model is a dynamic representation of an asset and mimics its real-world behaviors. DT is built on data. [26]
Simulation	10	Development of big data analytics, faster algorithms, increased computation power, and amount of available data enables the simulation with the ability of real-time control and optimization of products and production lines. [27]
	11	Using a digital copy of the physical system to perform real-time optimization. [28]
	12	Digital Twin is a simulation-based systems engineering. [29]
Interaction, closed-loop control	13	The digital twin is a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information, and can forecast the future of the corresponding physical counterpart. [30]
	14	A system that couples physical entities to virtual counterparts, leveraging the benefits of both the virtual and physical environments to the benefit of the entire system. [7]
	15	A continuous interactive process between the physical manufacturing factory and a virtual digital factory. [31]
	16	Integrated multi-physics, multi-scale, multi-disciplinary attributes with real-time synchronization, faithful mapping, high fidelity, and the ability to implement the technical means of interaction and integration between the world and the information world. [32]
Full lifecycle	17	A digital twin is a virtual instance of a physical system that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle. [20]
	18	A digital informational construct about a physical system could be created as an entity on its own. This digital information would be a 'twin' of the information that was embedded within the physical system itself and be linked with that physical system through the entire lifecycle of the system. [33]
	19	multiphasic and multiscale simulation model that mirrors the corresponding physical twin, allowing the extension of the simulation to all life cycle phases of the system. [34]
Intelligence	20	DT's services should enable it to be self-adapting, self-regulating, self-monitoring, and self-diagnosing, or, in other words, self-evolving. [35]
	21	DT uses real-time data from IoT sensors and other sources to enable learning, reasoning and automatically adjusting for improved decision making. [36]
	22	A Digital expert or copilot can learn evolve, and integrate different sources of information for the considered purpose. [37]
	23	DTs with augmented semantic capabilities for identifying the dynamics of virtual model evolution, promoting the understanding of interrelationships between virtual models, and enhancing decision-making. [38]
	24	Digital Twin is a digital representation of a physical system that is augmented with certain cognitive capabilities and support to execute autonomous activities; comprises a set of semantically interlinked digital models related to different lifecycle phases of the physical system including its subsystems and components and evolves continuously with the physical system across the entire lifecycle. [39]
Integrated system	25	A digital twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin. [40]
	26	A digital twin is a set of virtual information that fully describes a potential or actual physical production from the micro-atomic level to the macro-geometrical level. [41]
	27	a model where each product is also directly connected with a virtual counterpart. [42]

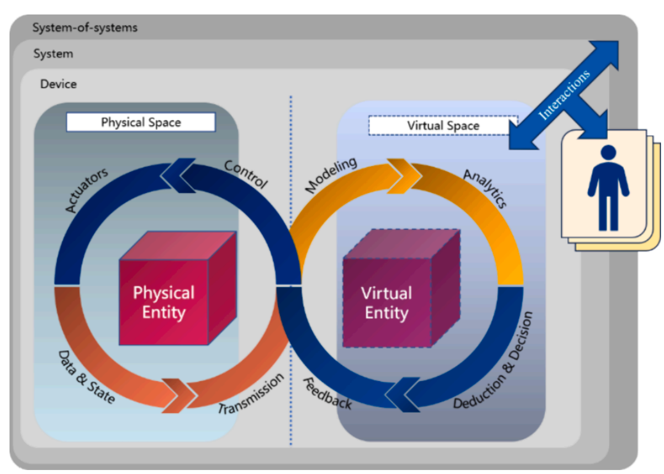

Fig. 5. Digital twin conceptual model.

description, ensure continuity in developmental stages, and clarify task objectives, this study revisits prior contributions in DT maturity. Based on previously identified requisite capabilities of DT, data management capability is incorporated. Subsequently, the predecessors' work is scrutinized and contrasted from the perspective of these seven capabilities, as depicted in Fig. 6.

The research presented in Fig. 6 sufficiently demonstrates that many researchers have recognized the importance of maturity models for high-quality DT practice[20,43–52]. Notwithstanding the employment

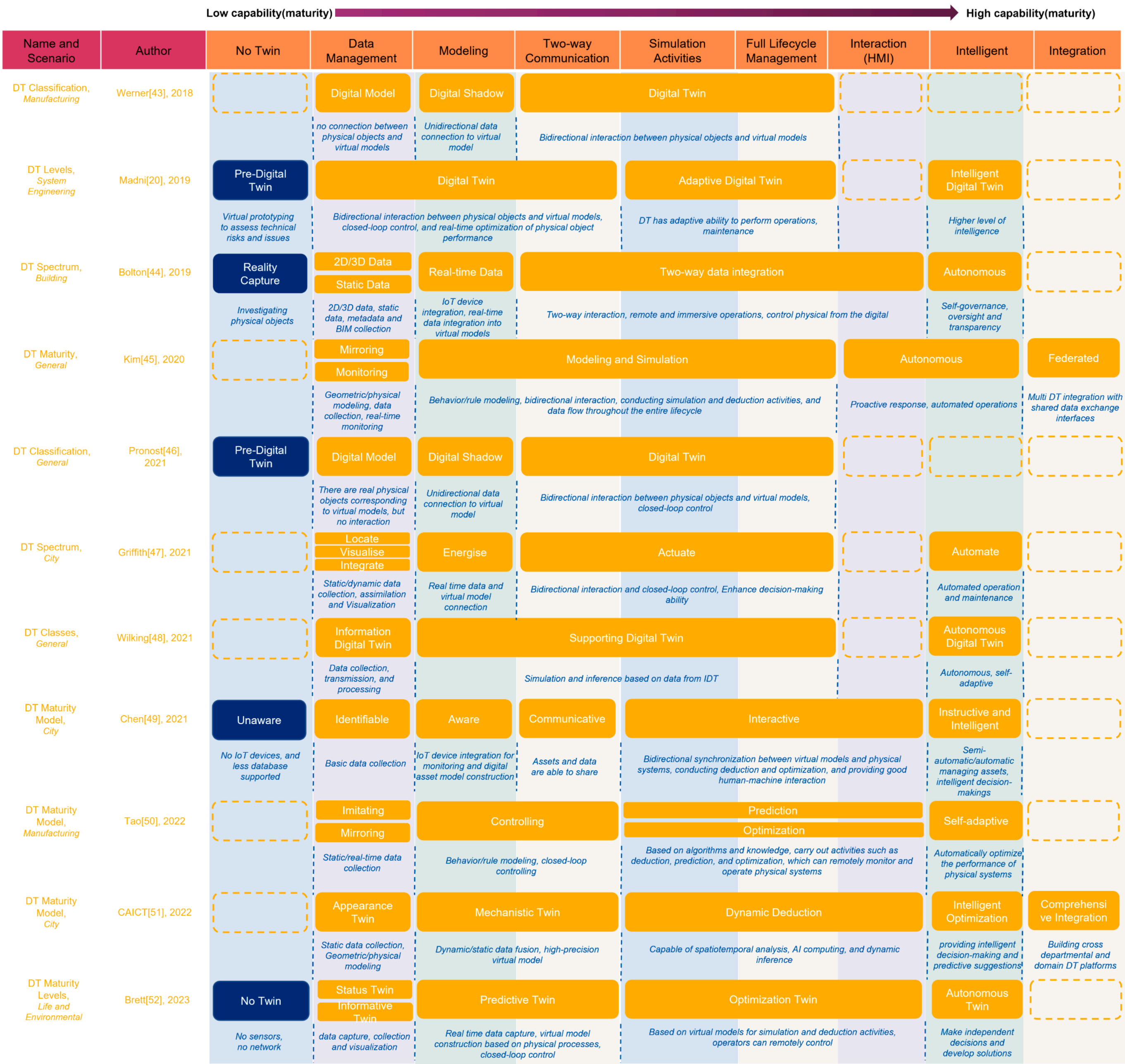

Fig. 6. Comparison of the various levels and capabilities of DT maturity.

of terminologies such as "classes," "classification," "spectrum," and "Maturity Levels," they offer valuable insights for delineating development phases and identifying functional capabilities in the DTMM development process outlined in this paper. However, an analysis of Fig. 6 reveals several deficiencies in these works: Some models inadequately encapsulate capabilities, leading to an absence of linear and continuous capability evolution across levels; ② The articulation of construction directions and development objectives within each level is ambiguous, posing challenges for developers in demarcating task boundaries; There is a lack of integration between various capabilities and their underlying technologies, hindering project managers from crafting efficacious development strategies and technological pathways; ④ Several maturity models are confined to the theoretical realm, without undertaking cross-sectoral, multi-disciplinary maturity assessments, thereby failing to ascertain the actual developmental stage of prevalent application domains. Consequently, this article endeavors to extend the foundational work of predecessors by aspiring to develop a maturity model characterized by more universally applicable developmental stage divisions, more exhaustive and linear coverage of capabilities, and lucidly defined task objectives. Concurrently, it seeks to amalgamate these capabilities with pertinent technology, aiding developers in appraising technical risks and complexities and devising viable technological roadmaps.

To promote the universality of the DTMM and contribute to DT standardization, the development process adheres to these principles: ① The maturity model is not designed for competitive assessment or certification; it primarily serves the purpose of self-assessment, focusing on ascertaining one's developmental level and identifying subsequent optimization directions; ② Informed by the experiences in developing software capability maturity models and data management capability maturity models, this study implements a five-level maturity stratification strategy; ③ In the maturity model, higher levels must include the lower levels.

Reflecting on prior advancements in maturity models, a discernible trend is evident: the stratification of maturity levels is evolving from fundamental DT capabilities towards more sophisticated, large-scale cross-system integrations. Integrating these insights with the capabilities of DT outlined in this paper and upon thorough contemplation, the maturity levels of DT are categorized into five distinct stages: digital model, digital shadow, digital twin, cognitive twin, and federated twin. This categorization is depicted in Fig. 7.

Building on the five-level stratification, the capabilities that DT should possess, such as data management, virtual modeling, simulation, Two-way communication, human–machine interaction, intelligence, integration, as well as functional characteristics of full lifecycle management and closed-loop control, are dispersed across the five maturity levels according to the difficulty of implementation and technical complexity of each capability. Table 5 delineates the requisite capabilities, task objectives, and pivotal technologies for each level of the DTMM.

