



Developing and leveraging digital twins in engineering design

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ABSTRACT

Digital twins are digital representations of real-world entities constantly fed by dynamic, bidirectional communication and updates throughout the lifecycle of these sophisticated paired systems. Developing digital twins in production engineering creates new avenues for engineering design in the context of digital transformation in manufacturing and sociotechnical systems. This paper reviews the foundational concepts, methodologies, and applications of digital twins in engineering design, covering both their architecture and development (engineering of digital twins), and their utilisation to enhance design activities (engineering with digital twins). An overview of the current state-of-the-art is presented, challenges are highlighted, and future research directions are addressed.

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1. Introduction

Since its emergence, the Digital Twin (DT) has been recognised as an effective paradigm for integrating real-world assets with their digital counterparts, generating significant enthusiasm across various sectors, driven by industry, media, and politics. DTs are called upon to achieve the Sustainable Development Goals (SDGs) by enhancing resource allocation efficiency (SDGs 6,9,11 and 12) and green technologies innovation (SDGs 3,6,7, 9 and 11) [239]. DTs enhance resilience and sustainability to address VUCA (Volatile, Uncertain, Complex, and Ambiguous) environments and Industry 5.0 requirements [17], which expand upon smart manufacturing and Industry 4.0 by prioritising human factors, sustainability, and resilience. Through virtual environments, DTs enable scenario simulation, failure prevention, and rapid adaptation to changes.

Constantly updated with data, DTs act as sophisticated digital counterparts of real-world entities, providing insights into the status and performance of products, processes, and systems throughout their lifecycle. Consequently, DTs have gained importance in production engineering, improving design capabilities and product performance, enhancing model-based and data-driven design [133], and enabling advanced abilities of description, prescription, and prediction in developing sociotechnical systems. The increasing interest in DTs has raised questions about their characteristics, uses, and similarities and differences from relatively similar concepts. Consequently, many definitions have emerged in recent years. The CIRP (International Academy for Production Engineering) has also contributed to the topic by proposing the following definition [216]: ‘...a digital

representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviours by means of models, information, and data within a single or even across multiple life cycle phases. ...’ [216], and illustrated in Fig. 1 [194].

If not stated otherwise in this keynote paper, the authors refer in their subsequent keynote sections to this definition.

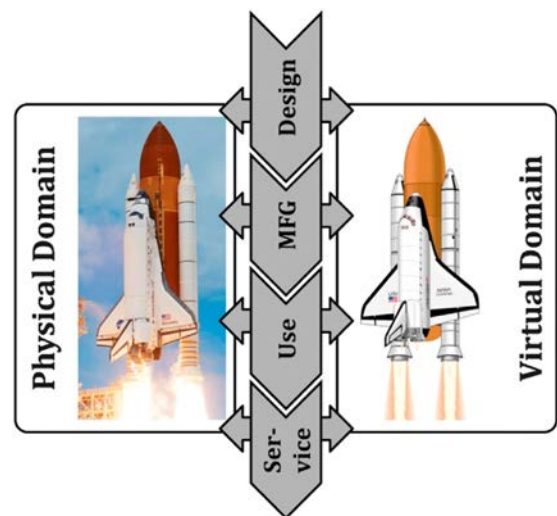


Fig. 1. Pictorial representation of the DT (adapted from [80]).

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Realising the full potential of DTs in engineering design requires significant research efforts and the overcoming of many challenges. These include establishing a shared understanding of DT definitions, fundamentals and foundations, developing DT methods and tools, investigating DT value chain and developments in engineering design, and identifying enablers for DT realisation.

1.1. Evolution of DT research

1.1.1. DT inception

The Apollo 13 mission contributed to the exploration of physical system twins, particularly using physical replicas for simulations [163]. This laid the foundation for remote diagnostics and system simulations using physical twins. However, the concept of DT, as we understand it today, took a significant leap forward, inspired by fiction such as Gelernter's *Mirror Worlds*, which envisions a complete, real-time digital counterpart of every real-world entity that mirrors its operations in real-time [68]. This concept expanded the scope and potential of twins beyond the initial framework of physical replicas. Furthermore, Grieves initially envisioned the 'Mirrored Spaces Model' to propose the 'virtual representation of a product or system that mirrors its real-world counterpart' [77]. This was further coined as the term *digital twin* in NASA's 2010 technological roadmap [205]: '... a digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin ...' and further developed in NASA's 2012 technological roadmap [180] as the 'Virtual Digital Fleet Leader' paradigm integrating multiple cross-cutting technology capabilities into a multi-physics, multi-scale simulation of the as-built vehicle or system.

1.1.2. DT research and development

DT has evolved significantly since its inception. Defined as a digital informational construct of a physical system that can be established as a separate entity, DT replicates the physical system and remains linked throughout its lifecycle [80]. Moreover, Grieves and Wickers [80] distinguished two types of DTs to cover lifecycle phases: the Digital Twin Prototype (DTP) (created during the design phase) and the Digital Twin Instance (DTI) (virtual counterpart of a specific physical product and interconnected throughout the product's lifecycle), and the aggregation of multiple DTIs, the Digital Twin Aggregate (DTA). DT Instances and Aggregates exist within their Digital Twin Environment (DTE), mirroring the real product's environment. Through the triplet: real space, virtual space, and linking mechanism, Grieves introduced DT's core concepts emphasising DT's role during the product's lifecycle [78,79]. Kritzinger et al. [123] differentiated DTs from digital models and digital shadows through the nature of bi-directional data flow.

Furthermore, DT's scope and characteristics have been broadened, enhancing simulation, monitoring, prediction, and prescription across the real-world counterpart's lifecycle through real-time data integration, thereby extending the lifespan and enhancing the performance of the real system [27,72]. DT has also been adapted to combine with diverse technologies like Internet of Things (IoT) and other digital tools for data capture, and real-time data analytics and synchronisation. Despite seamless integration of diverse DT-enabling technologies into manufacturing and conceptual advancements, a unified definition of DT remains elusive. The gap between potential and practical implementations continues to challenge researchers and developers.

Research output on DTs has surged, driven by advancements in IoT and Artificial Intelligence (AI). Initially prominent in manufacturing, DT concepts have extended to construction, urban management, and medicine, demonstrating their broad applicability and potential. Bibliometric analyses highlight DT research's interdisciplinary nature, with major contributions from Industry 4.0 and Cyber-Physical Systems (CPS). These studies underscore the structuration and evolution of concepts through systematic literature review methods [112,137,203,227], suggesting that while DT technology is nascent, its rapid growth (Fig. 2) and diverse applications make it critical for

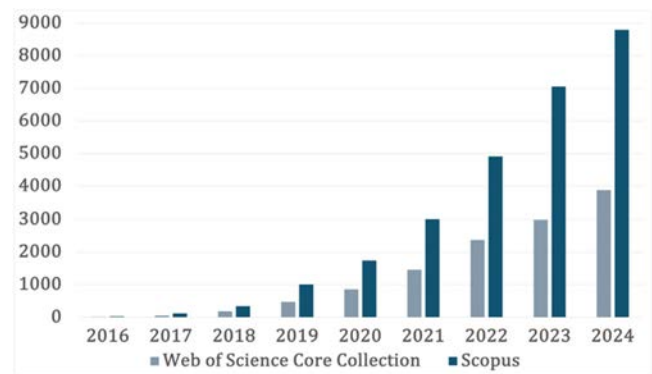


Fig. 2. DT publication growth (query: Title/Abstract/Keywords= "digital twin").

future research and industrial strategy, necessitating important efforts to address related challenges.

DTs have received increasing attention across different product life-cycle stages. The expanding literature and the number of review papers on DT definitions, taxonomy, characteristics, and applications highlighted several issues and a lack of consensus in both research and industrial practice [122,198,213,229,246]. DT literature and realisations emphasised manufacturing and use phases, with a limited focus on design and end-of-life stages [36]. They mostly addressed individual phases rather than the entire lifecycle, incorporating a combination of digital models, digital shadows, and digital twins [182].

The CIRP has established itself as a prominent force in the field of DTs in manufacturing. This is evident from the substantial body of work published (Fig. 3), particularly in the proceedings of CIRP conferences (Procedia CIRP). The CIRP Design conferences, in particular, have served as a key platform for disseminating cutting-edge research and developments in DT area. The community's influence extends beyond conference proceedings, with a significant contribution to the CIRP Encyclopedia of Production Engineering, including an entry on DT [216]. This demonstrates the community's role in shaping DT terminology and conceptual framework. Furthermore, the CIRP community's impact is underscored by its contributions to CIRP Annals and CIRP JMST with highly cited papers [112,194,213,230]. Additionally, the keynotes' papers likely provided comprehensive overviews of the state-of-the-art and future directions, further cementing CIRP's position at the forefront of DT advancement. Bergs et al. [19] reviewed DTs for cutting processes and presented recent research and implementation conditions in industrial environments. Guo et al. [82] explored DT implementation in additive manufacturing, electrical discharge machining, and electrochemical machining. These studies provided important insights into DTs for manufacturing and highlight the main challenges for future research.

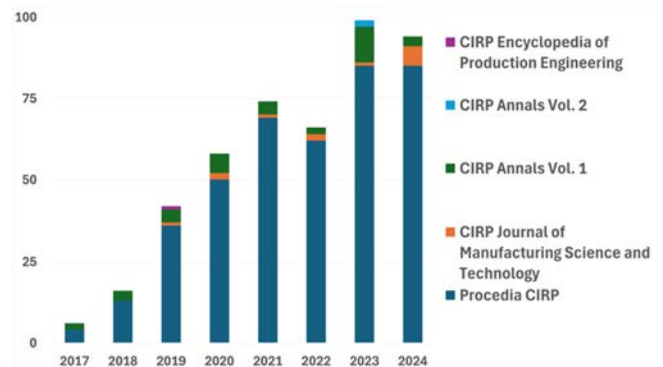


Fig. 3. DT publications by CIRP Editorial Products.

DT patent analysis (Fig. 4) indicates significant growth in applications and grants [222,253], underscoring the ongoing development and substantial innovation potential of DT, primarily in manufacturing and less evenly across other sectors.

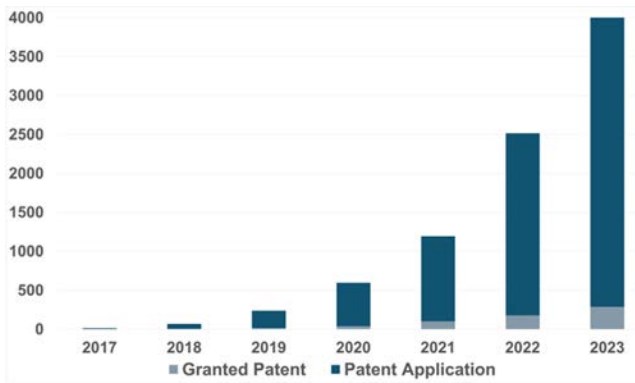


Fig. 4. Growth of DT patents.

DT software and platforms have evolved to offer versatile tools for modelling, simulation, testing, validation, and low-code environments [38]. Open-source and commercial platforms like Eclipse Ditto, Microsoft Azure Digital Twins, Amazon Web Services (AWS) IoT TwinMaker, ANSYS TwinBuilder, Dassault Systèmes 3D Experience, Siemens Xcelerator, Matlab/Simulink, and Asset Administration Shell (AAS) based DT frameworks [71,175], among others, are enhancing their capabilities, while reference architectures like makeTwin provide comprehensive, modular, and configurable solutions [226]. However, fragmentation and lack of standardisation in DT software development lead to closed ecosystems that hinder interoperability, complicate data and model integration, and challenge seamless communication between DTs, which are crucial for leveraging DT interoperability and compositionality across different manufacturing applications.

1.1.3. DT standardisation

The standardisation landscape for DTs is vast, involving multiple actors, which develop standards for reference architectures, data interoperability, data communication, and more, ensuring that DTs can support system operation in a global context. The ISO 23247 series [104–107] established a generic framework for creating DTs of Observable Manufacturing Elements (OME) such as personnel, equipment, materials, manufacturing processes, facilities, environment, products, and supporting documents. ISO/IEC/JTC1/SC41/WG6 is developing foundational standards for DTs, their related technologies, and applications to address the requirements of different application sectors [100–103]. The IPC-2551 standard [99], known as the 'International Standard for Digital Twins' establishes a comprehensive framework for DTs comprising three key components: Digital Twin Product, Digital Twin Manufacturing, and Digital Twin Lifecycle. Other supporting standards such as the AAS [97], developed by IEC/TC65/WG 24 play a key role in many industrial applications. The AAS acts as a standardised digital wrapper for assets in Industry 4.0, enabling seamless interoperability, communication, and integration of physical and digital components within manufacturing systems. Other Smart/Digital Manufacturing related standards covering data, models, Physical-to-Virtual (P2V), Virtual-to-Physical (V2P), and service dimensions, such as MTConnect, OPC Unified Architecture (OPC UA), and Message Queuing Telemetry Transport (MQTT), also contribute to DTs ecosystem-related standards [207] (Fig. 5).

These standards collectively ensure that DTs can be implemented and leverage complex systems throughout their lifecycle. However, gaps in DT standardisation necessitate unified, cross-disciplinary efforts. Enhanced collaboration and liaison between standardisation committees are essential. By fostering interoperable standards, customising DT frameworks for industry-specific needs and promoting scalable, flexible, and smart standardisation, the full potential of DTs can be realised. This aligns with the convergence concept in engineering, unifying various engineering processes digitally, integrating disciplines and technologies like data and models, IoT and AI, and relying on standards to create adaptable, interconnected, smart, and interoperable systems.

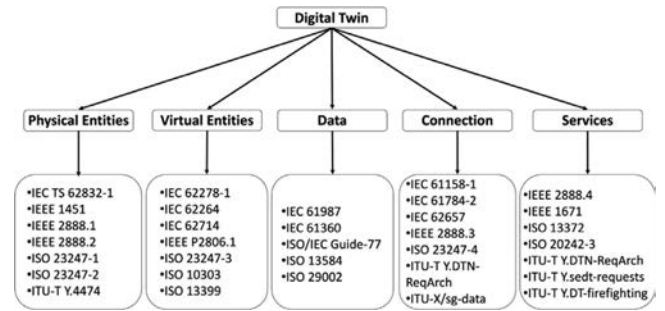


Fig. 5. Standards supporting DTs (adapted from [145,252]).