It should be noted that a higher level of maturity implies greater technical difficulty, and an increase in functional requirements will inevitably add to the system's complexity, potentially leading to unsustainable cost implications and investment risks. Therefore, if traditional technology can meet the functional demands, it is deemed sufficiently adequate. For instance, on a small scale, executing modeling, simulation, and bidirectional data exchange for a workpiece is both technically and economically feasible. On a grander scale, such as the Digital Twin Singapore project, there was comprehensive 3D virtual modeling of buildings, road networks, trees, and rivers. This initiative included simulations of traffic flow, crowd distribution, and pedestrian movement, along with various control and behavioral simulation capabilities[53]. Despite the lack of real-time bidirectional data exchange, this project remains a paradigmatic example of DT applications in the smart city field.

4. Enabling technologies and tools

The primary purpose of DTMM is to aid project managers in formulating viable development plans and technological strategies. However, prior maturity models inadequately aligned DT capabilities with their respective technologies. To rectify this, the present paper maps the capability requirements at each DTMM level to their relevant technologies. Data collection, analysis, and bidirectional communication demand data management technology; virtual modeling and simulation are contingent on modeling and simulation technology; human–machine interoperability hinges on HMI technology. Additionally, the capabilities in intelligence and integration necessitate artificial intelligence and cross-platform integration technologies. To reinforce DT security, the paper also synthesizes current research on cybersecurity threats and issues confronting DT. This culminates in the creation of a DT technology matrix, depicted in Fig. 8, aiming to advance the practical implementation of DT.

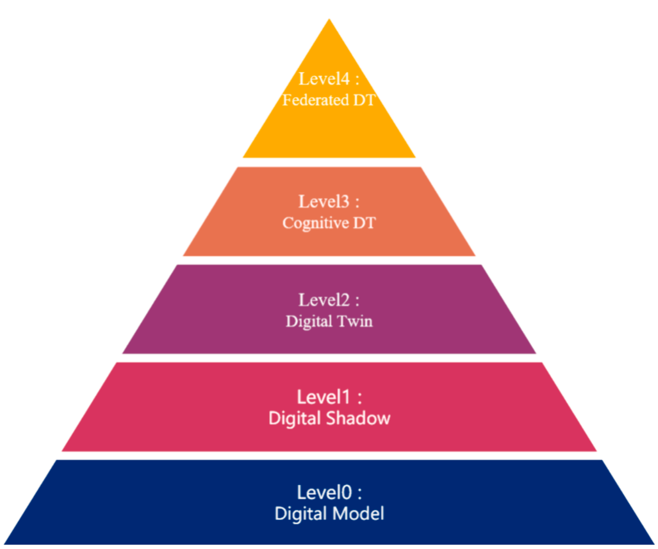

Fig. 7. The maturity model of the digital twin.

4.1. Data management

Data represents a pivotal challenge in DT implementation. The modeling, simulation, and bidirectional communication in DT entail processing vast volumes of historical and real-time data, often originating from diverse sources like sensors, cameras, and instruments, leading to the generation of extensive multi-source, heterogeneous data. Therefore, compared to previous digital methods, DT raises higher requirements for data collection, transmission, storage, processing, etc. More advanced technologies and architectures are needed to ensure DT data management, such as more powerful IoT infrastructure, cloud-edge computing, 5G, and advanced data transmission and exchange protocols. Crucially, the development of a robust data-sharing and interaction framework for DT is paramount.

DT's data sources may come from a variety of devices, software, and networks [54]. Various hardware devices, mainly including sensors, cameras, QR codes, instruments, etc., provide a range of historical and monitoring data to support subsequent DT modeling and sensory monitoring. To deal with such complex, multi-source, heterogeneous data collection and processing, a robust IoT infrastructure is undoubtedly needed as support. Under the IoT context, Minerva et al. discussed a universal DT architecture based on IoT [15], comprising layers such as perception, communication, middleware, and application. Kong et al. [55] segmented DT data management into four components to ensure DT's data support is both efficient and stable. The data representation module pertains to the hierarchical representation of data and character representation within applications. Data collection encompasses tools like sensor networks and RFID for gathering data. The data organization module focuses on data preprocessing and processing aligned with specific requirements. Finally, the data management module involves databases along with pertinent storage and retrieval strategies. Moreover, numerous researchers are utilizing IoT technology for DT data management, and their research findings are summarized in Table 6.

Effective data transmission is vital for facilitating bidirectional interaction between physical systems and virtual models, with prevalent technologies including Bluetooth, 5G, Ultra-Wideband (UWB), and ZigBee. Owing to the multitude of DT data sources, advanced transmission protocols are needed [66]. Jackson et al. [67] employed the MQTT protocol within a cloud platform and sensor network framework to enable the exchange of information between virtual models and physical entities, thereby creating a digital management portal. The features and suitability of communication protocols commonly employed in DT implementation are delineated in Table 7.

Currently, many researchers have turned their attention to cloud, fog, and edge computing technologies to cope with the complex data requirements of DT. Related works are shown in Table 8.

Finally, this paper combines the research work of Bhattacharya[77] and Tao et al.[11] to sort out the related technologies and tools for DT full life cycle data management, as shown in Fig. 9.

4.2. Modeling and simulation

High-fidelity virtual models constitute the cornerstone for DT to execute functions and services like monitoring, forecasting, optimization, and decision-making, thus making modeling and simulation pivotal in DT research. Presently, in the realm of DT modeling methodologies, the most advanced work, introduced by Tao et al. [78], initiates from four dimensions: geometry, physics, behavior, and rules, to forge virtual models. In a separate study, Tao [11] meticulously delineated the enabling technologies and tools pertinent to these four

Table 5
Capabilities expected at each level in the digital twin maturity model.

Maturity level	Reference name	Capability requirements	Task goals	Enabling tech.
0	Digital Model	– (Offline) can obtain the physical and geometric properties and characteristic data of physical objects; – Carry out geometric and physical modeling of physical objects based on a data-driven (offline) approach; – The constructed model cannot monitor and control physical objects;	– Collection and storage of historical data and metadata; – Appearance twin;	– Data Management (collection, storage, processing) ; – Modeling
1	Digital Shadow	– Modeling the behavior, process, and rules of physical objects using a hybrid approach driven by data and knowledge; –There is a one-way data link between physical objects and virtual models, and virtual models can synchronously and intuitively reflect the same running process and state of physical objects; – Breaking through certain temporal and spatial limitations in monitoring physical objects, that cannot be remotely controlled or still require human intervention;	– Mechanism twin; – Unidirectional data connection;	– Modeling ; – Data Management (transmission, assimilating)
2	Digital Twin	– The virtual model can receive historical data and real-time data from the physical object and can return the simulation results to the physical object. The two-way interaction between the two forms a complete data loop; – Further explore expert knowledge, mechanisms, and rules, and realize decision-making and optimization of physical objects (not necessarily intelligent); – Provides an HMI interface, allowing operators to monitor the operating status of physical objects and achieve remote control operations;	– Bidirectional data connection; – Simulation and deduction; – Remote monitoring and control;	– Data Management ; – Modeling and Simulation ; – Human-Machine Interaction ;
3	Cognitive DT	– Utilize various AI algorithms, strategies, and knowledge to semi-automatically/automatically construct optimization plans and decision suggestions, and provide feedback to physical objects. Virtual models and physical objects can maintain synchronization; – Provide an adaptive HMI method that does not require active human intervention and control;	– Intelligent deduction, optimization, and decision-making; – Virtual real synergy – self-evolution ;	–AI ; – Human-Machine Interaction ;
4	Federated DT	– DT has shared access to data and connection interfaces, and can combine higher-level cross-domain DT applications with other DTs; – On a larger scale, such as constructing a coupled nature-human-society twin platform, each DT works in concert to realize autonomous reasoning and prediction, simulate and justify multiple scenarios for the natural system and human society as a whole, and provide recommendations for relevant stakeholders.	– Multi DT integration; – Cross-domain platform level DT; – Advanced Intelligence	– Data Sharing Framework ; – Platform level integration technology; – AI

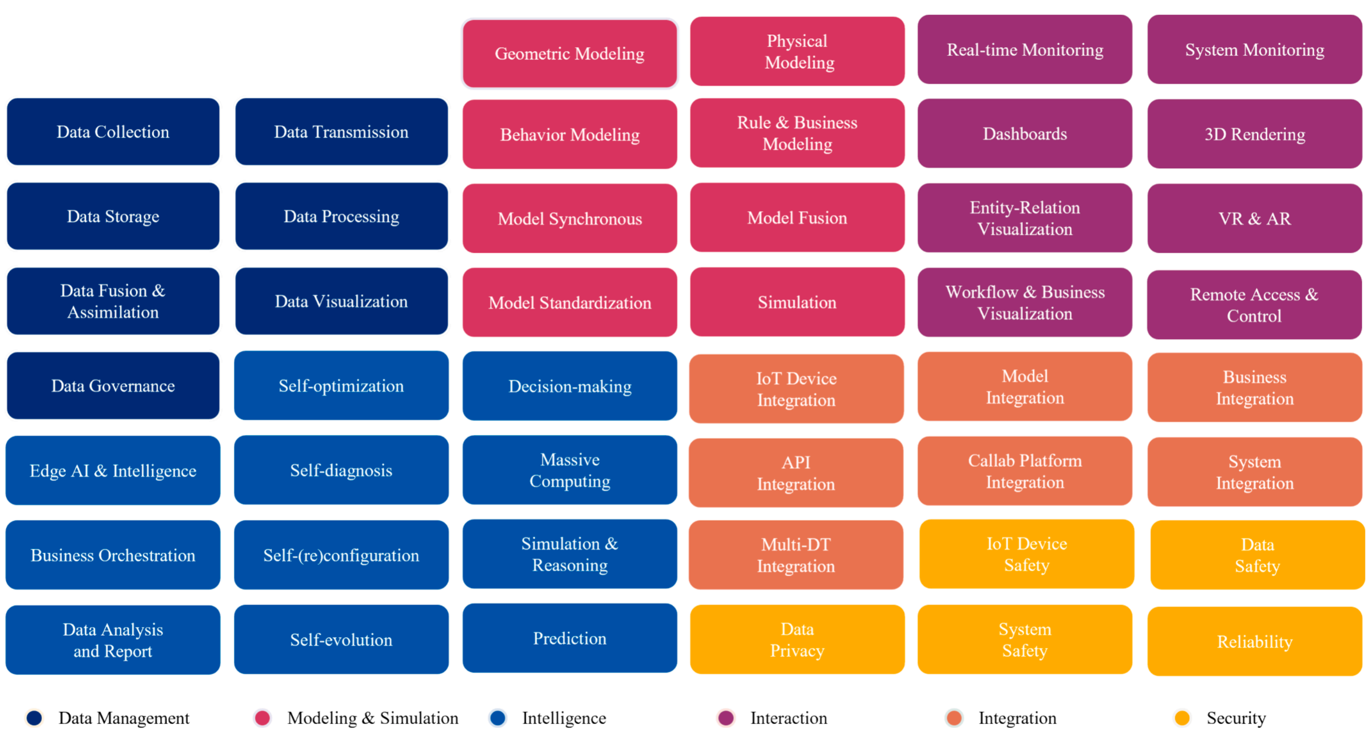

Fig. 8. Digital Twin Support Technology Matrix.

Table 6
Overview of related works integrating IoT into digital twin.

Ref.	Domain	Research contents
White [56]	Smart city	IoT devices and platforms play a central role in transferring data between physical entities and virtual models and unifying rich heterogeneous data.
Rajesh [57]	Automatic driving	Based on the ThingWorx IoT platform to realize real-time bi-directional data collection and feedback between virtual models and physical entities.
Zhao[58]	Logistics	IoT devices for indoor location services to support DT to achieve 96.5 % accuracy in identifying anomalous worker behavior.
Wang[59]	Manufacturing	The DT-oriented Big Data integration Framework (DT-BDVRL) is proposed, and IoT is used to ensure real-time synchronization of virtual models and physical assets, as well as the transmission of various data.
Jiang[60]	Manufacturing	IoT is used in the device acquisition and remote system layers of the DT system to support connectivity between sub-modules, isolate direct business access to devices, and strengthen the division and cooperation between the local and cloud.
Hinchy [61]	Manufacturing	The use of a large number of inexpensive IoT devices, such as sensors, to collect data in the manufacturing environment for the construction of virtual models of digital twins, and for simulation purposes.
Guo[62]	Manufacturing	Based on IoT, smart gateway, and wearable technologies, an assembly-oriented DT is proposed to collect important information including identity, status, and production process through IoT and aggregate it in a cloud platform.
Revetria [63]	Others	IoT devices provide data collection, transmission, and connectivity to support the real-time monitoring needs of AR-based digital twins.
Tan[64]	Others	5G uRLLC technology is used for bi-directional communication, providing high reliability, access efficiency, and low latency.
Lu[65]	Others	Combining DT and Federated Learning to Improve Communication Efficiency in IoT Edge Device Networks.

Table 7
Partial data communication and exchange protocols for DT connections.

Protocol	Features	Applicable scenarios
Message queuing telemetry transport, MQTT	Respond in seconds using a proxy-based publish/subscribe messaging model.	Provides cloud-based data transmission and monitoring of remote devices over low-bandwidth networks.
Constrained application protocol, COAP	The smallest packet is only 4 bytes.	For IoT devices with limited access to resources.
Data distribution service for real-time systems, DDS	Highly reliable, real-time transmission.	Suitable for wired networks, widely used in national defense and industrial control.
Advanced message queuing protocol, AMQP	Reliable and safe.	For communication between mobile devices and backend data centers.
Extensible messaging and presence protocol, XMPP	Instant Messaging, Client-Server-Client communication model, Distributed Networking	Available in instant messaging apps.
MTConnect	Open, scalable, real-time, and secure.	Ideal for data interaction between CNC, production lines, and robots.
TCP/IP	The most basic communication protocols in the network.	Any scenario that requires data transmission
OPC UA	Based on OPC unified architecture.	Suitable for factory-level data exchange

Table 8
Overview of related works integrating distributed computing into digital twin.

Ref.	Method	Advantage
Pan[68]	Cloud, Fog, Edge	Cloud, Edge, and Fog Computing Are Used to Handle Real-Time Hierarchical Management Tasks for Complex Logistics DT Systems.
Liu[69]	Cloud, Edge	Use edge computing at the endpoint to pre-process data before uploading it to the cloud platform, easing the computational pressure on the cloud.
Hofmann [70]	Cloud	Cloud platforms are responsible for heavy data processing and computation tasks and provide up-to-date status of physical counterparts.
Liu[71]	Cloud	Cloud-based platforms linking healthcare providers and patients allow real-time access to health data and analysis and return to the user.
Wang[72]	Cloud	Utilizing V2C communication, data is uploaded to the server via a cellular network, and all computational tasks are performed in the cloud.
Hu[73]	Cloud	The cloud platform implements bi-directional connectivity based on the MTConnect protocol to ensure synchronization between physical and virtual.
Lopez[74]	Cloud	Sub-DTs, interfaces, and heterogeneous subsystems are all integrated into the cloud platform.
Mi[75]	Cloud	The cloud platform serves as a data-sharing portal for all departments, where relevant stakeholders can upload and share data.
Xu[76]	Cloud	Combining the cloud with industrial robots enables two-way communication.

modeling facets, as illustrated in Fig. 10.

Building upon Tao's foundational research, Zhang et al. [79] have introduced a methodology for virtual model construction, encompassing Geometric Models, Physical Models, Capability Models, Behavioral Models, and Rule Models. The central innovation lies in the incorporation of the Capability Model to articulate the competencies of physical entities. Fan et al. [80] introduced a modeling approach termed GHOST, encompassing key elements such as geometric information, historical samples, object assemblies, snapshot collections, and topological constraints. The essence of this framework lies in the expansion of the data aspect within the five-dimensional model, targeting the efficient management of multi-sourced, heterogeneous data management in the intricate systems of DT.

In addition to the aforementioned modeling methodologies, prevalent approaches include model-driven and data-driven DT modeling methods. Model-driven strategies elucidate physical entities through their underlying physical mechanisms and processes. Data-driven approaches circumvent the intricate physical modeling procedures, adeptly employing input–output data to characterize physical processes. Table 9 provides a comparative analysis of these two modeling methodologies.

Discrete Event Simulation (DES) and Agent-Based Modeling (ABM) are frequently employed in DT modeling and simulation. DES effectively encapsulates business processes, whereas ABM delineates interactions and relationships among various entities within a system. Integrating these two methodologies fosters an efficient and comprehensive modeling approach. Jiang et al. [81] employed DES to segment the manufacturing system into seven fundamental components: controllers, actuators, processors, buffer zones, flowing entities, virtual service nodes, and logistics pathways. They encapsulated both the input–output data and control logic, modeling all discrete units and aligning them with various modules, thereby accomplishing the construction of the DT. Birgit et al. [82], utilizing a hybrid approach of DES and ABM, employed the Anylogic platform to model various components of a mechatronic production system, integrating diverse control logic. This approach successfully validated the potential of DES and ABM in DT simulation. Qiu et al. [83], following the same paradigm, modeled manufacturing workshops, delineating the physical space from geometric, physical, behavioral, and regulatory perspectives. Commencing with foundational logic, they employed DES flowcharts for modeling the

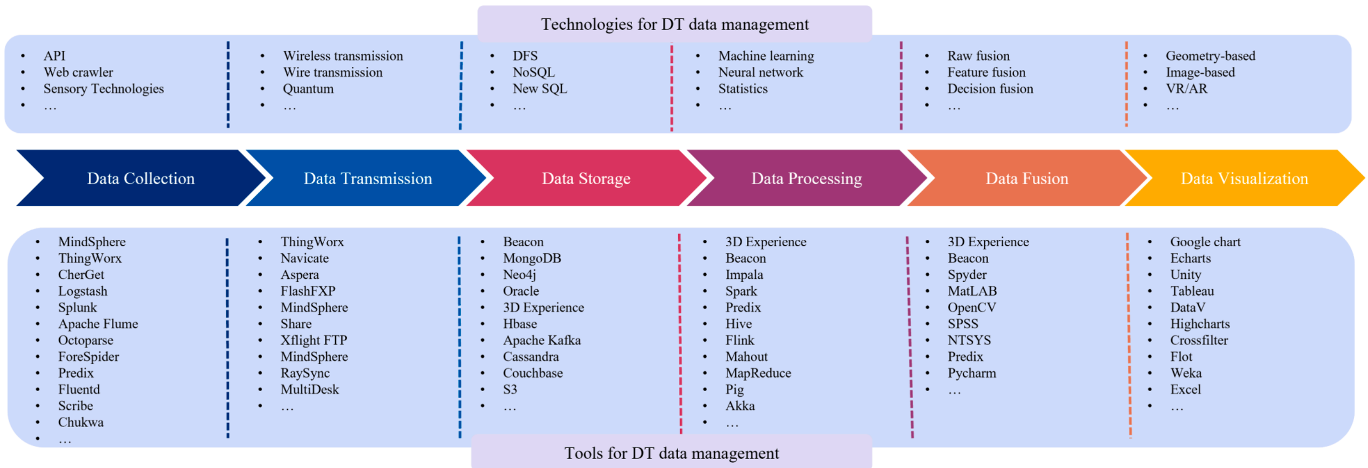

Fig. 9. Technologies and tools for data management in a digital twin.

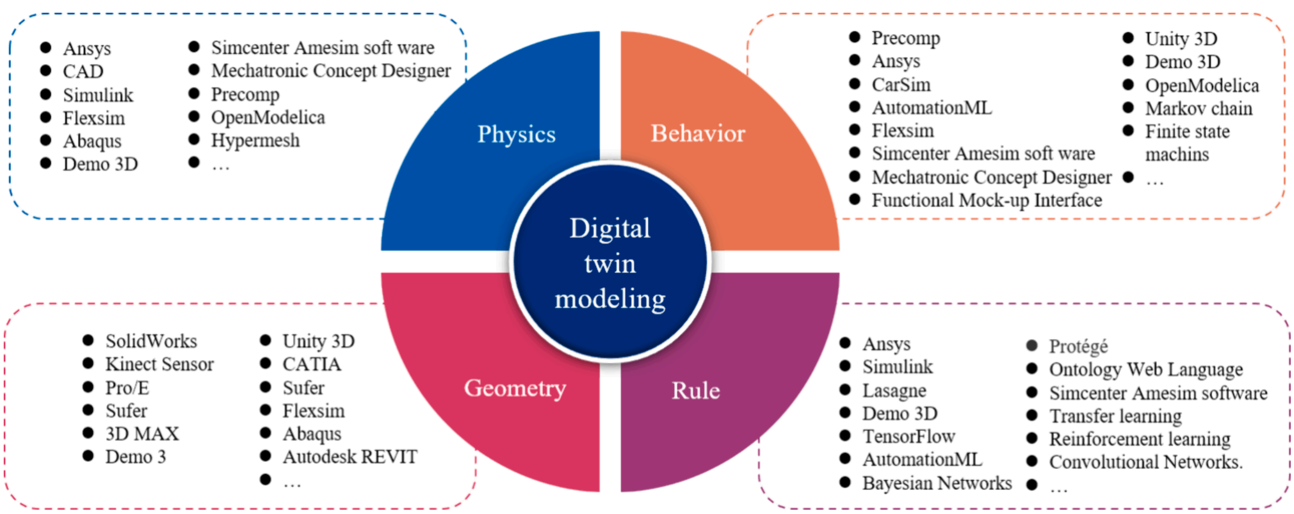

Fig. 10. Tools for digital twin modeling.[5].