1.2. Structure of the paper

By bridging methodological advancements with practical applications, this paper offers a holistic view of the current state-of-the-art in DTs. It systematically explores DTs in engineering design, shedding light on their defining characteristics (Section 2), and addresses two complementary directions: *engineering of digital twins* through architecting DTs and model-based approaches that allow for their structured and systematic design (Section 3), and *engineering with digital twins* by examining design characteristics of DTs to highlight core features, methods, tools, and opportunities for enhancing engineering design processes and activities (Section 4). The subsequent sections address DT implementations in industry (Section 5) and critical challenges, needs, and foresight for future research (Section 6). Section 7 concludes the paper.

2. Digital twin fundamentals

2.1. Distinctive features of DTs

From a data flow perspective, DTs emphasise a bidirectional, automated data stream that connects the physical and digital spaces throughout the entire product lifecycle, as illustrated in Fig. 6. This continuous data flow is crucial for real-time simulation and feedback [112]. The DT is continuously driven by data collected from the physical space, enabling it to encapsulate the characteristics of physical entities or processes and accurately mirror their states, thereby enabling dynamic and precise model updates and supporting the validation of DTs to ensure their accuracy and effectiveness [272]. Additionally, through the integration of various types of data (for example, historical maintenance data and real-time state data), decisions made within DTs contribute to optimising physical entities or processes [65,280]. After such decisions are executed, feedback data from the physical objects can be transmitted back to the digital space, thereby validating the decision accuracy and assessing the physical objects' performance post-execution. Consequently, an automated data flow from the physical to the digital space is essential for visualising and simulating the real-time states of physical entities or processes, ensuring accurate and timely responses.

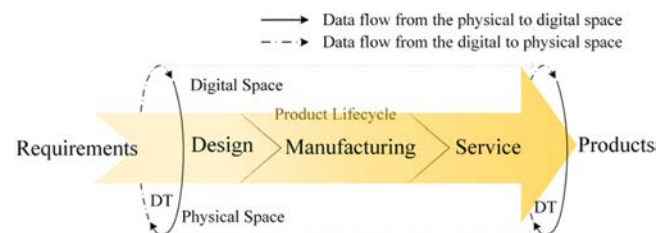


Fig. 6. Data flow perspective of DT in the product lifecycle.

Because of the interplay of physical and digital/virtual spaces, DTs are often compared to other existing concepts, approaches, and technologies such as Modelling and Simulation (M&S) [27], Cyber-Physical Systems (CPS) [224], the Internet of Things (IoT), Virtual and

Augmented Reality (VR/AR), and the metaverse [16]. Understanding their distinctions is crucial for the effective conceptualisation and utilisation of DTs, as described below.

DT vs. digital model. The similarity between the DT and the digital model lies in their ability to describe the characteristics of physical objects in a virtual space. While a digital model is considered an important component of DT, DT extends beyond this by incorporating physical objects and the interactions or connections between physical objects and their digital models.

DT vs. M&S (modelling and simulation). DTs rely on virtual models to achieve real-time reflections of the physical space within the digital domain, making modelling and simulation integral components of DTs. However, DTs extend beyond mere modelling and simulation. DTs also require the capability to influence the physical space based on the analytical outcomes generated within the digital space.

DT vs. digital shadow. Digital Shadow (DS) involves a unidirectional, automatic data stream from the physical to the digital space, providing a descriptive representation of physical processes [20,123]. Therefore, DS emphasises the role of data collected from the physical domain in updating the digital models of corresponding physical entities or processes. In this sense, the data used by DTs include those from the DS [218].

DT vs. digital thread. Digital thread provides a communication framework designed to deliver information on demand [212]. In the context of DTs, the connections between digital models and data from real assets or processes are integral. These connections might also be effectively supported by the Digital Thread, ensuring coherent and timely information exchange throughout the lifecycle of a product or process [110].

DT vs. IoT. In comparison to IoT, DTs use data collected by IoT devices to create a dynamic virtual model that mirrors the physical system. The IoT is primarily concerned with data collection and communication between devices, whereas DTs use this data to simulate and analyse the physical system, providing insights for decision-making and optimisation.

DT vs. metaverse. Both DTs and metaverses emphasise the richness of the digital space and the immersive interactions between physical and digital spaces. However, while DTs prioritise creating accurate, data-driven replicas to reflect the true state of physical objects or systems, the metaverse focuses on constructing a more imaginative and immersive virtual world, often with fewer constraints tied to physical reality.

DT vs. virtual reality (VR)/Augmented reality (AR). VR/AR can create a realistic and immersive virtual world, providing users with a sense of being fully present in the environment [85,115]. Compared to DTs, VR primarily focuses on creating imaginative virtual worlds with weaker connections to the real world. AR overlays virtual models onto the real world, immersing users in a blended reality and virtuality environment. In contrast, DTs are primarily concerned with accurately mapping the real world.

DT vs. CPS. DTs differ from CPSs in their focus on computational modelling, leveraging machine learning and artificial intelligence to create a live virtual representation of a physical system, rather than emphasising system engineering and control. While CPSs typically involve real-time control and feedback loops to manage physical processes, DTs aim to provide a comprehensive virtual model that can simulate, predict, and optimise the performance of the physical system over its entire lifecycle.

DT vs. smart product. The scope of DTs encompasses various physical entities, including products, cities, energy systems, and others. While a smart product refers specifically to an intelligent, connected product, DTs extend beyond this to include various categories of physical objects, making it applicable across diverse domains. In addition, DT makes it possible to provide look-ahead predictions of the behaviour of smart products.

DT vs. PLM/ALM/SLM. DTs provide a seamless connection between physical objects and processes and their digital assets throughout their lifecycle, offering an effective approach for managing Product Lifecycle Management (PLM), Asset Lifecycle

Management, and System Lifecycle Management (SLM). DTs enhance them by integrating real-time data and models, enabling more dynamic and informed decision-making processes.

Based on the above, DTs can be characterised from the perspectives of digital models, synchronisation, and integration as follows:

- (1) The fundamental function of DTs is to accurately reflect the real states of physical objects. Therefore, the foundation for creating a realistic mirror in the digital space lies in constructing digital entities at a certain level of fidelity. Fidelity covers several dimensions, including model fidelity, data fidelity, and communication fidelity, each of which is critical for ensuring accuracy and synchronisation. For instance, the digital model of a complex product should capture the geometric characteristics, physical properties, and operational mechanisms of the product. Such a digital model typically comprises multiple sub-models from various domains, each reflecting one or more aspects of the physical product [57]. Through model composition and fusion, both explicit and implicit associations are established between these sub-models, ensuring a cohesive representation of the physical entity [273]. Similarly, the digital model of a complex system consists of interconnected digital models that describe the essential components of the system and their relationships.
- (2) Synchronisation between the physical and digital spaces is a critical enabler for effective DT implementation. DTs achieve real-time reflection of physical objects within a digital space using synchronised models driven by data, providing an intuitive user interface. This synchronisation is primarily dependent on the continuous flow of real-time data from the physical to the digital domain, ensuring that the data driving the digital models closely mirror the real-time states of the physical entity [151]. Moreover, this data flow not only sustains the alignment of the digital models with physical reality but also serves to validate the accuracy and effectiveness of these models [263,274], allowing for the correction and update of any erroneous model parameters [259]. To collect the necessary data from the physical environment, a range of sensors, such as cameras, RFID tags, and infrared sensors, can be employed, tailored to the specific requirements of the given scenario.
- (3) DT requires the integration of different models and representations, multi-source data including data from physical objects at various lifecycle stages, historical data and information, and human expertise [45,225,276]. The close interaction among these elements is crucial for the effective functioning of DT.

These interactions involve the relationship between physical entities and their corresponding digital models, the interaction between DTs and users, such as human operators [181], and the integration of data generated across different lifecycle phases. The increasing complexity of manufacturing processes and product sophistication can lead to exponential growth of information throughout the product lifecycle. The ideal DT performance is achieved when it can autonomously optimise and control processes through the integration of models and data across all lifecycle phases. Consequently, the objectives at different lifecycle stages impose varying requirements on DTs, necessitating distinct models and types of information. Since DTs can be intended not only to mirror physical objects but also to manage them, the complexity of the physical objects is closely linked to the complexity of DTs.

In summary, DT features demonstrate great potential to bridge the gap between virtual and real entities. This innovative concept has been extensively explored and developed, thereby positioning DTs as key enablers of advanced capabilities in various domains.

2.2. DT definitions

To provide a complete view of the DT building blocks and concepts, Table 1 provides some generic definitions across various fields and derived from prominent academic sources and organisations. In analysing the listed definitions, several key insights emerge:

Table 1
Selected definitions of DT.

Publication	Definition	Year
NASA [72]	"...an integrated multiphysics, 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..."	2012
Boschert and Rosen [27]	"...a comprehensive physical and functional description of a component, product or system, which includes more or less all information, which could be useful in later lifecycle phases..."	2016
Grieves and Vickers [80]	"...a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level..."	2017
Tao et al. [230].	"...five-dimension digital twin architecture includes physical entities, virtual models, digital twin data, services and connections..."	2018
CIRP definition: Stark and Damerau [216]	"...a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases..."	2019
SEBoK [200]	"...a high-fidelity model of the system, which can be used to emulate the actual system..."	2019
AIAA [4]	"...a set of virtual information constructs that mimics the structure, context and behavior of an individual / unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its lifecycle and informs decisions that realize value..."	2020
Digital twin consortium [47]	"...a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity..."	2020
AIF [5]	"...an organized set of digital models representing a real-world entity to respond to specific problem and usages. The digital twin is updated in relation to reality, at a frequency and precision fitting the above problems and usage. The digital twin is equipped with advanced operating tools to understand, analyse, predict or optimize the operation and control of the real entity..."	2021
ISO 23247 [104]	"...a fit-for-purpose digital representation of an observable manufacturing element with a means to enable convergence between the element and its digital representation at an appropriate rate of synchronization..."	2021
ISO/IEC 30173 [101]	"...digital representation of a target entity with data connections that enable convergence between the physical and digital states at an appropriate rate of synchronization..."	2023
NASEM [164]	"...a set of virtual information constructs that mimics the structure, context, and behavior of a natural, engineered, or social system (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value. The bidirectional interaction between the virtual and the physical is central to the digital twin..."	2024

- The nature of DTs is ambiguous; for example, they are described as information systems, digital representations, a set of models, simulations, or a combination of physical objects and their digital counterparts.
- Most definitions describe a DT as comprising physical objects and a physical-to-virtual data flow. However, during the design phase, there is not necessarily a physical entity.
- Some definitions are overly idealistic and too critical to serve as practical definitions, such as those requiring high-fidelity models. For a more practical approach, the DT key characteristics should be tailored to actual use cases.
- There is no consensus on what constitutes a DT. Some definitions narrowly focus on digital models, while others argue for the inclusion of both digital models and physical entities. This inconsistency creates confusion and potential misalignment in the development and application of DTs across industries.
- Only a few definitions highlight the necessity for digital models to possess a certain level of fidelity. High fidelity is ideal for DTs; however, achieving it requires significant effort. The appropriate level of fidelity should be determined by the specific requirements of the application.
- Synchronisation is identified as a fundamental function of DTs, highlighting the importance of alignment between digital models and the physical entities. However, few definitions explicitly emphasise the requirement for synchronised models.
- While some definitions stress the simulation functions of DTs, others broaden this perspective, asserting that a DT not only controls but also predicts the states of physical entities or processes.

2.3. DT building blocks

Grieves introduced a three-dimension model (Fig. 7(a)), where a DT comprises three core components: a physical object, its virtual representation, and the connections between them [78]. The pursuit of more comprehensive services and enhanced information extraction has driven further exploration of the underlying principles of DTs. Building on this foundational concept, a five-dimension architecture of DT was proposed, comprising the physical entity (PE), DT model (VE), DT data (DD), services (Ss), and their interconnections (CN₁) (Fig. 7(b)) [230]. Subsequently, an eight-dimension model was developed to delineate the scope and type of DTs, with the dimensions including integration breadth, connectivity mode, update frequency, CPS

intelligence, simulation capabilities, digital model richness, human interaction, and product lifecycle [217]. This model was later extended to encompass nine dimensions by adding the new dimension of digital shadow data quality and granularity (Fig. 7(c)). Together, these dimensions are used to describe four key aspects of DT: context and environment, models and data, capabilities, and users [219].

In addition, an architecture for DT from a functional perspective has been outlined in ISO 23247–2 [105]. This architecture includes core entities, user entities, data collection and device control entities, and cross-system entities, all of which are integral to the implementation of DTs. IoT analytics reports have categorised DT technologies into three levels: hierarchical, lifecycle, and use cases level. With six hierarchical levels, six lifecycle stages, and seven common use cases, 252 potential combinations are possible. Each classification represents a distinct scenario compared to the others [48]. In the context of Industry 4.0, Aheleroff et al. [3] proposed an architecture that comprises a conceptual DT reference model structured as interlinked physical, digital and cyber layers. By using this architecture, complex DTs can be decomposed into simpler components, which simplify their modelling and implementation.

Through the synthesis of existing models, architectures and dimensions, several key observations can be made:

- Physical entities, digital models, and the interactions between physical and virtual spaces are essential elements of DTs.
- DT architectures are primarily developed and applied within the field of manufacturing, reflecting the sector's emphasis on optimising processes and improving efficiencies through digital-physical integration.
- DTs continuously evolve and expand over time, with more elements and dimensions being incorporated from various perspectives. This ongoing development reflects the growing complexity and sophistication of DT applications and the need to address emerging opportunities across different domains.

2.4. Key elements for DT conceptualisation

To illustrate the main concepts of DTs, we present a conceptual categorisation comprising four fundamental elements: physical entities, digital models, information, and lifecycle. This categorisation provides a clear understanding of the interrelated concepts that are essential for the development and implementation of DTs.