Table 9
Comparison between model-driven modeling methods and data-driven modeling methods.

Item	Model-driven modeling	Data-driven modeling
Interpretability	It can be understood in terms of physical mechanisms and operational processes.	black box model.
Data integration	The simulation process of incorporating historical data into physical models is more difficult.	All historical data and experience can be incorporated into the model.
Stability	The simulation is susceptible to non-convergence due to initial and boundary conditions.	The model is stable after training.
Uncertainty	Errors and uncertainties can be controlled.	Errors and uncertainties cannot be controlled.
Bias influence	The model is not susceptible to data bias.	Data bias can directly affect model accuracy.
Suitability	Can be generalized to scenarios with similar physical properties.	Poor applicability to unlearned samples.

entire production workflow of the workshop and utilized ABM for depicting operators, machinery, and logistics within the workshop. This methodology significantly streamlines the effort required in formulating underlying logic during the construction of virtual models.

4.3. Intelligent

NASA's 2010 Digital Twin roadmap articulated their goal to construct an intelligent and adaptive DT by approximately 2025, designed to facilitate increasingly complex space missions [84]. The DT community has consistently dedicated efforts to augment the intelligence of DT. Based on the initial concept of DT [85], it is designed not merely to depict the state of a system but also to comprehend the real system. Lu et al. [38] highlighted that DT should possess cognitive abilities to evolve throughout their lifecycle in synchrony with their physical counterparts. Consequently, a DT should be capable of inferring meaningful and actionable insights from data produced by its physical counterpart and the environment.

Presently, machine learning and deep learning algorithms constitute the principal technical methodologies for elevating the intelligence quotient of DT. This paper systematically reviews the pertinent literature, as delineated in Table 10.

4.4. Human-machine interaction

Within the DT system, the closed-loop paradigm, integrating physical entities and virtual models, facilitates remote monitoring, control, and optimization. This process yields extensive real-time data and simulation outcomes. In the absence of adequate visualization

Table 10
Overview of related works integrating ML and DL into digital twin.

Ref.	Algorithm	Technical approach
Maschler[86]	Transfer Learning, LSTM	The LSTM is first trained using virtually generated data to detect anomalies in the virtual space and then trained using real data to predict anomalies in physical devices.
Dong[87]	DNN	Optimize the network parameters of mobile edge computing based on DNN to improve the energy consumption efficiency of the power grid.
Lakki[88]	ANN	Using ANN to monitor cyber attacks on DT in remote surgery environments.
Min[31]	AdaBoost, LightGBM, XGBoost	ML algorithms are used to optimize productivity and yield in a digital twin for the industry.
Xu[89]	Transfer Learning	A digital twin device fault-assisted diagnosis model based on deep migration learning is designed. To mitigate the discrepancy between virtual and real data, an adaptive layer is integrated into the model.
Zohdi[90]	Machine Learning	Using genetic algorithms to predict environmental parameters for large forest fires to enhance proactive fire prevention.
Gu[91]	CNN	A gesture recognition model was constructed based on HA-SSD to remotely control a physical robotic arm of a space station.
Chakraborty [92]	Machine Learning	Analyzing serial data at multiple time scales and combining with Gaussian processes to predict the future operating state of the machine.
He[93]	ANN	Prediction of time series samples of grid element sensors using ANN based on historical datasets to enhance decision-aiding capability.
Xia[94]	Reinforcement Learning	Reinforcement learning was used to test scheduling strategies for DT shop floor machines and equipment, with datasets from both virtual model-generated data and real data.
Matulis[95]	Reinforcement Learning	A deep reinforcement learning algorithm based on proximal policy optimization is used to train the DT of a robotic arm in a virtual space to guide its physical counterpart to complete a given task.

techniques to succinctly and intuitively display this information, users may struggle to comprehend the insights and recommendations offered by DT, potentially resulting in a reluctance to adopt the solution generated by DT. Hence, effective human–machine interaction (HMI) methods are paramount. Currently, Virtual Reality (VR) and Augmented Reality (AR) are the leading technologies enhancing DT's HMI capacities, aiding users in decision-making for the simulated systems.

Liu et al. [96] underscored the significance of HMI capabilities for DT in their research, and by employing AR technology, they introduced an HMI framework for DT. Sensors harvest data from physical entities, forwarding it to the virtual model for analysis and archival. This virtual model executes data analysis leveraging both real-time and historical data, presenting the results on an AR-based HMI interface, thereby facilitating user interaction with the DT. Laaki et al. [88] developed a DT for a surgical operating room, with medical devices interconnected through a 5G network. Surgeons are enabled to remotely access and manipulate the surgical equipment using VR, illustrating that VR can facilitate immersive experiences and remote control in DT, significantly augmenting HMI capabilities. This paper further synthesizes relevant cases, as delineated in Table 11.

4.5. Integration

DT is a system, and in terms of a single DT, it involves data

Table 11
Overview of related works integrating VR and AR into digital twin.

Ref.	VR/AR	Advantage
Ma[97]	VR、AR	Designed HMI based on VR and AR for DT manufacturing system to enhance the interaction and control between operators and production equipment.
Ke[98]	VR、AR、MR	Based on MR, virtual models are fused with their physical counterparts to enhance user perception.
Karadeniz [99]	VR、AR	You can monitor the operational status and processes of physical devices in real-time and return optimized results to the operator.
Kuts[100]	VR	VR-based design of an industrial robot cell control twin program to teach robot operation and control in a virtual environment.
Rocca[101]	VR	VR-based manufacturing DT developed for use in safety tests to optimize product design solutions in virtual space.
Williams [102]	AR	Users can track the mobile robot and manipulate it through a head-mounted AR device, maximizing the robot's time in the O&M environment.
Lakki[88]	VR	Integration of medical personnel using head-mounted interactive devices into the patient's DT enhances the physician's diagnostic capabilities.
Schroeder [103]	AR	Using AR and web services, digital information generated from virtual models is superimposed on their physical counterparts, with strong visualization capabilities.

integration, model integration, API integration, etc. However, to achieve efficient engineering, amalgamating multiple DTs into a System of Systems (SoS) and establishing an interdisciplinary, multi-domain DT collaborative platform maximizes the potential and value of DT. Nevertheless, it must be acknowledged that the current solutions and technologies for multi-DT integration are relatively scarce. This is due to numerous pressing challenges in data management, modeling, simulation, etc., within DT, resulting in modest investment in DT integration across various sectors. Presently, the prevalent strategy involves the adoption of DT integration platforms offered by major manufacturers. This paper systematically categorizes these platforms according to their applicable scenarios and integration scales, as depicted in Table 12.

Table 12
DT integration platforms.

Platform	Feature	Applicable scenarios	Scale
Twin Builder	Supports DT modeling of multiple physical quantities	Multi-physics DT for equipment	Equipment/ Component
Altair	With design simulation, IoT, data analysis functions	Scenarios with high demand for data analysis	Equipment/ Component
PickMaster Twin	With DT prototype, support virtual commissioning	Virtual testing of production lines	Production line
MapleSim	Virtual commissioning support	Monitoring and virtual testing of production lines	Component/ Production line
PlantSight	integration of all plant construction and operation information with digital models	Builds digital factories and monitors factory operations and equipment health.	Workshop
Unity Pro	Modeling, Behavioral Description, HMI Processes	Scenarios with high requirements for real-time rendering	Equipment/ Workshop/ City
3DEXPERIENCE	Integration of all Dassault tools into the platform	Capable of integrated modeling of equipment and environment	Equipment/ Workshop/ City
iTwin	Integrated solution for 3D reality modeling	DT based on a 3D real-life model	Equipment/ Workshop/ City

4.6. Security

The criticality of DT security is unquestionable. Security threats to DT can significantly undermine user confidence, dealing a devastating blow to the DT system. Yet, according to the literature surveyed in this article, research on DT security remains comparatively limited.

As analyzed by Alcaraz et al. [104], the potential security threats to DT encompass physical threats, data tampering threats, system threats, access threats, data communication threats, and data storage threats. It is discernible that the security threats to DT primarily revolve around two aspects: firstly, those arising from technical issues, and secondly, those originating from lapses in security management.

At present, researchers predominantly employ blockchain technology to mitigate potential risks associated with the security and reliability of DT. Kanak et al. [105], integrating blockchain with DT following X-by-design and XaaS principles, introduced a blockchain-based distributed DT model. This model leverages decentralization to bolster the security, accountability, and integrity of the DT system. In cloud computing contexts, Thakur et al. [106] devised an authentication protocol utilizing blockchain, specifically targeting security threats in DT data management. They proposed an enhanced, tri-factor-based privacy protection authentication framework, equipping DTs to withstand diverse malicious attacks. Putz et al. [107] introduced EtherTwin, a blockchain-based DT information management solution, tailored to meet the security requirements of DT. The criticality of security and trustworthiness in DT is apparent. However, the current research in theories, technologies, frameworks, norms, and legal aspects related to DT security is notably scant. Consequently, ongoing efforts in standardization are necessary, with an emphasis on incorporating security considerations right from the inception of DT project planning.

5. Applications

For project developers and managers, comprehending and mastering the actual development trends of DT across various vertical domains is vital. This knowledge aids in effectively evaluating investment risks and returns, as well as assimilating the developmental experiences and lessons from peers, which are crucial for the high-quality deployment of DT. Consequently, this paper systematically reviews cases across six typical DT application domains: aerospace, intelligent manufacturing, energy and power, smart cities, medical health, and digital twin earth. As depicted in Fig. 11, the distribution of research literature across the fields in the collected samples of this paper is shown, where intelligent manufacturing accounts for nearly half of the publications. This sector represents the most active area in DT research and implementation cases. Further, this paper delves into the actual status across each vertical domain, grounded in the DTMM.

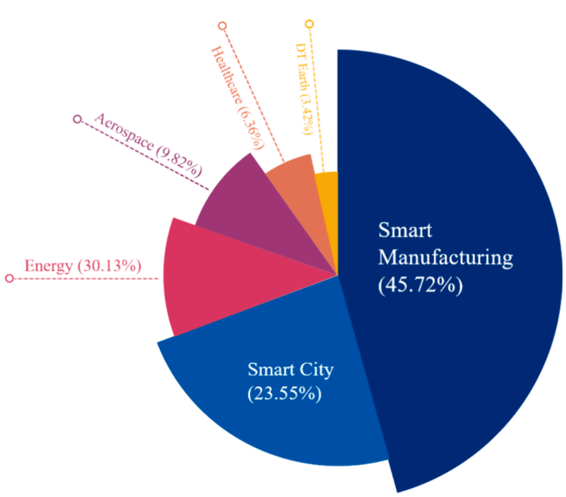

Fig. 11. Application field distribution of digital twin.

5.1. Aerospace

The aerospace industry stands as a trailblazer across all DT application domains. Beginning with the physical twin concept that originated from the Apollo program, followed by NASA's comprehensive definition and elaboration of DT, the United States Air Force Research Laboratory's (AFRL) successful DT-based applications in predictive maintenance and extending aircraft service life, and the subsequent engagement by Boeing, Airbus, and General Electric in DT, the aerospace sector has been instrumental in the genesis, evolution, and widespread adoption of DT.

In aircraft design and manufacturing, DT facilitates the rapid and superior development of new products, consistently enhances aircraft performance, and curtails the time and expense associated with predictive maintenance [108]. The commercial space firm SpaceX is endeavoring to utilize DT to optimize the design, development, and testing of its products [109]. Siemens, in collaboration with SpaceX, is aiding in the integration of DT into the design and manufacturing processes of SpaceX's Falcon rockets to minimize research and development costs as much as possible [110]. Liu et al. [111] introduced a DT modeling methodology for aerospace component processing, inspired by biomimicry. This approach segments the DT modeling process into geometric, behavioral, and procedural models, with its efficacy validated through the processing of aeronautical rudders.

Aircraft are characterized by their intricate structures and numerous components [112]. The assembly process is pivotal in determining the final quality, production cycle, and construction costs of the aircraft. Jin et al. [113] developed a reusable DT system designed to accommodate the requirements of rapid and repeatable modular assembly in aircraft. Sun et al. [114] proposed a DT-driven aircraft assembly and debugging method based on HPP theory and designed a theoretical framework for assembly and debugging, as well as a methodology for establishing a comprehensive information model for assembly and debugging based on DT technology.

In predictive maintenance, structural fatigue issues have long plagued the US Air Force. Consequently, in 2020, the AFRL declared the development of a DT for the supersonic bomber B1-B, aimed at predictive maintenance. This involved using a 3D scanner to collect data on each component and the fuselage of the aircraft, followed by rendering a high-fidelity replica on a virtual platform. This process assists in identifying any structural damages and high-fatigue areas on the fuselage, contributing to the creation of a thorough health maintenance record for the aircraft [115]. Ye et al. [116] tackled the critical issue of structural health assessment during the intermission phases of reusable spacecraft by introducing a DT focused on health management. The primary aim is to diagnose fatigue cracks. Utilizing the dynamically updated crack data within this framework allows for precise prediction of future crack propagation, consequently reducing maintenance intervals. Xiong et al. [117] developed a DT-driven framework for aircraft engine maintenance, termed the Implicit Digital Twin Model (IDT). By integrating a data-driven LSTM model, they validated the efficacy of IDT in the predictive maintenance of engines. Additional related efforts encompass the creation of a DT for engine blades [118], significantly enhancing the efficiency of blade repairs. Other researchers have employed cognitive modeling and collaborative simulation approaches to construct DT [119], facilitating the analysis of human behavior models in aircraft and the capability for safety testing in aerospace.

5.2. Smart manufacturing

The intelligent manufacturing sector is indisputably the most active domain for DT applications. At present, the application of DT in intelligent manufacturing can be categorized into three tiers: product level,

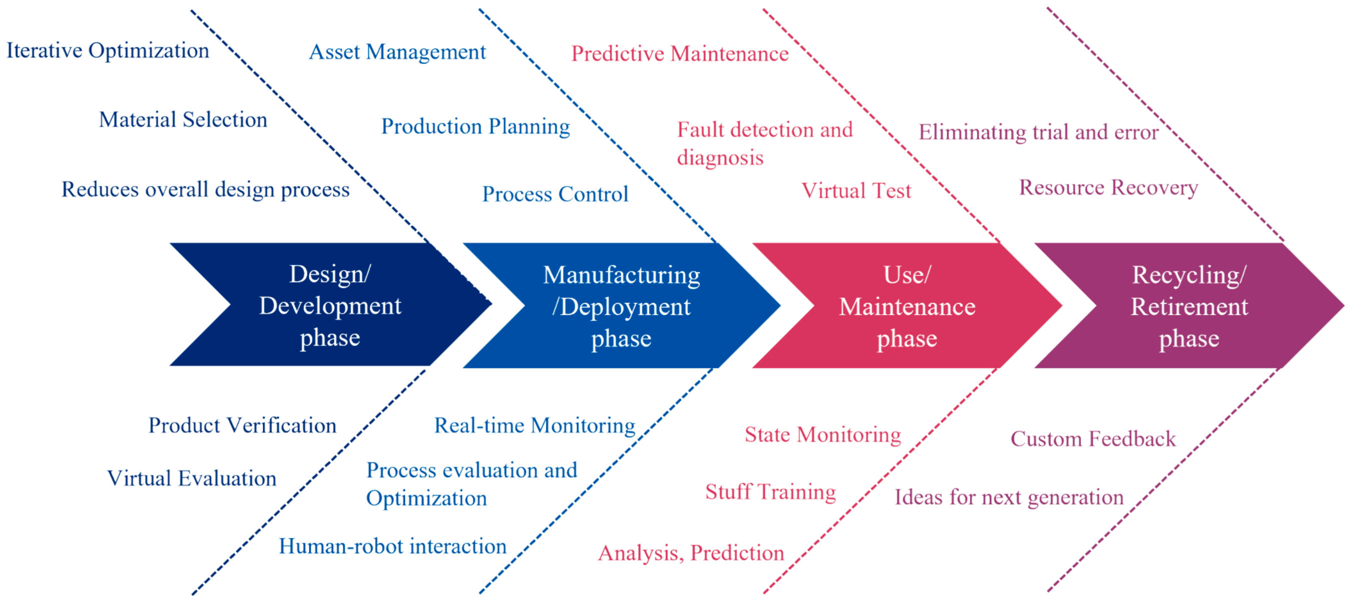

Fig. 12. DT's applications throughout a product's lifecycle.

workshop/factory level, and platform collaboration level.

The product level primarily concentrates on the application of DT across various stages of the lifecycle[120], as illustrated in Fig. 12. This includes the design, manufacturing, operation and maintenance, and recycling and disposal phases.

Design/Development phase During the design phase, DT enables designers to realistically validate product designs, expedite the iteration process of various product concepts, and significantly reduce manpower and costs [54]. Car manufacturer Maserati [121], aiming to cut costs in wind tunnel testing, constructed a DT of wind tunnel experiments to optimize the aerodynamic properties of their car bodies. Tao et al. [122], using the bicycle design process as an example, and relying on the designer's knowledge and experience, continuously garnered feedback data from the physical space. They proposed a DT-driven product design framework, which aids manufacturers in designing or redesigning next-generation products utilizing DT.

Manufacturing/Deployment phase DT can enhance various aspects, including asset management, production planning, and control of the production process. Bambura et al. [123], concentrating on the engine block manufacturing process, developed a DT comprising physical, virtual, and information processing layers. This model accomplished real-time synchronization between physical and virtual production lines. Mykoniatis et al. [124], utilizing ABM, designed a data-driven DT emulator for the virtual commissioning of production lines. Similarly, Birgit et al. [82] employed ABM and DT to effectively reduce downtime in production lines.

Use/Maintenance phase Once the product is delivered to customers and enters the operation and maintenance phase, Tao et al. [122] assert that DT can offer a range of operation and maintenance services during this phase. These services include real-time status monitoring, energy consumption analysis and forecasting, product fault analysis, and prediction, as well as virtual operation of the product. Xu et al. [89], leveraging transfer learning, introduced a DT-based fault assistance diagnostic method aimed at predicting potential faults in various devices along the production line.

Recycling/Retirement phase Presently, the disposal phase of products is frequently overlooked, leading to the loss or oversight of valuable data that could inform the development of next-generation products. Wang et al. [125], utilizing DT, developed an innovative recycling system for waste electronic and electrical equipment. This system bridges the data gaps across lifecycle stages and can be employed to simulate, monitor, diagnose, and control the state and behavior of its physical counterparts.

In the realm of Digital Twin workshops (DTW), Tao et al. [126] categorized them into physical workshops, virtual workshops, twin data of the workshop, and workshop service systems. They explored the concept, structural composition, operating mechanisms, characteristics, and key technologies of DTW. Qiu et al. [83]developed a DTW employing ABM and DES. This approach effectively tackles the challenges of integrating and assimilating multi-source heterogeneous data in workshops. Rodic et al. [127] integrated DES with heuristic algorithms, utilizing AnyLogic software to construct a comprehensive virtual workshop model aimed at optimizing complex manufacturing processes. Roque Rolo et al. [128] merged agent-based distributed control systems with DT to create a DTW architecture, intended to elevate the flexibility and applicability of workshops. Jiang et al. [81], employed DES to model DTW. Their contribution lies in establishing a data interaction mechanism between virtual and physical workshops.

At the platform level, DT aims to facilitate collaboration on a broader scale, not only within production lines and other production elements inside a factory but also among different factories. Such platforms are capable of integrating various lifecycle processes of products, data, and resources, establishing a cross-system, cross-platform collaborative environment [129]. Cheng et al. [130] proposed objectives for the fourth-generation intelligent factory, focusing on integration. They conducted analyses in four key areas: physical integration and data collection, digital virtual models and simulation, integration of data and information technology systems, and data-based production operations and management methods.

5.3. Smart grid

The DT grid forms an electric ecosystem consisting of physical grids, virtual grids, and an array of supporting technologies. Grounded in an abundance of reliable data and utilizing perception modeling theory, DT constructs a virtual grid mirroring the physical grid. This setup enables monitoring, early warning, simulation, analysis, testing, and control functionalities for the grid. It enhances the efficient allocation and cooperation of energy and information resources within the grid, fostering the reuse of digital resources and revolutionizing the grid ecosystem. DT is progressively permeating various business segments within the power industry.