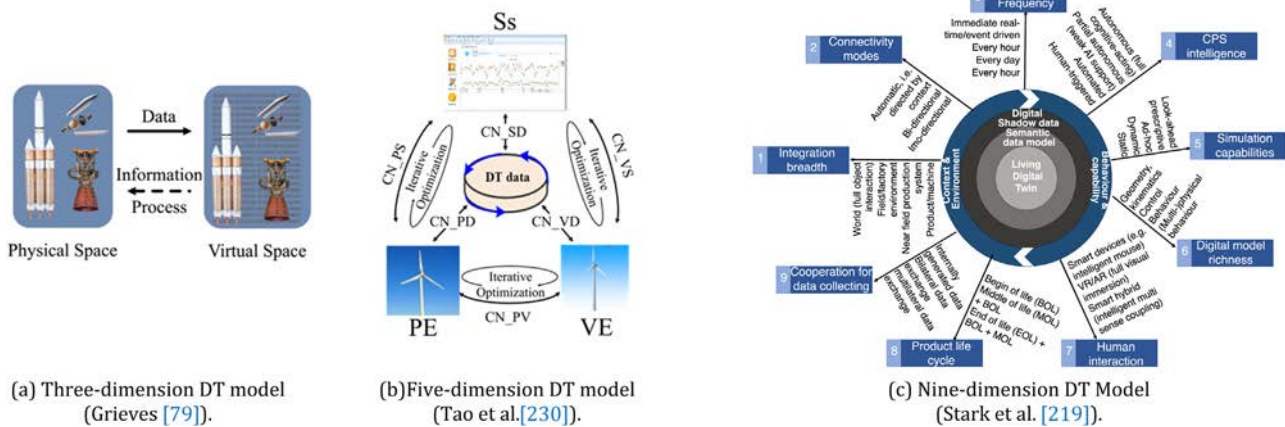


Fig. 7. Selected concepts and frameworks of DTs.

Physical entities are crucial components of DTs. Based on the granularity, they can be categorised into component, sub-system, system, and system of systems. These categories are relative concepts, depending on the granularity of the physical objects being considered. For instance, in the context of an aircraft, an aeroengine system may be classified as a sub-system. However, the aeroengine system itself is a complex assembly of mechanical, electrical, and other subsystems, and can thus be regarded as a high-level system within its own context.

Digital models are central to DTs, as they must accurately represent various properties of the corresponding physical entity [227], including geometric, physical, and behavioural attributes. Typically, a single digital model can only capture a subset of these properties. By integrating different types of models, a comprehensive DT can be created to represent the full range of characteristics. To achieve this, DTs must maintain an appropriate level of fidelity to ensure an accurate representation of the physical entity [194]. Fidelity requires a model that accurately represents the static structure of the physical entity while ensuring consistency in the dynamic response and interactions. It should also support real-time data updates and predictive capabilities to maintain synchronisation with the physical entity under varying operating conditions. However, fidelity should not be maximised indiscriminately; instead, it must be optimised based on application needs, balancing accuracy, computational efficiency, and cost to achieve optimal simulation and decision-making support. The increasing complexity of physical entities requires more models, multi-source data, and intricate relationships between models and data, which presents significant challenges in terms of model lightweighting, computing power, and data management [59,211].

Information plays a crucial role in the development and use of DTs. During the construction of a digital model, various types of information, such as property values, relationships, and other relevant data, are necessary to determine the model parameters. This information may include different DT data. Depending on the source, the data used in DTs can be categorised into three types: physical, simulation, and synthetic data. Physical data, such as property values, real-time positions, and in-process tasks are directly collected from the physical space using various sensors. Simulation data, on the other hand, are generated by the digital models, such as the pressure values and internal temperatures generated by the simulation software. Synthetic data are created by combining physical and simulation data and often enhanced with AI techniques. Digital models are continuously updated with data to perform functions, such as the monitoring of physical entities [154], so that DTs can immediately detect production anomalies and address them effectively [127,167]. As DTs evolve and are used, the available data and information will continue to expand, providing opportunities to extract further knowledge and insights from this enriched information base. Digital models and information provide a reliable foundation for both twinning and intelligent services such as interaction control, prediction, and optimisation where both model-based and data-driven methods can be

adopted to extract useful information from data and convert it into actionable knowledge.

Lifecycle encompasses design, manufacturing, service, and end-of-life stages and activities, and it is accentuated by the feedback loop that enables continuous interaction and synchronisation with the physical entity. Grieves et al. [80] aligned the DT with the product lifecycle through DT prototype, DT Instance, DT Aggregate, and DT Environment [112]. Abdoune et al. [1] used five main phases (design, validation, implementation, service, and maintenance) to identify the main characteristics of the DT lifecycle. Dalibor et al. [38] distinguished three phases (as-designed, as-manufactured, and as-operated) in line with the ISO/IEC 15288 system lifecycle. Stark [216] proposed a four-phase model (initiation, modelling, enrichment & utilisation, and reuse) to highlight the interactions with the product lifecycle (Fig. 8).

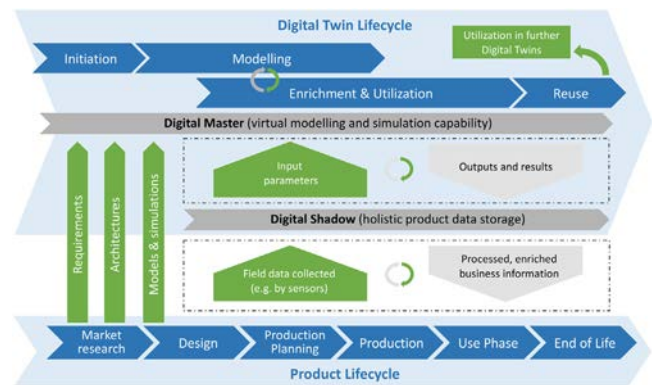


Fig. 8. Product and DT lifecycles [216].

DTs are envisioned to both design and manage physical products or systems throughout the entire lifecycle, necessitating digital models that accurately represent lifecycle characteristics. Data, models, and information from various stages of DTs' lifecycle can be collected and transformed into more valuable insights [186,234,244]. Despite this, the DT lifecycle phases and their relationship to the physical system are still unclear regarding the requirements of the alignment of the DT and the physical entity lifecycle phases [30].

3. Digital twin engineering

Digital Twin Engineering (DTE) refers to the processes, methodologies, and practices for the systematic design, development, utilisation and management of DTs (engineering of digital twins) [61,64,215]. It encapsulates the entire DT lifecycle and enables the integration of organisational and technological aspects to accurately mirror the state, behaviour and characteristics of the physical

counterpart, thus enhancing the capability of DT deployment, configuration, validation and testing [215].

DTE involves the specification, modelling, and verification of complex systems and requires interdisciplinary collaboration between domain engineers, software developers, data scientists, and system designers. DTE relies on a structured approach to fit for purpose framing, process standardisation, and scalability to address the challenges involved in the practical implementation of DTs. Additionally, DTE emphasises the alignment of business processes, and organisational deployment with technological and engineering elements such as system implementation and reference architectures. VPC (Virtual Product Creation), MBSE (Model-Based System Engineering), data engineering, and digital platforms constitute essential components for enabling DTE [215]. DTE may occur in two scenarios: 'greenfield' where the DT and the physical asset are developed together, and 'brownfield' where the DT is created post-deployment of the physical asset [31].

DTE is still in its infancy despite the emergence of active communities in system and software engineering and ongoing efforts in normative and standardised developments. Furthermore, the engineering of digital twins is a lengthy and costly process involving the consideration of multiple dimensions in terms of requirements, characteristics, models, and architectures within a complex, heterogeneous, and dynamic ecosystem.

This section summarises and outlines some key elements underlying digital twin engineering, as described in the literature. We propose to address the DTE through two complementary axes: i) architecting DTs that encompasses the value chain, requirements, characteristics, capabilities, and maturity, and ii) model-based approaches that allow for a structured and systematic design of DTs. By formalising the architecture and models while considering the DT lifecycle, it becomes possible to ensure the foundation of the DTE.

3.1. DT value chain

The DT value chain encompasses multiple stakeholders and ecosystem partners that drive the development, deployment, and use of DTs [147]. Within this ecosystem, customers and platform providers interact with DTs through interconnected digital environments to derive value and ensure practical implementation. DTs facilitate closer integration of various stages of the value chain by providing a seamless flow of information between design, manufacturing, operation, and retirement phases. This integration helps align the product lifecycle with customer needs and market demands, ensuring that value creation is maximised throughout the product's life [18]. By providing a shared, accurate model of the product or system, DTs enable all parties to contribute to and benefit from collective knowledge. Data generated at each stage are accessible and usable, thereby enhancing interoperability and reusability. Key stakeholders include those directly involved in the creation, operation, integration, and use of DTs, those that provide support services, infrastructures, and technologies for the development and operation, and those that play a supporting role, indirectly influencing the ecosystem through research, security, standardisation, and value-added services (Fig. 9).

3.2. DT requirements

DT requirements, derived from stakeholder needs and refined through the value chain, encompass foundational attributes such as synchronisation, low latency for real-time performance, high-fidelity to accurately emulate the physical entity, reusability and modularity for long-term viability, and sustainability that ensures that DTs remain resource-efficient across extended lifecycle stages, reusable, re-deployable and aligned with long-term goals. The key DT requirements, as investigated in [38], include real-time capability, accuracy/precision, reusability, interoperability, scalability, performance, human-centricity, sustainability, and resilience. Durão et al. [52] highlighted 26 requirements, with real-time data, fidelity, and integration being the most frequently cited.

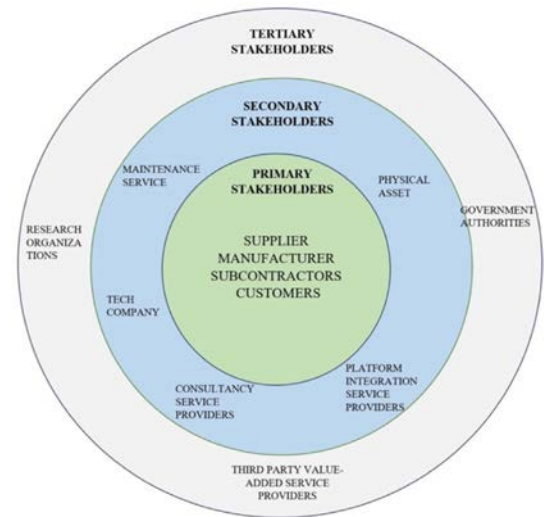


Fig. 9. Stakeholders within the digital twin ecosystem [237].

The functional requirements encompass visualisation, simulation [138], prediction [116,238], control [176], optimisation [32,65,277], and management [43,249]. Non-functional requirements include resilience, safety, availability, privacy, security, consistency, interoperability, stability, expansibility, and fidelity [9,57,194]. The resilience requirement ensures that DTs can manage uncertainties and disruptions. Security and safety requirements must safeguard data, models, operational records, and other critical information from leaks while also ensuring operational safety. The availability requirement ensures that DTs are accessible and usable when required. Privacy is concerned with protecting the user's data, information, and records. Consistency is vital for ensuring that digital models remain synchronised with their physical counterparts. Interoperability facilitates collaboration across various domains by enabling information sharing. Stability ensures that the DT remain largely unchanged under specific conditions. Expansibility allows DTs to evolve with the changing requirements of the physical entities or processes. Fidelity ensures that digital models accurately represent the characteristics of the physical entities they emulate [194].

To be specifically tailored to DTs, the requirements shall be explicitly linked to their defining characteristics. However, traditional requirements engineering methods are still limited in their ability to manage the dynamic requirements change that can occur during DT development and operational deployment.

3.3. DT capabilities and characteristics

The capabilities and characteristics of DTs are essential for understanding their nature and functionality. Various frameworks and models have been proposed in the literature to characterise DTs, including their primary components, dimensions, and qualifiers [69]. The Digital Twin Capabilities Periodic Table (CPT) [192] introduced by the digital twin consortium, provides a comprehensive architecture-agnostic solution for the design, deployment, and management of DTs.

The CPT uses a Composable Digital Twins (CDT) reference model to support the development of applications with composable enterprise architectural patterns, enhancing scalability and reusability through microservice-based orchestration and reusable Packaged Business Capabilities (PBC) [30]. Capability categories within the CPT include data services, integration, intelligence, user experience, management, and trustworthiness, each of which can be further decomposed into sub-capabilities tailored to specific digital twin use cases (Fig. 10). However, while the CPT effectively visualises and organises capabilities, it relies heavily on external knowledge and lacks a structured architectural framework for integration [74].

DT characteristics provide a framework for understanding and evaluating the capabilities and limitations of digital twins. The DT



Fig. 10. Digital twin capabilities periodic table outline [191].

eight-dimensions model [217] specifies different characteristics of the targeted digital twin by differentiating the context and environment and the behaviour and capability. The 8 dimensions include: integration breadth, connectivity mode, update frequency, CPS intelligence, simulation capabilities, digital model richness, human interaction, and product lifecycle, and these dimensions have been extended to include cooperation for data collection [219]. Through consistent work, Jones et al. [112] identified 13 DT characteristics (Table 2), while Su et al. [220] summarised a set of characteristics including: fidelity, maturity, consistency, closeness, credibility, complexity, granularity, and identity which is evaluated through four attributes: completeness, trueness, precision, and latency.

Table 2
Digital twin characteristics according to [112].

Characteristic	Description
Physical entity/Twin	The physical entity/twin that exists in the physical environment
Virtual entity/Twin	The virtual entity/twin that exists in the virtual environment
Physical environment	The environment within which the physical entity/twin exists
Virtual environment	The environment within which the virtual entity/twin exists
State	The measured values for all parameters corresponding to the physical/virtual entity/twin and its environment
Metrology	The act of measuring the state of the physical/virtual entity/twin
Realisation	The act of changing the state of the physical/virtual entity/twin
Twinning	The act of synchronising the states of the physical and virtual entity/twin
Twinning rate	The rate at which twinning occurs
Physical-to-virtual connection/Twinning	The data connections/process of measuring the state of the physical entity/twin/environment and realising that state in the virtual entity/twin/environment
Virtual-to-physical connection/Twinning	The data connections/process of measuring the state of the virtual entity/twin/environment and realising that state in the physical entity/twin/environment
Physical processes	The processes within which the physical entity/twin is engaged, and/or the processes acting with or upon the physical entity/twin
Virtual processes	The processes within which the virtual entity/twin is engaged, and/or the processes acting with or upon the virtual entity/twin

3.4. DT architectures

DT architectures are comprehensive frameworks for the creation, implementation, and management of DTs. The advantages and roles of system architectures have already been highlighted in the context of Cyber-Physical Production Systems (CPPS), as emphasised by Monostori et al. [159]. DT architectures can be categorised based on several dimensions, including their level of abstraction and detail, the specific domain to which they are applied, and the specific technology in use [170]. Many DT architectures for manufacturing have been reported in the literature [7,57,60,128,184], and most of them are built upon the 5C architecture of cyber physical systems [129].

The main characteristics of DT architectures are layered patterns that include the physical layer, data and network layer, virtual layer,

and application layer, supported by service-oriented architectures, microservices, and component-based architectures [62]. A DT architecture model to support the Digital Twin as a Service (DTaaS) paradigm [3] was developed based on these characteristics and RAMI4.0. However, the increasing complexity of manufacturing information requires reference architectures to guide the design of system architectures enabled by common metamodels and characteristics, as underscored by a review of various architectures for digital manufacturing [113].

In addition, ontologies play a crucial role in supporting semantic interoperability through DT reference architectures. A universal architectural and ontological concept system using STEP EXPRESS-G language was proposed in [51]. ISO 23247 provides a structured framework to develop tailored DT implementations, to enhance composability and interoperability [63,208]. The standard comprises four parts, with the second part defining the reference architecture. The reference architecture shown in Fig. 11 categorises entities into four main domains: device communication, digital twin, user, and cross-system entities, each with specific functionalities guiding DT implementation across various stakeholders [118] described a method for building a digital twin of a robot work cell using ISO 23247 and open-source software for collecting data and multibody modelling simulation of machine tools and robots [50] proposed a domain-level ontology for manufacturing that builds upon the existing ISO 23247 series. Current DT architecture implementations likely consider only a few functional entities, often focusing on functional aspects and describing digital shadows rather than DTs.

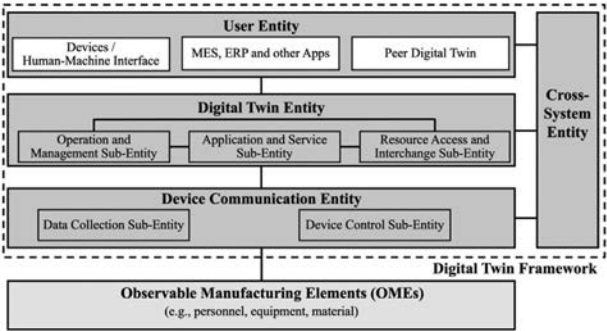


Fig. 11. ISO 23247 Reference Architecture [105].

DT reference architectures, while enabling the design and implementation of advanced and scalable systems, have several shortcomings that hinder their wider adoption and practical usability. These challenges range from interoperability issues, such as the lack of semantic standards and siloed architectures, to scalability and modularity problems that challenge real-world implementation. Real-time synchronisation constraints, including latency and substantial resource consumption, further impede the adoption of such DT architectures.

3.5. DT maturity

Maturity models are tools used to conceptualise and measure the maturity of a system in terms of a specific target state. Maturity and readiness are interrelated concepts. While the maturity assessment captures the current state during the process, readiness captures the starting point and initialise the development process. In manufacturing, various models and tools for assessing readiness or maturity have been reported [13,197].

Hu et al. [91] introduced a qualitative and quantitative maturity model for DTs in high-tech equipment with six maturity levels (basic, connection, integration, perception, interaction, and autonomy). Tao et al. [228] proposed a five-level model for industrial systems, incorporating capabilities like virtual modelling, simulation, and intelligence capabilities, providing 19 criteria for DT maturity evaluation. The DT eight-dimension model [216], although not designed for

assessing the maturity, proposes different levels and scales that can be used to measure the functionalities and sophistication of DTs. A comprehensive maturity model, such as the one developed by Uhlenkamp et al. [240] assesses DTs across seven categories and provides a structured framework for evaluating and improving DTs.

A detailed review of the existing DT maturity models was presented in [33]. In general, digital twin maturity models can be classified based on the evolution of DTs from basic digital representations to connected fully autonomous systems (Fig. 12) [120]. The analysis of the literature and industrial realisations reveals that most reported DT applications in manufacturing have achieved a medium maturity level, characterised by high-fidelity virtual models, limited two-way communication capabilities and a moderate degree of automation [145]. Additionally, standardisation efforts, such as those reported in ISO/IEC 30186 'Maturity model and guidance for a maturity assessment' are still in their early stages.

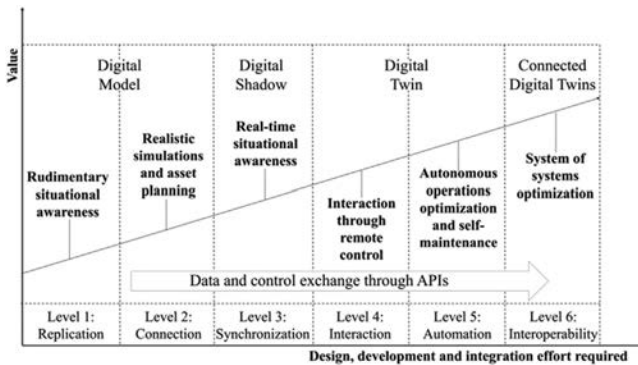


Fig. 12. Digital twin maturity model according to [120].

3.6. Model-based design and development methods for DTs

The integration of Model-Based Systems Engineering (MBSE) with DT development has evolved significantly since Madni et al. [152,153] first viewed DT as an extension of MBSE practices (Fig. 13). Bickford et al. [22] proposed a systematic DT development process throughout the system lifecycle, which is supported by the traditional MBSE process. The diamond model proposed by Boeing [199] leverages DTs to represent physical systems throughout the product lifecycle and incorporates a digital thread to connect the digital models or simulations provided by DTs, thereby facilitating the integration of physical and virtual spaces to support product design and production. Other studies have proposed simplified methodologies or refined MBSE with specific tools and implementation domains [177]. This integration has gained momentum as a structured approach to formalise the requirements used for DT development [69] and to handle lifecycle issues, real-time data synchronisation, and system-of-

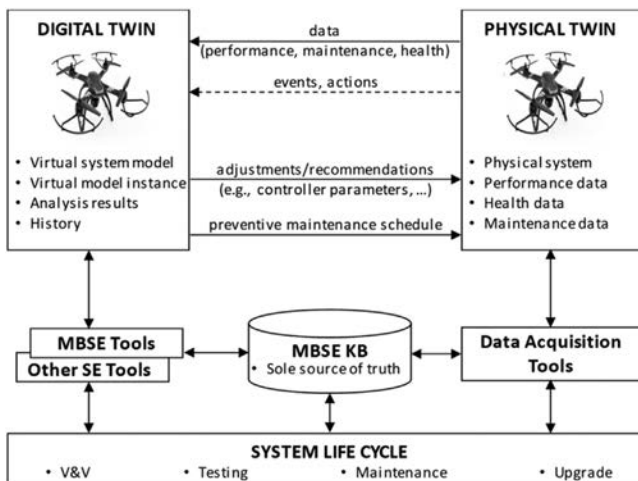


Fig. 13. DT-enabled MBSE framework [152].

systems challenges. Although MBSE provides a robust foundation for DT design and development, practical adoption in industrial applications still requires exploration. Additionally, the synergy between MBSE and DT, particularly in spanning the physical system lifecycle, presents new opportunities for lifecycle traceability, synchronisation, and system adaptation.

Model-Driven Engineering (MDE) [196] plays a growing role in DT engineering, particularly focusing on software dimensions. MDE emphasises the use of models to design, build, and maintain complex systems, providing structured approaches to handle heterogeneous models, model updates, and cross-disciplinary collaboration through shared modelling languages and tools [25]. Beyond design activity, MDE supports continuous refinement, data integration, and real-time execution. The application of MDE to DTs has led to substantial progress in modelling, automation, modular architectures (e.g., AAS), and runtime adaptation, facilitating synchronisation with physical systems, reducing manual coding efforts, and integrating domain-specific engineering [275]. A consistent research theme in MDE in the context of DTs is the use of Domain-Specific Languages (DSLs), such as SysML and AutomationML, to enable the specification of the structural and behavioural aspects of DTs [130,261]. Grounded on MDE, the Models and Data (MODA) framework [35,54] is a conceptual reference framework that integrates models and data in a systematic, data-centric, and model-driven approach. It supports the entire lifecycle of sociotechnical systems, particularly software-intensive ones with a focus on explicit consideration of both models (abstract system representations) and data (runtime information or measured system values) to create more adaptive and synchronised DTs. The MODA framework highlights the interplay between the static design abstractions from the models and the dynamic runtime realities captured by the data from the physical entities.

3.7. DT models

DT modelling has attracted considerable attention as it is critical for the consistency and fidelity of digital twins [227]. Three main classes of modelling approaches have been reported in the literature [204]: model-based, data-driven, and hybrid approaches.

The role of model and data in DT modelling have been emphasised in [54] to develop a conceptual framework using the MODA framework [35] and three distinctive roles that models can play: descriptive, predictive, and prescriptive role. DT modelling involves the consideration of various heterogeneous models with different granularities and scales. Segovia et al. [202] classified DT models into structural models and behavioural models. Tao et al. [223,230] categorised the virtual entity into geometric, physical, behavioural and rule models. Similarly, Böttjer et al. [29] used this categorisation in the context of unit-level DTs based on a systematic literature review of 96 papers. Thelen et al. [231] classified modelling approaches into Geometric modelling, Physics-based modelling, Data-driven modelling, Physics-informed ML, and System modelling. Abisset-Chavanne et al. [2] extracted different models from 23 industrial use case types, including geometrical, topological, physical and mathematical, and functional models. Zio et al. [288] reported different model representation types varying according to the application domain.

Geometric models are fundamental in the development and implementation of DT models and are the basis of the digital mock-up and the digital master. They rely on sound methods and tools inherited from geometric and solid modelling [188] to achieve a realistic representation of a physical system's nominal shape and dimensions. Furthermore, mesh-based and point-based representations support the reconstruction and reverse engineering of physical systems with improved accuracy regardless of the shape complexity [14].

Actual research shows that the reconstruction is not limited to parts but is extended to assemblies and kinematic systems while updating the nominal CAD model of individual parts. Methods that automatically generate accurate geometric models by combining CAD designs with real measurements are reported in [76] and [83]. Similarly, [206] introduced a new fitting technique that efficiently

reconstructs or updates editable CAD models to maintain coherence between a product and its DT [55] developed a multi-geometric representation framework for a Kinematic Digital Twin (KinDT) synchronising the as-built model with the as-designed model in the context of work cell calibration and gesture control in robotic applications (Fig. 14). However, achieving greater accuracy and incorporating non-geometric data with enhanced semantics remains a challenge for geometric models of DTs.

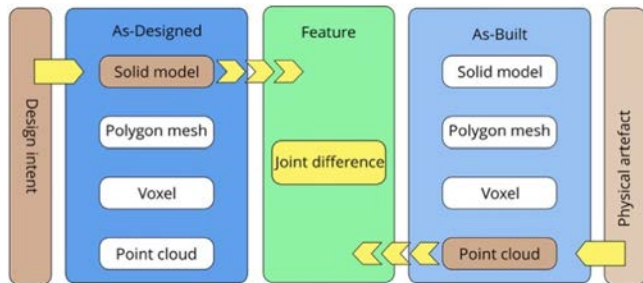


Fig. 14. Application of KinDT to gesture control [55].

The Skin Model Shapes (SMS) paradigm [15,193] integrates geometric errors and deviations of parts assemblies in geometric representations and contributes to comprehensive geometric representations for DTs [108,146] and sound model for accurate geometric DTs and Physics-based DTs [190]. Rooted on the Skin model concept for Geometrical Product Specifications (GPS) and tolerancing [161], SMS provides new insights for DTs as a reference model, emphasising the distinction between DT abstraction (Skin model) and representation (SMS), the twinning process through observation and prediction, and overall lifecycle uncertainty management by mirroring operations [193] (Fig. 15).

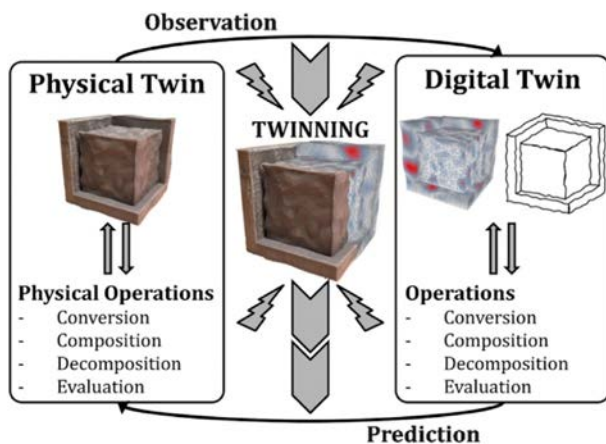


Fig. 15. DT reference model based on SMS and mirroring operations [194].

Physics-based models play a crucial role in DT modelling. These models can be analytical, numerical, empirical or domain-specific all grounded in the fundamental physical mechanisms and governing laws of the systems being modelled [121]. Their accuracy relies on thorough understanding of the underlying physical principles. Among these models, Finite-Element Methods (FEM), Partial Differential Equations (PDE), and multibody dynamics (MBD) are widely employed in engineering and manufacturing applications [19,81,82,162,269]. Behavioural models are well suited to representing event-based interactions and the temporal dynamics of physical systems. They rely on discrete-event and hybrid systems methods, control theory, and co-simulation methods to complement structural models [11,75,160,250]. Data-driven models rely heavily on statistical methods and machine learning techniques. They have become popular for analysing complex datasets in engineering applications, and their applications for DT modelling have been reported in

different applications [66,67]. Hybrid models based on data integration and assimilation enhance physics-based models by incorporating historical and real-time data, allowing for the refinement of the models and improving their accuracy and prediction capability [189].

However, the computational expense of high-fidelity DT models is a challenge, making realistic simulations and real-time applications difficult to achieve. Additionally, the accuracy of these models depends on the correct calibration of the model parameters, which can be complex and time-consuming. This complexity highlights the need for advanced computational techniques and efficient data management to ensure that DTs can accurately and efficiently represent and predict the behaviour of their physical counterparts. Methods based on inverse problems, surrogate models, and reduced order modelling can address some of these challenges [59]. Inverse problems can be used to estimate the model parameters from the observed data, which is essential for calibrating high-fidelity models. Surrogate models for approximating high-fidelity models enable faster simulations and real-time applications. Reduced-order models (ROMs) simplify complex models while retaining essential features, further reducing computational costs.

3.8. DT verification and validation

The successful implementation of DTs requires verification and validation (V&V), which are essential for ensuring the trustworthiness, credibility and reliability of DTs [48,164,262]. Verification enables to confirm that the DT meets the specified requirements (i.e., 'Did I build the DT correctly?'), while validation assesses how accurately the DT represents the real system for its intended fit-for-purpose (i.e., 'Did I build the correct DT?') [241,242]. Verification, validation, and uncertainty quantification (VUQU) extend beyond V&V to encompass uncertainties in data integration, twinning, and service functionalities throughout the DT lifecycle.