Regarding the construction of the DT grid, Jiang et al. [131] introduced a reference architecture (OKDD) for DT grid modeling, encompassing Ontology Body, Knowledge Body, Data Body, and Digital Portal. They applied OKDD in the practical implementation of a DT grid, using vacuum circuit breakers and 35KV substations as cases. This application preliminarily validated the method's feasibility. Their significant contribution is in offering a unified descriptive representation and standardized approach for the DT grid, along with the capability for knowledge reuse. In the field of power system analysis and forecasting, Song et al. [132] developed a DT-based state estimation method for real-time monitoring of the power grid's status and predicting future grid conditions based on potential events. Regarding optimized operations, Gao et al. [133] introduced a DT-driven smart microgrid multi-agent collaborative control architecture, from which they formulated a multi-objective optimization scheduling strategy. In evaluating the health status of electrical equipment, Tzanis et al. [134] constructed a DT grid model using a hybrid data-model-driven approach. This model comprises a data-driven machine learning subsystem and a discrete deterministic subsystem, enabling nearly real-time fault identification within the power grid. In terms of security, Atalay et al. [135] assessed the common attacks that smart grids might encounter at three levels: the physical layer, the interaction layer, and the information layer. They introduced a DT-based smart grid security testing lifecycle method, anticipated to serve as a standardized tool and evaluation framework for ensuring grid security. Danilczyk et al. [136] developed ANGEL, a DT-driven microgrid security application framework. ANGEL can model the network and physical layers of microgrids and offer real-time data visualization. This aids users in evaluating the health status of physical devices and the overall security level under diverse operating conditions.

5.4. Smart city

During the development of smart cities, DT has emerged as a crucial technology for realizing this objective, being recognized as a key direction in the evolution of smart cities. Utilizing DT, city administrators strive to dismantle information barriers horizontally across sub-domains like energy, transportation, and municipal governance. Vertically, they aim to achieve comprehensive coordination and integration, spanning from high-level urban planning and construction to grassroots public services.

In the realm of urban planning, Lin et al. [137] employed Wireless Sensor Networks (WSN) and Building Information Modeling (BIM) technology to explore the DT application in smart city underground parking lots, aiming to enhance environmental management. For urban building management, Ruohomaki et al. [138], leveraging open data from the IoT, developed a DT framework for urban buildings in Helsinki—mySMARTLife. This framework integrates geographic information, geometry, topology, and appearance of buildings, facilitating comprehensive energy efficiency upgrades of urban architecture. Lu et al. [139], concentrating on buildings within the campus, devised a virtual model. Utilizing virtual models and real-time data, along with various AI algorithms, they evaluated the asset conditions and maintenance status on the campus. In the field of urban transportation, Khan et al. [140] applied DT to optimize vehicular traffic. This involved continuously exchanging real-time information, such as location, speed, and routes of vehicles, between physical vehicles and virtual traffic models. They predicted and simulated potential scenarios to minimize vehicle travel times. Similarly, the DT system developed by Onile et al. [141] leverages the travel information of all road users to determine optimal routes. This approach aims to reduce travel time for each vehicle and minimize overall fuel consumption. In urban disaster management, the DT of Dublin Docklands in Ireland, developed by White et al. [56], offers rainfall and river water level data to forecast potential flood occurrences. This innovation is employed in devising long-term flood prevention strategies and in planning the urban skyline.

Beyond the mentioned application scenarios, numerous countries and regions are endeavoring to coordinate urban complexities, the strong interdependencies among various elements, and the interrelations across different sectors on a grander scale, integrating them into a single platform. For example, the National Research Foundation of Singapore initiated the "Virtual Singapore" project [142]. This project integrates 3D maps, urban models, and data platforms with aspects such as building structures, materials, geometric configurations, and facility components, culminating in a complex and dynamic virtual city platform.

5.5. Healthcare

As the COVID-19 pandemic rapidly spreads globally, the realm of human medical health and hygiene services encounters unprecedented challenges. This situation compels governments and health organizations worldwide to initiate diverse digitalization initiatives and research. Gartner, a leading global research and advisory firm in advanced technology, observed in its 2020 report [143] that "the topic of digital twins in healthcare is emerging, attracting increasing interest from various stakeholders.".

In the field of personalized medicine, leading companies are leveraging DT to construct virtual models of the human body or organs. They offer precise, personalized treatment plans by integrating real-time vital health data of patients. The Living Heart was developed by Dassault Systèmes [144] and launched in 2015. This model comprehensively accounts for the mechanical, structural, and electrical properties of the heart. Owing to this model, clinicians can simulate various heart functioning scenarios to forecast patient outcomes, enabling continuous iteration and optimization of treatment plans. This model has now evolved into a novel method globally employed for the creation, design, and testing of new medical devices and drug therapies. Similarly, Siemens Healthineers has also pioneered an alternative DT cardiac model [145]. The Human Digital Twin (HDT) represents the comprehensive digital embodiment of the human form, a task far more intricate than digitizing individual human organs. This endeavor necessitates an intricate balance of internal and external human traits, coupled with an emphasis on societal attributes and the environmental impacts on humanity. In Miller et al.'s [146] definition of HDT, it must encapsulate a diverse array of attributes, encompassing the physical, physiological, perceptual, cognitive, and personality dimensions. The formidable challenge of constructing an HDT is apparent, rendering its current status predominantly theoretical. Nevertheless, Lin et al. [147] inspired by advancements in DT across various sectors, have proposed a universal system framework for HDT. They delved into the complexities of the construction process, encompassing human perception, organ modeling, torso modeling, activity modeling, and social interaction modeling.

In pharmaceutical development, DT can facilitate cost-effective testing of new drugs, thereby assuring their safety and efficacy. Each stage of the drug development process is characterized by the generation of substantial data volumes. DT utilizes this data to construct models [148], potentially expediting the clinical trial phase in drug research and necessitating fewer patient allocations for drug administration [149]. Moreover, DT is poised to play a pivotal role in the innovation and manufacture of new vaccines, aiding scientists in identifying optimal antigens, with the development process being virtually achievable.

Regarding the operational management of healthcare facilities, General Electric has innovated the GE Healthcare Twin platform [150], while Siemens Healthineers has formulated a DT system tailored to address the operational challenges faced by Dublin's Mater Private Hospital [151]. In the aforementioned examples, challenges like escalating patient demands, aging infrastructure, insufficient bed capacity, and prolonged wait times in hospitals are tackled. The deployment of DT aids hospitals and governmental bodies in the efficient management of medical resources, significantly elevating the standard of patient care and treatment.

5.6. Digital twin Earth

Digital Twin Earth is a dynamic, interactive information system that integrates various models and observational data. Leveraging AI techniques and visualization tools for joint analysis, it hypothesizes operational scenarios and conditions to probe the Earth system's evolutionary dynamics.

At present, prominent DT Earth initiatives encompass the European Space Agency's Destination Earth (DestinE) [152] and NASA's Integrated Digital Earth Analysis Systems (IDEAS) [153]. DestinE aims to create a high-fidelity digital model of Earth on a global scale, enabling the monitoring and forecasting of interactions between natural phenomena and human activities. Integral to the European Commission's Green Deal and Digital Strategy, DestinE is instrumental in propelling the EU towards its ambitious green and digital dual transformation. The program primarily involves DT for polar glaciers, hydrology and water resources, the impacts of climate change and extreme weather, forests, food security, and marine environments.

IDEAS leverages DT to craft a virtual depiction of the Earth system. This initiative focuses on the lifecycle data management of the Earth system and employs sophisticated knowledge and algorithms to simulate and infer extreme weather phenomena, such as heavy rain, floods, and droughts, as a strategy to address contemporary challenges of global warming and population growth. At present, IDEAS has made substantial strides in the field of water resources, specifically, in flood forecasting and the management of water resources. [154].

Beyond the aforementioned national and organizational-led DT Earth initiatives, meteorological agencies globally are extensively employing DT. The meteorological sector possesses distinctive advantages in areas such as IoT infrastructure, data governance, data computation and analysis, and the capability to construct and simulate models. Indeed, many of the field's foundational efforts can be viewed as DT. The inherent characteristics of DT, entailing real-time interaction and closed-loop control between physical entities and virtual models, are in perfect harmony with the diverse demands of contemporary precision meteorology. For example, enhancing decision-making scenarios like air traffic management, flood forecasting, severe weather monitoring, and adaptation of wind turbines necessitates near-real-time weather forecasting. To fulfill this objective via the development of a DT Earth, assimilating an increased volume of observational data and outcomes, along with the creation of high-precision virtual models, is imperative. In response to these challenges, Li et al. [155] have devised a DT Earth data management architecture, grounded in data science and integrating big data assimilation, machine learning and deep learning, causal inference, and reinforcement learning technologies.

5.7. Discussions and findings

The preceding section synthesizes the research outcomes in the typical application domains of DT, offering an initial insight into its current usage scenarios and trajectories. This article elaborates further, culminating in a summary presented in Fig. 13. Furthermore, based on the DTMM proposed in this paper, a comparison of typical application cases across various vertical domains was conducted. This entailed a systematic arrangement of the employed technologies in data management, modeling, simulation, human–computer interaction, intelligence, and integration. Ultimately, the assessment outcomes for each vertical domain are delineated in Table 13.

Table 13 reveals that the development level and maturity of DT differ significantly across various sectors. The aerospace sector exhibits a higher degree of maturity, attributed to its substantial financial and human resources, formidable technical reserves, independence from market fluctuations, and robust resilience to risk. Owing to its pioneering advantage and the most extensive repository of theoretical and technical expertise, the manufacturing sector ranks highest in maturity. It typically validates the efficacy of constructed DT in laboratory settings and proceeds to test them in industrial environments. Nonetheless, numerous challenges persist in practice, including the complexity of multi-objective optimization in product life cycles, the absence of advanced integration technologies for workshop and product data, and a

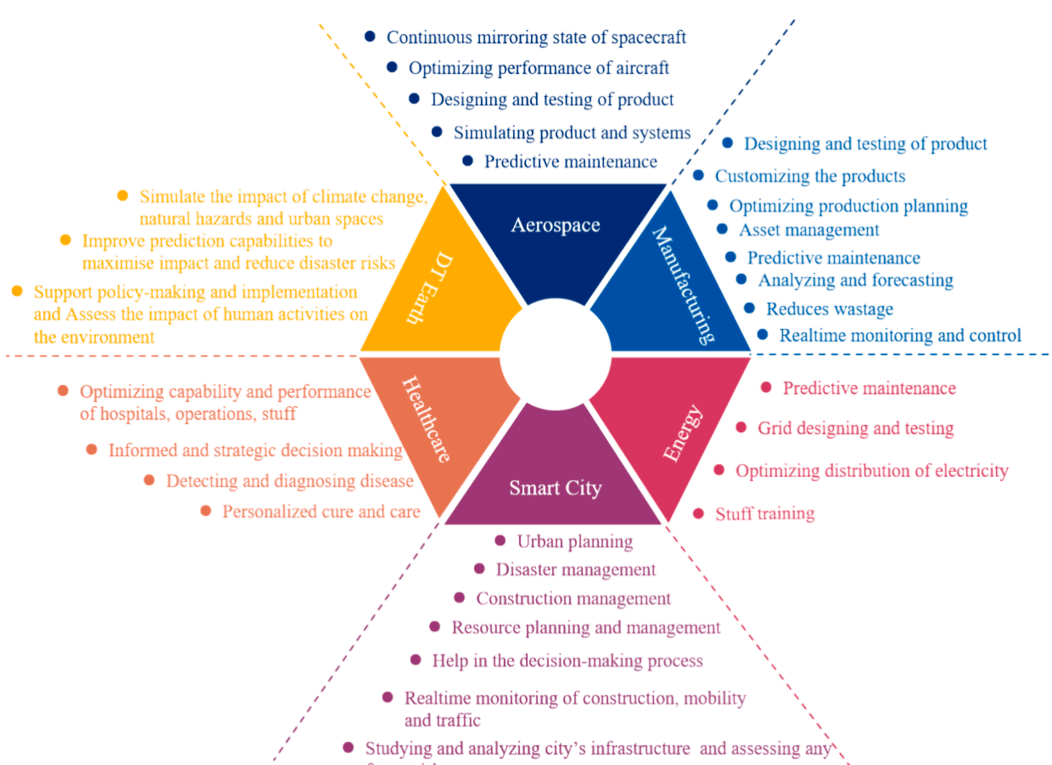

Fig. 13. Application scenarios and directions of DT in different fields.