Bitencourt et al. [23] explored the current state-of-the-art of V&V practices for DTs in manufacturing and revealed a lack of comprehensive methodologies and techniques at different DT maturity levels. Shao et al. [209] identified various sources of uncertainties, such as measurement uncertainties, data errors during data collection and processing, modelling errors due to simplifications, and interpretation errors in data presentation. Ríos et al. [187] further explored the uncertainty of data in DTs, reviewing the modelling of measurement uncertainty and suggesting that DT V&V could benefit from formal methods and AI-driven software testing approaches. Additionally, Zhang et al. [274] underscored the significance of ultra-fidelity models in DT implementation and advocated for consistency evaluation phases before and after model assembly and fusion to ensure model accuracy. Zio et al. [288] emphasised the need to quantify the sources of uncertainty in safety-critical applications, ensuring a noise-free, uninterrupted data stream, and addressing the challenges of latency and refreshing time. Perisic et al. [178] proposed the Quintuple Helix Conceptual Framework as a comprehensive and structured approach to V&V throughout the DT lifecycle. Zahediyami et al. [271] suggested a comprehensive software testing approach for DT V&V, employing unit, integration, and system testing in a bottom-up manner based on the modular architectures of DTs and their similarities with software engineering testing techniques. Wagg et al. [247] expanded the traditional V model to a W model by incorporating DT V&V during the final phases of the DT lifecycle. This enhancement helps ensure requirement compliance and reduces system uncertainties.

Overall, DT V&V requires a holistic approach that integrates data fidelity, model accuracy, and service functionality, supported by advanced testing methodologies and frameworks that address the inherent uncertainties and complexities of DTs across the entire lifecycle. From the standardisation perspective, even if the current ISO 23247 series provide a framework and guidelines for implementing digital twins in manufacturing, the V&V aspects are not yet covered. In addition, the American Society of Mechanical Engineers (ASME) V&V standards are dealing with best practices and guidelines regarding computational modelling and simulation, which may be relevant to the development of DTs. Finally, the specificity of DT consisting of

various models and processes requires individual and comprehensive V&V. Validating a single instance of the full system model can be challenging, making extrapolation from component V&V to the full system difficult to achieve [271].

3.9. Synopsis of DT engineering

DTE integrates processes, methodologies, and best practices across the entire value chain and lifecycle of DTs and ensures seamless data flow and collaboration among diverse stakeholders, aligning requirements and performance with the evolution of the twinned system. DTE requires expertise from systems engineering, software development, data science, and domain-specific fields. Structured, model-based approaches like MBSE and MDE, along with modelling and simulation techniques, emerging standards such as ISO 23247, and rigorous VVUQ practices provide frameworks for achieving interoperability, scalability, and lifecycle traceability while ensuring the fidelity and reliability of DTs.

Despite its growing prominence, DTE remains inherently complex, demanding continuous refinement of methodologies for integrating heterogeneous models, data, and services, which poses important challenges for engineering design.

4. Exploring engineering design characteristics of DTs

This section presents the fundamental basis for how engineering design concepts have been considered for DTs across manufacturing, by considering the application areas, design principles, and methods applied. As an overview, it is observed that DTs are relevant in all stages of design, whether it be conceptual, detailed, or considering the lifecycle. It has also been observed that although the typical application of DTs is at the single asset/process level, there is growing interest in considering connected/federated twins [43]. The value creation depends on a range of factors such as being real-time, synchronous, responsive, adaptive, customised, remote control, resilience and anomaly detection, consistency retention, and complex systems interoperability [30,94,126,164].

The DT application areas are also vast, with a focus on intelligent/smart manufacturing, robotics applications, human-machine collaborations, additive manufacturing, dynamic sustainability and lifecycle analysis, and finally new business models. Numerous technologies have been applied to enable DTs, including AI/ML, edge computing, blockchain, agent-based modelling, AR/VR, 5 G, ontologies and wider information management frameworks, knowledge mapping, multi-sensory methods linked to data fusion, and physics-based modelling.

4.1. Core features and enablers

This subsection focuses on the core factors, enablers, and features of DTs. As noted in Fig. 16, DT development requires a systematic approach to enable continuous value creation. The figure aims to illustrate a summary of numerous examples from the literature on the steps to develop DTs. The process starts with data collection

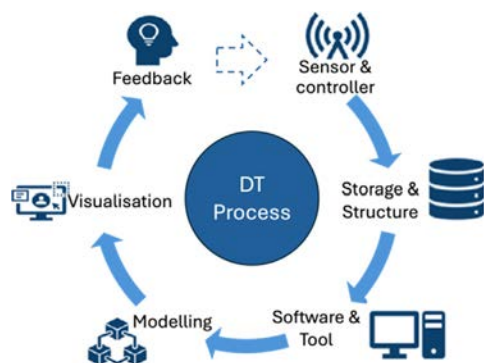


Fig. 16. DT development process.

through *sensor and controller* and involves data management (*storage and structure*), DT architectures, reference models (*software and tools, and modelling*), resilience and smart DT (*visualisation and feedback mechanisms*). Feedback takes place across all stages to enhance the overall performance of the DT. These concepts are explained further in this subsection.

4.1.1. Data management and DT integration

Liu et al. [143] identified bandwidth competition and significant delays as barriers to DTs accessing enterprise clouds, which necessitates more reliable and efficient data exchange processes. A blockchain-based approach was proposed to enable peer-to-peer data exchange among DT-based manufacturing systems. D'Amico et al. [43] examined the evolution of DTs and their application in maintenance and proposed an ontological approach for developing DTs into structured Cognitive Twins (CTs). They emphasise that a top-level ontology is essential for creating CTs. Wang et al. [248] integrated DT with MBSE for analysing and predicting system design complexity, presenting a framework called System Design Digital Twin in 5 Dimensions. This framework offers services for complexity measurement, effort estimation, and change propagation prediction using unified SysML stereotypes. Vogt et al. [244] discussed data exchange within DTs in the automobile industry, proposing a communication loop that facilitates direct intercommunication between the DTs of products as CPS and production resources as CPPS. Huang et al. [94] addressed data management problems by achieving a two-way data feed between product and digital instantiation using blockchain technology. They proposed a peer-to-peer network to improve data sharing efficiency, ensuring secure data access through cryptography.

4.1.2. DT architectures and reference models

Stark et al. [217] emphasised the advantages of horizontal and vertical integration in manufacturing using DTs and explored the methodological, technological, operational, and business facets of DT development and operation. Similarly, Zheng et al. [284] noted the scarcity of DT reference models in smart manufacturing and proposed a generic CPS system architecture for DT development using a novel tri-model-based approach, including digital, computational, and graph-based models. Lim et al. [136] developed a generic DT architecture reference model for cost-effective, context-aware product family design optimisation. Boyes and Watson [30] provided a process for analysing DT characteristics, facilitating the characterisation and comparison of DTs. The proposed common functional characteristics help mitigate confusion arising from the numerous DT definitions.

4.1.3. DT resilience

Vrabic et al. [245] addressed DT robustness and resilience by developing an approach to manage uncertainty and disruptions, ensuring that the DT remains representative. They presented an intelligent agent-based method to maintain the robustness and resilience of the DT. Similarly, Huang et al. [95] proposed a hybrid learning-based DT for manufacturing processes, focusing on adaptability and accuracy at the shopfloor level. Their model handles heterogeneous data sources, precise modelling, and uncertainties in dynamic industrial environments, employing AI techniques and machine tool expertise. This approach integrates metadata from design, planning, manufacturing, and quality stages into a digital thread. Lugaresi et al. [149] devised a method to validate DTs in production planning and control, describing the data types and validation processes. They assessed the similarity between the physical system and its digital counterpart using a data-driven comparison technique.

4.1.4. Smart DT

Longo et al. [148] argued that while Industry 4.0 emphasises AI integration into 'things' it overlooks the essential human role in manufacturing tasks like machine setup and maintenance. Their work facilitates intuitive access to Ubiquitous Knowledge within the manufacturing system, which is intended for use by employees. Additionally, they presented a prototype of a Service-oriented DT that

uses a flexible ontology-oriented knowledge structure and combines augmented reality with a vocal interaction system for intuitive knowledge retrieval and application. Tomiyama et al. [234] highlighted that smart products are software-intensive, data-driven, and service-conscious, and they promoted the need for new capabilities, including DTs, underpinned by advanced tools, methods, and models. Having smart products enables the process of creating DTs, as they have the capabilities to sense data and embed analytical functions to react and respond to changes. Negri et al. [165] aimed to enable feedback actions on equipment control systems. They proposed developing a DT by integrating a discrete-event simulation model with the Manufacturing Execution System (MES).

4.2. Value creation opportunities

This subsection examines the value creation opportunities that emerge with DTs in manufacturing. Fig. 17 provides an overview of the themes identified in the literature, which are mapped across the different phases of manufacturing. These are further elaborated on in this subsection.

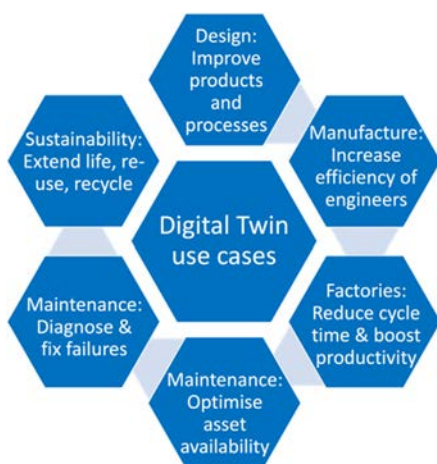


Fig. 17. DT-based value creation opportunities in manufacturing.

4.2.1. Design

DT design. Traoré [236] noted the lack of a unified understanding of the DT concept, leading to ambiguity in developing concrete solutions. Schleich et al. [195] summarised recent DT advancements and illustrated use cases across various product lifecycle phases. Wu et al. [265] critiqued existing DT modelling methods for their reliance on modular representation, which limits their applicability and the detail of the components and operational rules, and proposed a five-dimensional framework for conceptual modelling to better represent complex relationships. Osho et al. [173] conceptualised a 4Rs framework: Representation, Replication, Reality, and Relationship, for modular DT creation. Jiang et al. [109] addressed the challenge of effectively creating a DT model at the design stage of complex manufacturing systems and ensuring its utility throughout the lifecycle, focusing on rapid virtual model creation and physical-virtual connection mechanisms. Alelaimat et al. [10] discussed the automatic acquisition of organisational DTs, assuming that DTs of organisations provide value and that Belief-Desire-Intention (BDI) agents effectively represent DTs.

DT accuracy and representativeness. Vrabčić et al. [245] emphasised the necessity for DT to consistently and accurately mirror real processes to enhance manufacturing productivity. Erkoyuncu et al. [58] identified the adaptive connection of existing brownfield systems and their data as barriers to DT adoption. Zhang et al. [272] addressed a similar issue regarding the use of the Internet of Things to ensure consistent interaction between virtual and physical spaces. A new challenge arises in updating models when DT models become inconsistent with practical situations. To address this issue, they

proposed a general DT model update framework and further explored multi-dimension model update methods.

DT-based control. He et al. [88] introduced a DT control service system framework employing a master–slave design pattern and an event state machine. They focused on low carbon product design, using carbon footprint analysis to assess the environmental impact of physical entities, considering information uncertainty and cost factors in the carbon footprint analysis.

Human-robot collaboration (HRC). Dallel et al. [40] created a digital version of an industrial workstation using a DT of a real workstation with a robotic arm and Virtual Reality (VR) to extract a digital human model. The DT simulates human-performed assembly operations to generate self-labelled data. Xu et al. [268] established requirements for DT to achieve precise control of physical robotic systems through a high-fidelity digital model and sensory data, aiming to prevent delayed condition updates that cause inaccurate simulations and robotic control. Wang et al. [255] developed a DT for collaborative manufacturing tasks involving humans and robots to address safety and reliability concerns.

Design for X. In the context of Design for Additive Manufacturing (DfAM), Haw et al. [86] examined the use of DTs for product design in AM and addressed their potential, challenges, and limitations. Chen et al. [34] investigated the discrepancies in defining and developing AM DTs and reviewed the existing approaches. They proposed a four-layered framework, comprising service, model, data, and interface, to improve the reusability in AM digital twin development. Jin et al. [111] outlined the main components and principles of DTs for AM and detailed the workflow of DTs for AM.

Tolerancing. Wärmefjord et al. [258] conducted an extensive interview study to identify industry barriers to fully leveraging DTs for variation management and geometry assurance. They highlight the necessity of high-quality inspection data linked to 3D models for a complete and reliable DT. Schleich et al. [194] proposed a comprehensive reference model utilising DTs for geometrical variation management based on fundamental standards for geometrical product specification and verification, where digital twins predict the physical twin, and observations from the physical twin update the digital twin. Söderberg et al. [214] developed DTs for product and production system design during the design phase, subsequently using them for inspection preparation and process control.

4.2.2. Smart manufacturing and factories

Smart manufacturing, from a design perspective, refers to the design of manufacturing processes that benefit from dynamic data management and automated data analytics to realise better manufacturing output.

Manufacturing system design. Stark et al. [218] identified a significant challenge in the current manufacturing system design and architecture that relies on traditional engineering methods, making it difficult to manage the increased system complexity. They introduced a novel architecture for modular CPPS design, which includes capabilities for modular construction kits, simulating functional behaviour and validating it with virtual prototypes. Leng et al. [131] addressed the need for high flexibility in hardware and software for individualised manufacturing by proposing an open architecture production line (OAPL) and a DT-based flexible operating approach. Anbalagan et al. [12] explored the use of CAD models and manufacturing simulations within DTs to optimise product design.

DT design. Wang et al. [251] argued that there are significant opportunities to improve energy power batteries through better DT designs. They highlight that smart manufacturing often fails to provide detailed representations of components and operational procedures, which by design DTs could offer.

Synchronisation and data management. Perno et al. [179] emphasised using vast data generated daily in manufacturing to optimise processes, enhance competitiveness, and streamline supply chains. Liu et al. [144] discussed the necessity of DTs for addressing challenges in traditional process parameter optimisation, noting issues with accounting for process uncertainties and meeting real-time and predictive requirements in intelligent manufacturing. Wang

and Luo [254] explore synchronising the real and digital worlds for closed-loop iterative optimisation in smart factories. Mo et al. [158] combined DTs with modular AI algorithms to dynamically reconfigure manufacturing systems, including layout, process parameters, and operation times, to adapt to changing market demands. Zhu et al. [286] identified the challenge of presenting extensive data intuitively within a DT. They introduced an AR application using Microsoft HoloLens to visualise DT data of a CNC milling machine in a real manufacturing environment.

Automation in manufacturing. Leng et al. [132] emphasised the need for high flexibility in manufacturing systems to meet the increasing demands for individualised products. They proposed a novel DT-driven approach for the rapid reconfiguration of automated manufacturing systems, consisting of a semi-physical simulation that maps system data and provides inputs for optimisation. Müller-Zhang et al. [157] stressed the importance of an adequate scheduling system to ensure production efficiency, capable of managing diverse process flows and unforeseen changes. Their approach used DTs and Deep-Q-Learning for integrated process planning and scheduling in service-based production. Kumbhar et al. [124] highlighted the difficulty of identifying bottlenecks in complex manufacturing systems due to resource interdependencies and interactions. They developed a DT framework to detect, diagnose, and improve bottleneck resources using utilisation-based bottleneck analysis, process mining, and diagnostic analytics.

DT applications. Li et al. [134] proposed an HRC safety control framework and method based on DT to ensure real-time safety in HRC processes. Magnanini et al. [154] discussed the need for changes in manufacturing systems and how DTs facilitate rapid adaptation. They developed a DT based on an analytical model to evaluate the performance of a manufacturing system, considering joint parameter variations. Liu et al. [142] addressed the challenges in managing diverse requirements and processing sites, advocating for cyber-physical integration in machining sequences. They introduced a multidimensional modelling approach using DTs for intelligent machining, focusing on design and execution phases.

4.2.3. Maintenance

Predictive maintenance and PHM. Van Dinter et al. [49] developed DT-based predictive maintenance systems for complex systems. Sun et al. [221] addressed prognostic and health management (PHM), focusing on the dynamic evolution of a target object's health status over varied time scales. They introduced a dual time scale DT modelling and analysis method. Following PHM business rules, time series signals are decomposed into fine-grained scales and adaptively constructed into short-time and long-time scale DTs. Tao et al. [230] also emphasise the role of DTs in PHM, proposing a method that leverages DT-driven PHM to enhance accuracy and effectiveness, specifically applied to wind turbines.

Degradation assessment and costing. Farsi et al. [60] tackled early-stage cost estimation challenges by proposing a new DT architecture employing adaptive data structures and ontologies to automatically generate cost models from lifecycle data. D'Amico et al. [44] presented a conceptual DT framework for the degradation assessment of a Complex Engineering System (CES), aiming to collect digital data through a network to plan the system's through-life requirements.

4.2.4. Lifecycle and sustainability

Seegrün et al. [201] reviewed sustainability-focused DT applications throughout the product lifecycle, noting that most literature emphasised the beginning-of-life, with limited approaches for end-of-life and entire lifecycle applications. Although several papers (e.g., Timperi et al. [233]) have proposed frameworks for lifecycle integration via DTs, they often lack empirical analysis and remain conceptual. The necessity of interoperability for life cycle integration is frequently discussed (e.g., Böttjer et al. [29]). Overall, the current literature indicates that DTs are emerging as a method for enhancing lifecycle and sustainability considerations, but there is insufficient maturity and evidence of suitable concepts for broad impact.

4.3. Methods and tools

This subsection focuses on evaluating the methods and tools that have been used with DTs across manufacturing, covering design, manufacturing, service, and lifecycle considerations. Fig. 18 illustrates an overview of the alternative methods and tools used in DTs. An important point here is that DTs bring together a range of methods and tools, rather than individual methods or tools in their own right. Further insights on the methods and tools that have been used are explained in more detail in this subsection by considering relevant considerations across design, manufacturing, maintenance and the lifecycle perspective.

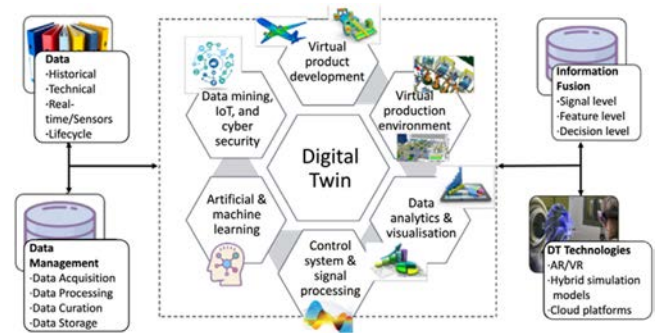


Fig. 18. DT-related methods and tools.

4.3.1. Design

Customisation. Wang et al. [256] proposed a data-driven smart customisation framework enhanced by DT to improve stakeholder collaboration in the customisation process. Traoré [236] offered a unifying reference framework serving as both a conceptual basis and a guide for custom solutions. The proposed technology-agnostic, three-layered model integrates existing DT concepts under a common structure.

Design synthesis. Xie et al. [266] proposed a framework for designing next-generation elevator fairings using a DT approach, involving the creation of a digital model and multi-objective optimisation to enhance the design. Haynes et al. [87] introduced a super-system DT that collects data from a product's environment for early design activities. Liu et al. [139] conducted a case study on automobile connecting rod production and found that DTs in the design stage offer benefits like verifying manufacturing feasibility, optimising production plans, identifying early-stage issues, and improving efficiency, cost, and quality. DTs enhance customer-focused design and operational forecasting. Zheng et al. [281,282] introduced a DT-enabled design approach for Smart Product-Service System (PSS) innovation, encompassing platform development, data acquisition, analytics, and innovation. Wang et al. [256] explored how DT helps PSS designers understand the product context by integrating user and environmental data, thereby enhancing the awareness of customer behaviour. Wu et al. [264] proposed a function-oriented Smart PSS optimisation approach using DTs to improve conceptual design. Durão et al. [53] proposed a DT data architecture for PSS, applying a Design Science Research approach, fulfilling requirements like supporting service offerings, data acquisition, integration, and real-time monitoring. Kunath et al. [125] integrated DTs of manufacturing systems into decision support systems, defining them as data-oriented representations linked to physical elements by information systems. Onaji et al. [172] proposed a product-process DT integration that provides a platform for increased flexibility, control, and management of the production system for easy adaptation to changes in product type/quality during production. Renard et al. [185] established a framework that enables the deployment of scalable DTs from sensors to services in an iterative manner to facilitate their integration into existing manufacturing architectures.

DT design. Wu et al. [265] introduced a method for conceptual modelling of a DT using a five-dimensional framework to represent the complex relationships between DT objects and their attributes.

Wang et al. [251] developed a DT method based on the five-dimensional digital twin model and the UNISON decision framework [92]. Li et al. [134] focused on the design phase, integrating virtual simulation and VR technology to create DTs of various HRC scenarios for testing and analysing potential safety hazards. During production, the DT is driven by real-scene data, enabling real-time online visual monitoring and optimisation of the HRC process. Liu et al. [141] noted the lack of a systematic and efficient DT modelling method that can adaptively develop high-fidelity multi-scale and multi-dimensional DTs for machining processes. To address this, they proposed a DT modelling method based on biomimicry principles to adaptively construct a multi-physics DT of the machining process, developing multiple DT sub-models, such as geometry, behaviour and process models. Wang et al. [246] introduced a DT-driven virtual commissioning method to simulate machining processes and achieve optimal commissioning. A DT model, constructed with a multi-domain unified modelling language and a virtual-real mapping strategy, describes the response characteristics of CNC Machine Tools.

Synchronisation and data management. Erkoyuncu et al. [58] proposed a DT design framework utilising ontologies to co-evolve with a complex engineered system by capturing data in terms of variety, velocity, and volume throughout the asset lifecycle. Human et al. [96] introduced a design framework that supports systematic decision-making for designing a DT system to integrate data from a complex physical system. This framework comprises six steps: needs and constraints analysis, physical system decomposition, services allocation, performance and quality considerations, implementation considerations, and verification and validation. It employs a general reference architecture that combines a DT aggregation hierarchy with a service-oriented architecture, enabling the separation of computational load distribution, incremental development, and modular software design.

Design for change. Vrabčič et al. [245] presented a method to manage uncertainty and disruptions in complex manufacturing systems through a DT that detects and self-adapts to maintain accuracy. They proposed an intelligent agent-based architecture to enhance DT robustness (accuracy) and resilience (timely updates). Leng et al. [131] achieved physical reconfigurability by integrating various open architectural platforms and an open architecture machine-tool. They proposed a DT-based online process emulation and multi-physics simulation in characterising operation status. Damgrave et al. [41] introduced a digital twinning method that provides clear, contextually relevant information from multiple viewpoints, thus supporting function-oriented development and integrating diverse perspectives.

4.3.2. Smart manufacturing and factories

Robotics and human-machine collaboration. Xu et al. [268] proposed a digital twin-based Industrial Cloud Robotics (DTICR) framework for robotic control, segmented into physical IR, digital IR, robotic control services, and DT data. Wang et al. [255] introduced a deep learning-enhanced DT framework for detecting and classifying human and robot actions in manufacturing, enabling autonomous decision-making via a fully-supervised detector based on a faster region-based convolutional neural network. Niermann et al. [169] address the synchronisation challenges in robotics with a modular, system-agnostic, human-centred software framework that unifies programming across systems using visual programming and a graph-based interface. Li et al. [134] proposed an HRC safety control framework based on DT technology, integrating virtual simulation and VR for testing safety hazards during design and monitoring safety distances in production using machine vision and convolutional neural networks. Hu et al. [90] developed a Petri nets-based DT framework for dual-arm cooperative systems, representing hybrid operations and avoiding complex decoupling calculations in bi-manual manipulation. Zhang et al. [278] addressed the limitations of current DTs for robotic machining by employing Knowledge Graphs (KG) and Function Blocks (FB) for knowledge representation, data integration, optimisation and real-time control. Zhang et al. [279] proposed a DT-enabled robotic grasping system to collect large-scale multimodal

datasets and apply domain randomisation and adaptation to bridge the sim-to-real transfer gap.

Synchronisation and data management. Botkina et al. [28] introduced a DT for Cutting Tools, facilitating automatic data collection and continuous model adjustments during production. Yi et al. [270] developed a three-layer DT reference model for smart assembly process design: a physical space layer detailing assembly components, an interaction layer with communication and data processing modules, and a virtual space layer for process planning, simulation, prediction, and control management. Dai et al. [37] proposed an ontology-based information modelling method to create DTs for as-fabricated parts. Pan et al. [174] proposed a multi-level cloud-enabled DT system for real-time monitoring, decision-making, and control of synchronised production logistics systems, where IoT-driven real-time information allows accurate capture of dynamics in the physical layer and effective evaluation in the digital layer. Zhi et al. [285] introduced a complex assembly modelling method using DT, incorporating geometric shape, position constraints, and physical state to integrate real-time assembly process data. They also explored Skin model generation based on tolerance principles for digital product representation. Saren et al. [190] developed a general architecture for accurate DTs (ADTs) combining Skin Model Shapes and Physics-based models DTs (PDT) twinned with a thermal mechanical package assembly for precision microstructures. Zhu et al. [287] presented a DT-driven framework that enables operators to manage product changes and accelerate start-up phases.

Machine learning and deep-learning methods. Perno et al. [179] introduced a framework for developing ML-based DTs to predict critical process parameters in real time. This framework was validated through a case study at an international process manufacturing company, where plant data were collected and processed, predictive models were developed for two key parameters, and a DT application was developed to visualise predictions. Liu et al. [140] proposed a DT-driven method for predicting surface roughness and adaptively optimising process parameters. A DT monitors the machining process in real-time and serves as a data source for optimisation. An IPSO-GRNN (Improved Particle Swarm Optimization-Generalized Regression Neural Networks) model predicts tool wear and surface roughness. If the predicted surface roughness does not meet the requirements, the DT system triggers adaptive optimisation of cutting parameters based on tool wear predictions. Villalonga et al. [243] focused on dynamic production schedule updates through automated decision-making supported by a fuzzy inference system, which uses asset conditions and production rates from local and global DTs. Blasek et al. [24] examined a large language model (LLM) output quality for defining DT requirements, comparing domain expert-defined requirements for an air conditioning facility with those generated by ChatGPT, and derived prompt engineering conclusions from this experiment. Mo et al. [158] explored the use of DTs to enhance the robustness, responsiveness, and productivity of industrial systems. They proposed a paradigm integrating DTs and modular AI algorithms for dynamic reconfiguration of manufacturing systems, enabling adaptive decision-making in response to market changes, supported by a knowledge graph.

4.3.3. Maintenance

Predictive maintenance and PHM. Van Dinter et al. [49] developed and evaluated a reference architecture using UML diagrams based on the feature model. Negri et al. [166] addressed the ongoing challenges in production scheduling under uncertainty by proposing a framework that exploits the DT synchronisation with health assessment models. Toothman et al. [235] introduced a DT-based framework for standardised communication and resource organisation in health monitoring, featuring a reusable state-based model of mechanical system health. Huang et al. [93] proposed a DT-driven anomaly detection framework for real-time health monitoring and anomaly prediction in industrial systems, leveraging edge AI for high-performance detection in a dynamic edge/cloud network. Marquez et al. [155] designed a condition-based maintenance application for train axle bearings using a generic framework for digital

maintenance management based on DT. Aivaliotis et al. [6] developed a methodology for advanced physics-based modelling to enable DT in predictive maintenance. Ghosh et al. [70] highlighted the role of DTs in autonomous monitoring and troubleshooting in smart manufacturing, developing a sensor signal-based digital twin for intelligent machine tools. They underscored the role of DTs in enabling machine tools to autonomously monitor and troubleshoot. This research proposes a sensor signal-based DT for intelligent machine tools.

Degradation assessment and costing. Lv et al. [150] identified three main challenges in unmanned maintenance. To address these issues, they proposed a bio-inspired Learning Intelligent Distribution Agent (LIDA) cognitive-based DT architecture for self-constructed, self-evaluated, and self-optimised unmanned machine tool maintenance.

4.3.4. Life cycle and sustainability

Oettl et al. [171] devised a method to evaluate the strategic benefits of DTs throughout the product lifecycle. D'Amico et al. [42] analysed survey data and highlighted that DTs should be adaptable, scalable, interoperable and support assets throughout their lifecycle. This study identified the drivers of DT development, including autonomy, customer satisfaction, safety, situational awareness, optimisation, and sustainability, but it noted barriers such as a lack of expertise, funding, and interoperability. Timperi et al. [233] explored data-based business and DT-enabled solutions in manufacturing across all product-service lifecycle stages. Seegrün et al. [201] identified current sustainability-focused DT applications in the manufacturing industry through a systematic literature review. Ke et al. [114] proposed an intelligent redesign method for used products based on DT, comprising a redesign process framework, features analysis, an intelligent redesign framework, and the application of the redesign process. Li et al. [135] developed a DT-driven information architecture for dynamic sustainability assessment throughout the product lifecycle. He et al. [88] introduced a three-layer DT architecture model for product sustainability, incorporating data, mapping, and application layers, with carbon footprint optimisation as the goal. Ke et al. [114] presented an obvious design-inspired DT approach for product redesign. Bertoni et al. [21] developed a DT framework to enhance the design of long lifecycle sensitised solutions within a PSS context.