Table 13
Comparison of DT applications in various realms based on DTMM.

Domain	Ref.	Goal	Physical Object	Data management	Modeling	Two-way communication	Simulation	Interaction(HMI)	Intelligent	Integration	Maturity Level
Aerospace	[115]	Reduced operating costs	B-1Bbomber	Sensor network	3D scanning	–	–	VR	–	–	3
	[116]	Aircraft health management	Aircraft	Sensors	CAD	Application interfaces	ABAQUS	–	Dynamic Bayesian Network, Knowledge base	–	3
	[118]	Improve maintenance efficiency	Blades	Camera-based visual sensing tech.	Physics-based model	–	–	–	Markovian algorithm	–	2
	[117]	Fault diagnosis	Aircraft engine	Sensors	Data-driven, DL	–	–	–	LSTM	–	3
	[119]	Remote monitoring, optimization	Production line	IoT network	Data and knowledge-driven	Eclipse ditto	Airbus Cyberange, Gazebo	Dashboard, wearable device	–	imodel.js, ditto	3
	[111]	DT modeling	Air rudder	Sensors	Biomimicry	XML	CAE	3D visualization	–	–	3
Manufacturing	[123]	Improvement productivity	Engine block	PLC sensors	Object-oriented	TCP/IP, ODBC interfaces	TPS	TPS visualization	–	–	3
	[89]	Fault diagnosis	Production line	PVS	Data-driven	PLC	PDPS	DEKG	Transfer learning	–	3
	[67]	DT modeling	CNC, robotic arms, AGV	Sensor network	Data and knowledge-driven	MQTT	Tecnomatix Plant Simulation	–	Knowledge base、ResNet18	–	4
	[124]	Virtual Commissioning	Mechatronics production workstation	Sensors	Hybrid DES-ABM	TCP/IP	Anylogic	–	Multi-Agent	–	3
	[82]	Reduce downtime	Production systems	Sensors	ABM	ACL massage	AASX	–	Knowledge base, Multi-agent	–	3
	[128]	Production line simulation	Production line	Sensors	ABM	–	Anylogic	3D demonstration	Multi-agent	–	3
	[81]	Production scheduling	Workshop	Sensors	DES	MQTT	Simcad Pro	Dashboard	–	–	3
	[83]	Self-evolution workshop	Workshop	Sensors	Hybrid DES-ABM	–	Anylogic	Graphical user interface	Reinforcement learning	–	4
Smart grid	[136]	Grid security	circuit equipment	SCADA	MATLAB	Modbus	MATLAB	ANGEL GUI	–	–	3
	[135]	Grid security	Smart grid system	Edge、Cloud	Knowledge-based modeling	MQTT	–	Graphical user interface	Knowledge base	–	3
	[131]	Grid modeling	Vacuum circuit breaker	Sensors	Data and Knowledge-driven	–	CAD	Digital-portal UI	–	–	3
	[156]	Grid management	Power line	Sensors	ABM	–	Python	–	Reinforcement Learning	–	2
Smart city	[137]	Parking lot planning	Parking lot	Wireless sensor network	BIM	–	BIM	–	–	–	2
	[139]	Asset monitoring	Building	Sensors	BIM	–	CAD	Autodesk Revit	–	–	3
	[157]	Urban governance	Building	Sensors、cloud	BIM	–	OPAL-RT	eLUX app	ML	–	3
	[158]	Urban governance	Building	Sensors、Fog、	BIM、3D scanning	MQTT	ANSYS	–	ANN、CNN	–	3
	[56]	Urban plan	Urban infrastructure	Sensors	BIM	–	SUMO、Unity	–	–	–	3
Healthcare	[159]	Human health management	Human body	X73、Cloud	–	–	–	wearable device	CNN	–	2
	[144]	Personalized treatment for heart disease	Heart	Heart monitoring equipment	3D Modeling	–	3DExperience	3DExperience	–	3DExperience	3
	[160]	Personalized healthcare	Human body	Medical Data API	Data-driven	–	ANSYS	–	AI	ANSYS	2
DT earth	[154]	Earth observation	Earth	NOS	Data and knowledge-driven	–	ESDT	–	AI	–	–
	[153]	Flood forecasting	Water circulation	SDAP platform	Physical model-based	–	–	–	–	–	3

deficiency in comprehensive decision-support technologies for workshop managers. In the smart grid, the majority of cases harness the closed-loop control attributes of DT between physical entities and virtual models to optimize power grid control, forecasting, and maintenance operations. Presently, the paramount anticipation among power sector professionals regarding DT is its potential to revolutionize two critical areas: the integration of traditional grids with distributed energy resources, and the bespoke allocation and distribution of electricity. However, research in these domains remains largely theoretical. While smart cities represent a sector with a multitude of DT applications, the maturity level remains moderate. This is largely due to the high costs, considerable investment risks, and technical complexities involved in constructing DT at an urban scale. Most DT city projects proposed by countries and regions are still in the planning or initiative phase, with a focus on pilot projects in sub-domains like building management, traffic planning, and pedestrian control. The healthcare and DT Earth domains exhibit relatively lower maturity levels compared to other sectors. This is attributed to the significantly higher modeling scale and granularity, as well as computational complexity, necessitating the leadership of prominent companies or international organizations in research and implementation efforts.

The majority of DT cases across the aforementioned sectors are situated at maturity level 3. However, they largely fall short of realizing high-fidelity virtual models and two-way communication in a stringent sense. Nevertheless, considering technological and economic feasibility, if the developed DT can satisfy the practical business requirements of the application scenario, such a compromise is deemed reasonable. Hence, this paper assigns a maturity rating of level 3 to these cases. It is apparent that scarcely any DT attain maturity levels 4 or 5, underscoring a substantial disparity between their current intelligence and integration capabilities and the envisaged potential of DT. DT, as a conceptual technology, necessitates support from a multitude of technologies for its realization, yet these very technologies also pose constraints. Presently, challenges of varying magnitudes are encountered in areas like data governance, modeling and simulation, and human–computer interaction. Moreover, the journey to develop adaptive, self-evolving DT and multi-DT integration platforms that transcend systems and domains is still far from completion.

6. Challenges and future directions

6.1. Challenges and limitations

The implementation complexity of DT is contingent on the scale and structure intricacy of the application, potentially encountering challenges in engineering techniques, project management, and even commercial or social realms. Drawing from the reviewed literature and the assessment results of DTMM, the implementation of DT may confront the following challenges:

6.1.1. Data management challenges

Data stands as the central driving force behind DT, yet the stringent requirements for real-time computing, real-time communication interaction, and real-time control in DT continue to position data management as a foremost challenge in its implementation.

In the realm of data collection and transmission, DT may demand an increased number of high-precision sensors, alongside more sophisticated data transmission protocols and architectures. This undeniably calls for a robust IoT infrastructure, prompting the need for further advancements in sensor technology and multimodal approaches; For data processing and analysis, DT necessitates low-latency, high-reliability, and scalable data processing architectures, as well as computing analysis platforms capable of tackling large-scale data processing challenges. Current research on cloud-fog-edge technologies for supporting DT data processing and analysis is in its nascent stages; About data fusion and visualization, the urgent integration of real-time with historical data, as well as the amalgamation of physical with simulation data, demand immediate attention. Visualizing unstructured and complex data calls for novel methodologies and technologies to enhance human–computer interaction capabilities.

Consequently, DT requires a more robust, authoritative, and standardized data ecosystem or framework for information sharing and exchange. This is essential to tackle challenges associated with data management in DT, including clarifying responsibilities related to data ownership and legal considerations.

6.1.2. Modeling and simulation challenges

Presently, numerous researchers have introduced methodologies and solutions addressing the modeling challenges of DT, successfully implementing DT through data-driven, model-driven, knowledge-driven, and a combination of DES and ABM-driven paradigms. Yet, certain scholars have raised questions about the existing DT modeling methods, suggesting that most implemented DTs should be referred to as Digital Shadows rather than Digital Twin. This stance primarily stems from considerations of economic and technical feasibility, indicating that no cases have yet succeeded in constructing a truly high-accuracy, high-fidelity virtual model. However, certain scholars have critiqued the current modeling methods of DT, positing that most of the implemented DTs should be identified as Digital Shadow, not Digital Twin. This is mainly due to considerations of economic and technical feasibility, where the cost of constructing high-precision virtual models is unaffordable in some scenarios. The quest for high-fidelity virtual models in DT is commendable and crucial, as it significantly dictates the accuracy of subsequent simulation deductions and DT's functionality. Nevertheless, given the current state of technology and considerations of total cost and investment risks, a more practical solution is to ascertain the requisite model fidelity level based on specific business requirements.

Regardless of whether it's DT or traditional digitization approaches, the pursuit of high-fidelity virtual models remains an enduring objective. Therefore, it is still necessary to make every effort to explore various advanced modeling technologies, especially in aspects such as model updating, model fusion, and model verification.