This section presented a synthesis and summary of the state-of-the-art in engineering with DTs across different phases of manufacturing. The overall conclusions highlight several overarching findings. There is extensive research in DTs, but there is no convergence on design methods. Additionally, there is limited agreement on where DTs are most suitable for implementation. Interoperability remains a major challenge, as data and model interfaces are typically constrained to specific use cases, with limited consideration for broader integration possibilities. While there are many DT use cases, empirical evidence demonstrating potential benefits and providing guidance for DT design is limited. Moving towards full automation with DTs is highly sought after, with numerous examples across advanced manufacturing use cases. Finally, DTs can enable integration across the lifecycle by using a common and scalable approach.

5. DT realisations and implementations

5.1. DT use cases and business functions

DT realisations are suggested to be targeted towards the following main use cases and business functions in accordance with the operational use of technical systems such as assets, products, objects, machines, etc. [73,215]:

- a) **Entry level:** provide IT-links to internet accessible web servers via information tags at physical objects to obtain digital datasets of physical objects,
- b) **Base level:** study, monitor, survey, and diagnose operations (incl. analyse and understand efficiency and effectiveness),

- c) **Advanced level:** drive and control performance (predict and dynamically adjust system parameters),
- d) **Professional level:** measure, assess and optimise operational use, and identify associated value creation benefits as part of digital data business models,
- e) **Full Lifecycle level:** identify rest product life, across lifecycle potential of living systems in real operation, including related sustainability measures,
- f) **Foresight level:** gain feedback and deeper technical insights for engineering design and analysis of future generation systems and qualify prediction and simulation models accordingly.

5.2. Prerequisites for DT implementations

To achieve information readiness and to enable infrastructure for DTs spanning across typical PLM environments by twinning engineering models (i.e. digital master / digital prototypes) and operational recordings (digital shadow) from living products, objects, and assets, the following preparation steps are being developed in industry:

- The rather generic model and metadata descriptions of products and factory equipment in typical PLM environments, as part of the virtual product creation phase in the Beginning of Life (BoL) phase, need to be expanded to specific 'instance one' type of representations to provide the specific individual digital master or prototype model for twinning it with life data in operations as part of the Middle of Life (MoL) phase.
- It is necessary to make data and information snippets available from different repositories of industrial information management: 'although cross-industry digitalization of production and logistics, as well as the IoT capability of many products, are currently creating a digitally available data basis for the first time, which can make information from each of these phases usable, it value-adding information is still lying dormant in widely distributed data silos and is difficult to access. Even if all the data is theoretically available, the sheer volume and the lack of cross-connections make data-based solutions cost and resource drivers – if they can be implemented at all with native IT' [26]. Therefore, the realisation of DTs requires robust mechanisms of data connectivity and linking.
- The implementations and business functions of DTs via the underlying twinning engines make it indispensable to align operational data, information elements, and master/prototype models with business process knowledge and data/model semantics.

Fig. 19 shows the solution set of a DT of Bosch IoT. The DT consists of a *Digital Twin Registry* and related *Aspect Models*. The Digital Twin Registry provides an IT-linkage to a 'place' in an IT environment where the DT is hosted and described. The Aspect Model describes the DT of an asset, object, process, or product. The type of description leaves open the area of interest is, i.e. whether it is a passive description or an active model. It is anticipated by Bosch that it is advantageous and necessary in industry to offer possibilities to describe the DT via ontologies implemented via knowledge graph solutions.

SAMSON company [232] highlighted a DT realisation of a valve system. Valve systems are widely used in all kinds of industrial factories, both in process industry and in discrete manufacturing, as well as in energy and transportation systems. The *entry level Digital Twin* of a valve is provided to make it easily possible for maintenance, repair and replace activities to find important information of the delivered product. Standard 2D-code and optional RFID codes are applied to products as type labels to provide additional information sets via static digital shadow e-type information sets. They can be invoked by computers, handheld tablets, and/or smartphones by scanning RFID or by entering the respective serial number. Such entry level DTs are limited to main (static) encoding of product types, lots, batches, and characteristics and do not offer dynamic recordings as

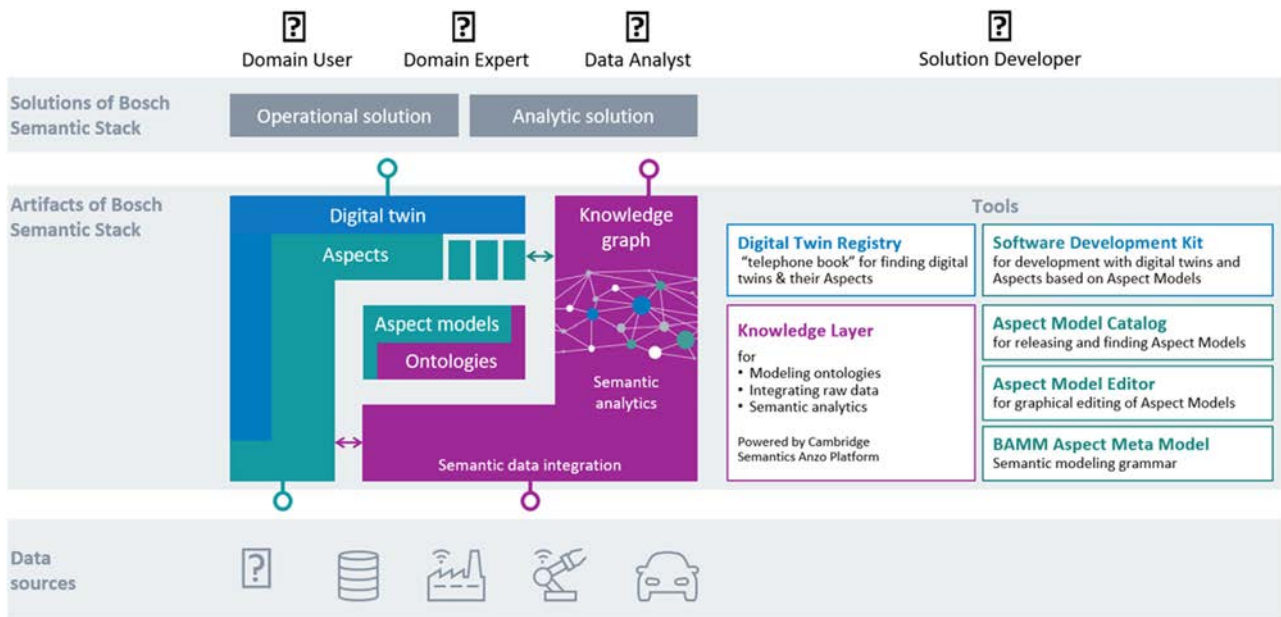


Fig. 19. Bosch IoT digital twin description within the Bosch Semantic Stack architecture (courtesy of Robert Bosch Manufacturing Solutions).

part of the asset usage. Such realisations request a company wide web server architecture with public internet access around internally hosted and firewall protected data servers. This kind of *entry level Digital Twin* usually concentrates on offering metadata, such as product properties, general product information, declaration of conformity, standards certification, type of examination, production types, safety integrity level (SIL), and material information. To achieve the next levels of business function, the base and advanced levels, it is necessary to realise a more refined set of digitally and semantically connected regime of the digital shadow data with model world of the digital master and prototype [216].

Fig. 20 shows the solution architecture of Siemens for an *executable Digital Twin* (xDT) which belongs to the class of *advanced level Digital Twin* and beyond, i.e. which can also serve as a foundation for the DT levels d), e) and f). The term 'executable Digital Twin' means that the model of the digital master/prototype is an 'active one' in the sense that it can be executed in run time mode as a type of ongoing live modifiable simulation. As shown in the figure, the DT envisioned by Siemens assumes an executable Digital Twin version of a simulation originally used as part of a Digital Prototype. The twinning between such xDT and the operational sensor data of the digital

shadow is assumed to be realised in an Edge PC environment close to the physical asset. It is obvious that this type of category c) and above level xDT require a solid understanding of the type of application field of the DT. In addition, it becomes necessary to realise the set-up of a full regime of associated digital prototype-related simulation applications at the model side and the corresponding IT infrastructure set-up for the deployment environment for the digital shadow operational data at the physical asset.

Siemens does not specify whether their solution of an xDT is assumed to be different or the same for the DT operation modes according to the classification of Stark [215], i.e., the analyse & understand (A&U) and the drive & control (D&C) mode.

In [210], Siemens provided an insight into how Simcenter systems simulation was used to model the dual patient-single medical ventilator system and to assess the ability of the ventilator to maintain two patients. In addition, it is explained how the system model can be further used as the xDT leveraging Functional Mock-up (FMU) interfaces to provide real-time insights during the ventilator operation.

The RAUCH Furnace Technology GmbH in Austria [8] specialises in researching, developing, and implementing advanced melting

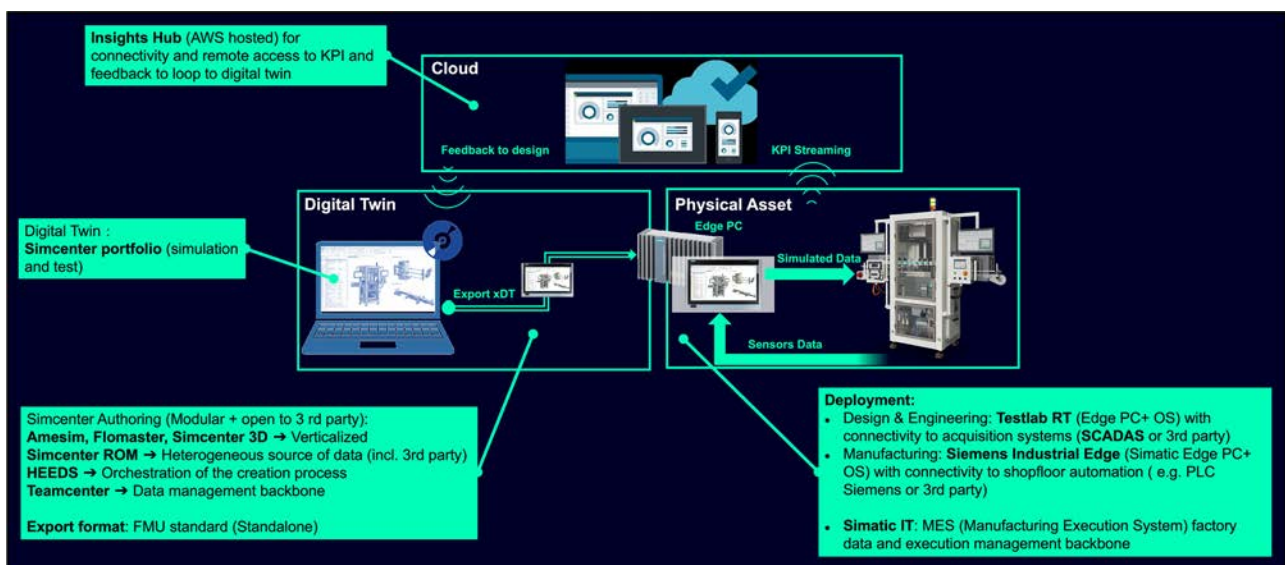


Fig. 20. Solution architecture for the advanced level executable digital twin by SIEMENS (courtesy of Siemens AG).

technology solutions for processing magnesium, zinc, and non-ferrous metals. Together with the IT engineering specialist ITficient AG from Switzerland and the international CADFEM group, RAUCH Furnace Technology GmbH has developed an *advanced level Digital Twin* of a furnace chamber in production and implemented a predictive maintenance DT solution to monitor and extend the health condition of the steel furnace chamber which has too extreme environmental conditions such as high temperature with steep temperature gradients of the furnace gas, corrosive protective gas, inhomogeneous radiation power of the flame and the static pressure of up to 4 tons of melting liquid. Intensive analysis has revealed that the lifetime of the crucible (the melting vessel) is highly dependent on the segregation of the melting alloy: since there exist intermetallic alloys that differ in their intrinsic densities, they can cause high differences in heat transmission, which can cause an inhomogeneous distribution of temperature at the outer shell of the crucible. This, however, causes high stress levels at the welding seams, which might result in cracks and leads to failure of the entire system. The function of the DT has been targeted to closely monitor the involved manufacturing process parameters in the direct context of the crucible in the furnace chamber to get advanced warnings of malfunctions and hence to avoid defects of the crucible of the furnace chamber and the subsequent failure of the entire furnace.

For predicting the remaining service life of the crucible, the corresponding DT must offer the following:

- Availability of accurate simulation models (digital master/prototype) for the temperature distribution in the furnace room (result of the flow simulations, with Computational Fluid Dynamics (CFD) and the stress in the weld seams (result of the structural mechanical FEM calculations),
- Qualified reduced-order models of the simulation models for the decisive prediction parameters (i.e. special adaption of the digital master/prototype),
- Constant delivery of operational data signals (as part of the digital shadow) from the real temperature sensors in the furnace (as close as possible to the crucible),
- Derived virtual temperature sensors as part of the simulation models (the digital prototype) in the alloy of the crucible and
- Environmentally robust IT edge cloud infrastructure closely integrated in the furnace chamber system for storing, managing and analysing digital shadow data and executing the DT in conjunction with the reduced-order models of the digital master/prototype.

Based on the developed solution, the partners are heading towards the next levels, i.e. professional, full lifecycle and foresight level.

The company MathWorks Inc. leverages their analytical tools MATLAB for data-driven Models in combination with their SIMULINK models with respect to continuous time models, discrete time models, physical models, state machines and discrete event models.

As shown in Fig. 21 those modelling techniques form the basis for building the overall DT models (i.e. establishing the link between operational shadow data with the digital master/prototype model regime).

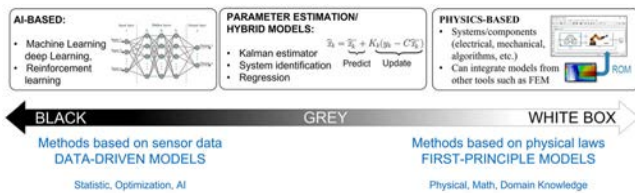


Fig. 21. Modelling techniques placed on a scale from white-box to black-box to establish overall digital twin models by MathWorks Inc. (courtesy of MathWorks Inc.).