6.1.3. Intelligent challenges

In numerous literature, DT is described as a complex system capable of autonomously, adaptively, and self-evolvingly performing tasks such as monitoring, controlling, forecasting, optimizing, and decision-making, which poses higher demands on the intelligence level of DT. Presently, the application of machine learning and deep learning techniques has augmented the intelligence quotient of DT to a certain degree, yet the aspirations of numerous academics extend well beyond this scope. At present, several scholars grounded in cognitive science propose that DT should embody cognitive attributes and faculties akin to attention (selective concentration), perception (creation of valuable data representations), and memory (adaptive encoding and retrieval of information and knowledge), consequently putting forward the notion of the Cognitive Digital Twin (CDT). The envisioned trajectory for CDT encompasses a heightened level of autonomy in realms like data management, modeling, simulation, HMI, and integration, empowering it to independently undertake diverse tasks and endeavors, and ensuring the concurrent evolution of virtual models and physical systems across various lifecycle phases. As an emerging concept derived in the development process of DT, CDT is still in the conceptual phase. Yet, the ascendance of large language models (LLMs) and AI Agent technologies has brightened its future outlook. Therefore, combining LLM and AI Agent to perfect the theoretical framework of CDT and put it into practice can further enhance the intelligence level of DT, which is undoubtedly the cutting-edge research direction of DT.

6.1.4. HMI and integration challenges

For the HMI of DT, the prevailing approach involves employing AR and VR technologies to convey real-time data and information to users in a more streamlined fashion, consequently augmenting their decision-making proficiency. However, researchers in the manufacturing sectors, contend that attaining a higher echelon of adaptive DT is challenging with current technological means. Thus, from a human–machine interaction standpoint, melding theories such as Human in the Loop and ergonomics, they propose a tripartite DT theoretical framework of "human-physical-virtual," aiming to fully leverage human subjective agency to shatter the existing developmental shackles of DT.

The integration aspect of DT, encompasses the integration of IoT infrastructure, models, business processes, systems, and APIs. However, the present state reveals that fundamental data networks suffer from non-uniform transmission protocols and interfaces, with disparities in connection ports and data interfaces between edge controllers and the cloud. This inconsistency exacerbates the challenge of subsequent system integration to develop a SoS level multi-DT collaborative platform, rendering it akin to a fanciful castle in the sky. To a certain degree, the obstacles in DT integration resemble managerial dilemmas rather than technical ones, requiring the initial design phase of DT to contemplate and stringently comply with the standardization of interfaces and protocols. Currently, there's a pressing demand for sharing frameworks and best practices in data management and integration for DT.

6.1.5. *Security and privacy challenges*

Concerning the security and privacy aspects of DT, it typically amasses extensive data for the creation of virtual models. Yet, akin to all information technologies, it confronts a plethora of cyber threats and assaults. The accuracy and dependability of DT hinge on the integrity of data procured from physical domains. Compromise or assault on such data might result in inaccurate modeling and analysis, precipitating erroneous simulation results and decision-making, or in worst cases, data theft or alteration, consequently undermining the credibility of the entire DT system. Concurrently, in its operational phase, DT may gather an array of privacy-sensitive data and information from users, exposing these to both physical and virtual open network environments, and potentially harboring substantial risks at legal and ethical levels. Consequently, there is a pressing demand for a security and privacy reference framework or best practices at the IoT infrastructure, data management, model management, and DT system operational levels, necessitating, of course, the engagement of relevant standardization bodies.

6.1.6. *Standardization challenges*

The extent of standardization in technology is a substantial indicator of its maturity. The standardization of technology serves as a beacon, guiding practitioners toward viable implementation strategies and solutions while minimizing development timelines and costs. As the DT market rapidly evolves, a robust standardization system becomes imperative to expedite DT implementation, enhancing clarity, ensuring quality, and fostering service excellence.

It is heartening to note that significant efforts have been made by various standardization organizations and institutions in the establishment of DT standards. For instance, in November 2023, ISO and IEC jointly released standards on the concepts and terminology of DT, namely ISO/IEC 30173–2023. In the manufacturing domain, efforts are underway to develop ISO 23247–1 4 Manufacturing DT Framework Standard. The first part of this standard offers general principles and defines requirements for developing DT in manufacturing. Additionally, the National Institute of Standards and Technology (NIST) has issued a draft NISTIR 8356, outlining definitions, common low-level operations, usage scenarios, and exemplary use cases.

While ISO and IEC have indeed released standards pertaining to the concepts and terminology of DT, there still remains a deficiency in standards and protocols concerning DT-related models, data, connections, and services during project implementation processes. Addressing the critical aftermath of the current DT standardization initiatives, Wang et al. [161] have methodically reviewed existing referable standards from five perspectives: physical entities, virtual entities, data, connections, and services, as illustrated in Fig. 14, to further the advancement of DT standardization efforts.

6.2. *Future directions*

Based on the evaluation results of the development trends in various fields based on DTMM and the analysis of related challenges and limitations, it can be observed that the ultimate goal of DT is to establish a ecosystem, namely multiple interconnected DTs, to conduct collaborative simulations on a larger scale, thereby assisting policymakers in decision-making. However, based on the evaluation results of DTMM, it can be seen that this goal still has a long way to go, which is also the greatest challenge facing DT. Therefore, this paper proposes several working suggestions to promote the construction, upgrade, and sustainable development of DT.

1) Advancing the formulation of DT maturity standards, consolidating consensus on DT design and development, and formulating holistic DT construction plans. The maturity model systematically elaborates on the task objectives and requisite capabilities at each stage of DT construction process, enabling relevant standardization organizations to guide the implementation process of DT stages based on the maturity model, thereby forming actionable DT planning, construction, and development schemes.
2) Leveraging the maturity model, assess and evaluate existing DT projects, determine their construction levels and effectiveness, and provide guidance for the iterative upgrade of relevant projects. Based on the maturity model, launch the DT maturity ten-point project, incubate the best practices of DT, and promote globally the high-value implementation and construction experience of DT.
3) From the maturity model, it can be observed that the ultimate goal of DT is to achieve multi-DT interconnection and interoperability, which requires considering mutual integration and interoperability between DTs at the outset of DT construction, but this is also the most easily overlooked aspect. Currently, noteworthy interoperability solutions include the Destination Earth project, which proposes four solutions for multi-DT integration into a digital ecosystem, namely unified data and model standards, shared data and models, innovative services, and the creation of knowledge exchange communities [162]. In addition, there is also the DT interconnection information exchange framework proposed by the UK National Digital Twin Body [163]. It is hoped that pertinent organizations and institutions will propose standardized architectures for DT interoperability and integration.

7. Conclusion

Almost two decades have elapsed since Professor Grieves introduced the DT concept, with its development gaining significant momentum only in recent years. However, due to the severe lag of standardization behind market development, DT still lacks a formal or widely accepted definition, and there is no unified construction and operation process. The diversity in technical approaches and product forms across various vertical fields poses a challenge to the high-quality development of DT. There is an urgent need for a unified framework capable of effectively amalgamating the phased goals, capability necessities, and technical specifications of DT. This framework would aid stakeholders in evaluating project risks and technical complexities, ascertaining the actual development stage and project merits across various industries. Consequently, this would facilitate the dissection of project objectives and the formulation of viable DT implementation strategies, underpinning the triumphant execution of DT projects.

Therefore, drawing on an analysis of diverse DT definitions and preceding advancements in maturity, this paper introduces the DTMM, which embodies a continual progression in capabilities and objectives.

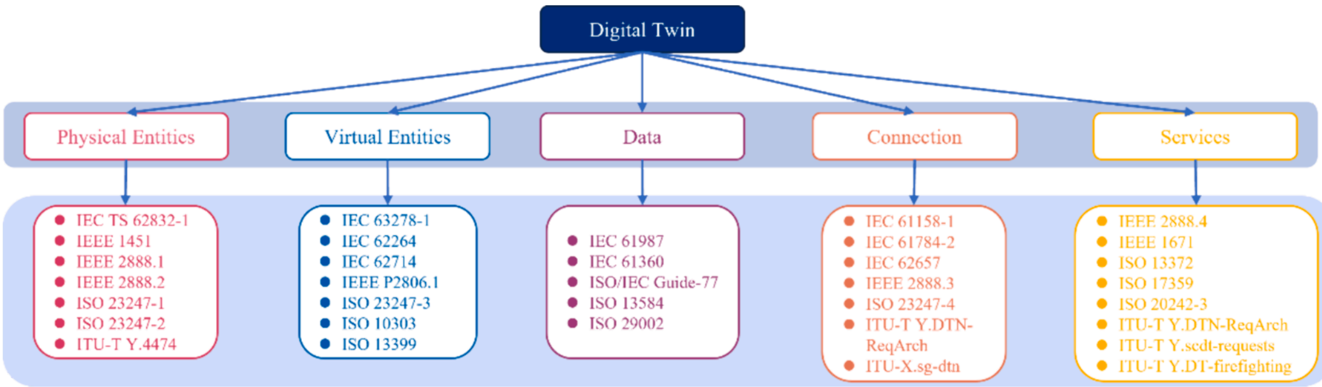

Fig. 14. Current standards and specifications that can be referenced for digital twin.

Furthermore, rooted in the capability requisites of each tier within DTMM, systematically reviews and summarizes the presently accessible empowering technologies and tools from vantage points like data management, simulation, intelligence, HMI, integration, and security. This aims to assist developers in crafting pragmatic and effective technical pathways. Building on this, to ascertain the efficacy of DTMM, assessments were carried out on the developmental status and levels across six vertical domains: aerospace, intelligent manufacturing, energy and power, smart cities, medical and health, and DT earth. The analysis reveals that more instances have attained a maturity level of 3, characterized by high-fidelity virtual models, two-way communication capabilities, and a moderate degree of automation. Yet, only specific subsystems within the manufacturing field have achieved Level 4 maturity, with cases reaching Level 5 maturity being exceedingly rare. Consequently, it is apparent that DT currently remains in its nascent stage.

This research endeavors to provide references for different individuals to correctly recognize and understand DT, and offer valuable guidance for researchers to further carry out theoretical studies. Moreover, it aids developers, project managers, and policymakers in evaluating whether existing DTs meet projected business requirements, bridging the gap between the final product and the envisaged vision. This facilitates a more rational establishment and execution of DT development plans and routes while providing references and guidance for the improvement and optimization of DT. The forthcoming phase of this study involves leveraging technologies like LLMs and AI Agents, predicated on the review results of DTMM, to elevate the intelligent capability of DT in data management, modeling, simulation, and associated business activities, thereby facilitating higher quality promotion and application of DT, contributing to the healthy development of the DT industry.

CRediT authorship contribution statement

Yang Liu: Writing – review & editing, Writing – original draft, Methodology, Investigation. **Jun Feng:** Funding acquisition, Conceptualization. **Jiamin Lu:** Resources. **Siyuan Zhou:** Resources.

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.

Acknowledgments

This research was supported by the National Key R&D Program of China (Grant No. 2021YFB3900601).

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