As described in [260], the approach provided by MathWorks Inc. to build an *advanced level Digital Twin* for a complex technical system such as the electric power system for a drilling rig requires a

comprehensive manual, expert-like digital master/prototype model refinement and associated digital shadow parameter tuning to reach a well matching DT model. In such an approach, it is, however, not yet possible to flexibly change the operational data inputs on the fly. It requires hands-on expert model synthesis and analysis.

The company Dassault Systèmes extends the perspective of digital twins via virtual twins [46]:

- Digital twins are digital representations of real-world entities or systems, in the form of a software object or a model that mirrors a unique physical object, a process, an organisation, a person, or another abstraction.
- Virtual twins do offer, in addition, integrated end-to-end systems to accelerate collaboration to enable people to design, simulate, produce for the market, and to analyse data in the context of the entire lifecycle.

Dassault Systèmes provides the digital platform solution 3DEXPERIENCE to realise their digital twin solution concept called *Virtual Twin Experience* (see example for Manufacturing in [119]).

A Virtual Twin Experience is a representation of reality based on mathematical models and scientific principles. It is a virtual replica of a physical object, system, or process that accurately reflects its behaviour in the real world. In the context of Dassault Systèmes, the *Virtual Twin* refers to the use of advanced technologies and the 3DEXPERIENCE platform to create comprehensive virtual models that can interact with and be synchronised with their real-world counterparts.

Fig. 22 illustrates Dassault Systèmes' Virtual Twin Experience using DELMIA and DELMIA APRISO solutions in the assembly process of sealing at a distributor housing, incorporating eight virtual/physical assets. As part of the BaSys 4.2 project involving 23 partners (<https://eclipse.dev/basys/>), Dassault Systèmes developed a process in which a virtual asset created in a CAD system or through CAE simulations is connected to a manufacturing cell or station by loading its specifications from the AAS, as indicated by connections 1 and 2. The asset transmits its specifications to DELMIA Operations Engineering (OE). Then, the capability of the asset is validated by checking whether the asset can be used in the production scenario and whether it can meet the production requirements. The validated scope is then sent to DELMIA Apr ISO (see connections 3 and 4). The asset can then be used in the context of production scenario.

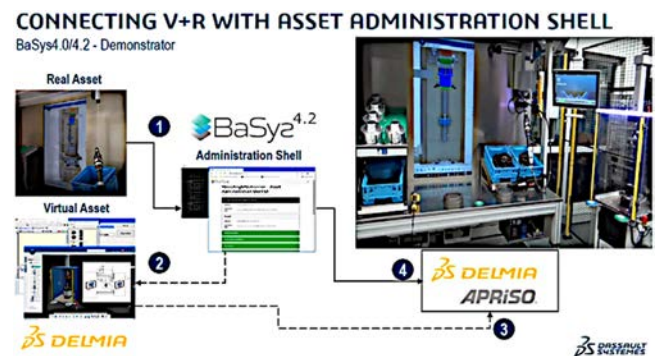


Fig. 22. Connecting virtual and real assets as part of the BaSys 4.0/4.2 demonstrator at the company ZF with manufacturing solutions of Dassault Systèmes (courtesy of Dassault Systèmes).

This realisation example shows the connectivity steps between a digital master / digital prototype (the virtual asset) and the digital shadow of a real object (in this case the real asset) by bridging the proprietary digital twin solutions (DELMIA) and standardised digital twin solutions (Industrie 4.0 AAS, eclipse middleware) as part of the base and advanced levels and as the basis for the further levels.

Overall, numerous classification frameworks for DT maturity exist throughout the academic literature [119]. Such classifications should help organisations, enterprises, industrial managers, engineers and IT specialists to establish the right skillset and competence with

appropriate associated methods and technologies in real-time operation. In addition to the proposed level definitions for generic DT use cases and business functions outlined earlier in this section, other classifications can also be employed for digital implementations and realisations by using:

- Technical characteristics and involved technologies,
- Time durations,
- Twinning connections between data and models,
- Manual, automatic, and autonomous interactions,
- Technical system depth and breadth,
- Transformational potential,
- Number and type of involved elements.

It cannot yet be concluded which type of classification will deliver the greatest benefits to DT developers and implementers in the future. It will depend on future research and development outcomes, as well as the creation of future standardisation templates. Future research, particularly those exploring DT networks of digital twins, will likely unveil more sophisticated classification methods.

In summary, this section demonstrated that the first fundamental and standardised technology elements, such as the AAS, exist and can be leveraged to establish connections between physical assets and their virtual representations as part of the digital twinning. The other examples of this section illustrate and explain, that most of today's DT realisations remain limited to the entry and base levels. To reach an advanced level and beyond, substantial engineering and design effort are required to develop and implement a DT for real-life problems. The high efforts are caused by the need to combine expert knowledge to combine digital model richness, sensor and actuator fidelity, associated signal processing, data analytics, and IT integration. This can only be achieved by dedicated development projects that leverages experts from different domains in engineering, IT and data science.

6. Challenges and future research directions

Despite significant advancements, challenges persist in several key domains that hinder the full realisation of DTs. Drawing upon the reviewed literature and the findings on DT applications, realisations and implementations from previous sections, this section summarises research gaps and future research directions for deploying DTs in engineering design.

6.1. DT integration in engineering design

DTs enable designers to generate new designs that are more aligned with customer needs by testing various iterations in a simulated environment before physical realisation. Furthermore, DTs can provide real-time feedback on product performance, enabling continuous improvement and optimisation throughout the product life-cycle, not only reducing development time and costs but also allowing for more innovative and customised solutions. DTs as new solution elements in product and production system development allow for integrated views of system design and system operation. Consequently, it will be indispensable to develop new data and model management frameworks and architectures to accommodate this new capability. In particular, design collaboration and novel predictive capabilities in the context of Design for X (DfX) and human-DT interaction practices should prioritise the development of interaction mechanisms, low-latency connections and real-time synchronisation in large, distributed, and secure networks.

The research and implementation of DTs in engineering design also needs to focus on enhancing the interoperability and standards to facilitate seamless integration with existing systems and open-source platforms. Developing robust and efficient computational models to manage heterogeneous data while providing accurate predictions requires further exploration into machine learning and artificial intelligence that can also assist in processing, interpreting, and verifying and validating DT models and data, enabling predictive

analytics and optimisation that would be unfeasible with human analysis alone. Furthermore, it is becoming crucial to consider the environmental impact of DTs and to explore their use in promoting sustainable design practices.

6.2. DT challenges in engineering design

Leveraging DTs in engineering design presents multifaceted challenges that impede their full adoption and effectiveness. These challenges span multiple dimensions of digital twin engineering, from model-data integration and lifecycle management to secure interoperability and human-system collaboration frameworks. Additionally, evolving standardisation needs and verification and validation requirements must be addressed, requiring coordinated research and development efforts as detailed below:

6.2.1. Models and data

As an effective approach to integrate physical and virtual spaces, DTs unite models and data throughout all life cycle phases, enabling a model-data-driven approach. In the design of complex systems, the multitude of models, ranging from early conceptualizations to detailed multi-physical simulations, present challenges for real-time simulation, necessitating constant updating, fusion, and verification of these models. Creating high-fidelity models that balance accuracy and feasibility must account for the constraints associated with integrating Machine Learning, Scientific Machine Learning (SciML), and Model Order Reduction (MOR) techniques [59]. The lack of interoperability of the models hinders the interconnection and integration of DTs. Standardised modelling approaches require more use of meta-models, co-simulation and Functional Mock-Up Interfaces (FMI) and developing a unified domain and models' terminology [275,276].

Additionally, the rapid increase in real-time data volume requires efficient data processing and storage solutions, which demand advanced data management and integration solutions and necessitates advancements in sensor technology, data transmission protocols, and low-latency data processing architectures. The integration of real-time and historical data, as well as simulation data, also poses significant challenges in terms of the fusion of heterogeneous data sources and development of standardised data formats, which requires achieving syntactic and semantic interoperability through ontologies and category theory [112,145,275]. As DTs continue to evolve and be utilised, they generate increasing amounts of data and usage information, such as simulation results and model update operations. DTs also iterate or be rebuilt to remain aligned with their physical counterparts. The growing volume of data and information poses significant challenges for data management.

Furthermore, although some DT-related data, models, and information are valuable for the design and development of next-generation products and systems, other items may not be as useful. To address these challenges, future efforts should focus on how to effectively identify and select valuable information from DTs and manage it as a digital asset for potential future use. Overall, the new research field of *Digital Twinning Core* has emerged: how to describe, develop, and operate the solution space for semantically aligning and syntactically connecting, linking, and integrating digital master and digital prototype models with the digital shadow operational data to realise the variety of DT use cases and business functions.

Integrating these challenges into engineering design means evolving from static and isolated design tools to dynamic, model-data-driven tools. Designers can achieve faster, more accurate design iterations, and better collaboration through highly integrated, adaptive, and intelligent design environments.

6.2.2. Lifecycle integration

Different lifecycle stages have diverse and varying requirements, and data and models from these stages may have implicit relationships. For instance, data and models from a previous product generation can optimise new designs, and user evaluations of earlier products are crucial for redesign. Manufacturing processes and production time costs of the designed products can also be considered.

Thus, further research is needed to identify and select relevant information across the lifecycle phases. Exploring whether a single DT should be employed for the entire lifecycle of the physical entity or if distinct DTs are necessary for each phase of the lifecycle is a knowledge gap that needs to be addressed [156]. Moreover, the long lifecycle of complex systems such as airplanes requiring a substantial dataset from heterogeneous sources is a challenge to DT continuity and DT methods to enable their use along the product lifecycle [267]. As described already in Section 5, future investigations will have to focus more intensively on the full lifecycle level and the foresight level with respect to the anticipated DT use cases, target capabilities, and business functions.

6.2.3. Interaction mechanisms and communication

Enhancing the automated flow of information between physical and digital systems ensures low-latency, real-time synchronisation and adaptability of DTs, which is achieved through advanced communication networks and data processing [168]. The balance between computational resources and communication latency is crucial for integrating cloud computing with DTs, which requires further investigation [183]. Regarding real-time considerations, integrating edge computing with DTs shows significant potential for reducing the latency associated with transferring large data volumes to cloud servers. Another approach involves exploring methodologies to identify optimal twinning rate-application scope relationships in DTs, which are still under investigation [79,275]. DTs have evolved beyond mere synchronisation with their physical counterparts by incorporating advanced feedback mechanisms that enable intelligent and autonomous behaviour. This evolution allows DTs to not only mirror the state of physical systems but also to optimise the performance of physical assets. The integration of sensing and processing capabilities enables DTs to comprehend their environment, thereby facilitating more informed decision-making. Furthermore, the ability of DTs to proactively communicate with one another opens new possibilities for collaboration and system-wide optimisation.

Enabling the integration of DTs that proactively communicate with each other (*federated DTs*) represents significant progress. Federated DTs can achieve higher levels of coordination and efficiency across complex networks of interconnected physical and digital entities. Therefore, research needs to be intensified in the field of *Digital Twin Networks* from two perspectives:

- First, the development of centralised or distributed interaction mechanisms and communication patterns.
- Second, the enhancement of the targeted higher business function of federated DTs under the constraints of uncertainty, reliability, robustness, safety, and sustainable operation of the technical systems they support (see also the engineering roadmap of the research council Industrie 4.0 [98]).

To meet the specific demands of rapid design iterations and validation, DT development must address communication infrastructure challenges by leveraging edge computing for low-latency real-time feedback. Additionally, federated DT networks enable the coordination of different design components and subsystems, thus enhancing the overall system performance. Integrating these challenges into engineering design will provide engineers with an ICT environment featuring real-time updates, rapid predictive capabilities, and system-wide synchronisation for complex products.

6.2.4. Intelligence and autonomy

DT is perceived as a passive entity. In contrast, the Intelligent Digital Twin (IDT) is characterised by being active, online, goal-seeking and anticipatory [283]. The concept of the Cognitive Digital Twin (CDT), which incorporates cognitive attributes such as attention, perception, and memory, constitutes an emerging research area [39]. Integrating Large Language Models (LLMs) and AI Agents has the potential to enhance the intelligence of DTs. AI-DT integration allows for the development of self-evolving DTs that can adapt to changing conditions and requirements without constant human intervention,

enabling agility in the design and operation of smart products and PSSs. As DTs continue to advance, their ability to autonomously pursue both individual and cooperative goals will likely lead to more resilient, efficient, and intelligent products and systems across various applications. AI algorithms, such as reinforcement learning, are promising. The black box nature of AI in DTs raises safety and reliability concerns, particularly in critical applications. Explainable AI developments are required to address these needs.

6.2.5. Human-DT interaction and integration

Integrating human factors into DT is essential for engineering design. Developing interoperable human-centred DT platforms that facilitate real-time collaboration, simulate collective responses, and support decision-making across distributed design teams involves using intuitive ergonomic interfaces, augmented reality and virtual reality technologies, and optimised cockpits [267] to enable DTs to better meet users' needs. These interfaces allow designers to quickly understand critical information and make informed decisions. Beyond interface design, incorporating human factors involves modelling human behaviour, cognitive processes and decision-making patterns within a dynamic digital environment. This allows DTs to anticipate human actions, provide context-aware assistance, and simulate human responses.

Merging DTs, AI, and data technologies with human-centred design is challenging. Ethical considerations regarding privacy, security, and potential biases in AI systems must be carefully addressed to ensure responsible implementation of human-centred DTs in design.

6.2.6. Security and privacy

DTs collect privacy-sensitive data throughout their lifecycle, requiring robust security and privacy frameworks for data transmission and integrity. Compromised data and communication can lead to inaccurate models, erroneous simulation results, desynchronization, and data alteration, thus undermining the credibility of DTs. Some research has explored the use of blockchain technology to enhance security and privacy protection in DT wireless networks [257], but further research and additional efforts are still needed to address other security aspects (e.g., feedback mechanisms) due to potential cyber threats and attacks. The diversity and complexity of intra-twin and inter-twin communication [89] and the lifecycle of DT services can give rise to new threats that are not yet fully understood or anticipated.

By embedding security and privacy measures at every stage of the design process, design tools inherently uphold the highest standards of data integrity and trustworthiness. This security-by-design approach enables the creation of resilient smart products that effectively mitigate cyber threats and protect sensitive data.

6.2.7. Standardisation

The lack of comprehensive standards poses significant challenges for the implementation and interoperability of DTs. Although ISO/IEC standardisation efforts have addressed DT concepts, terminology, use cases, maturity models, reference architectures, and fidelity measures [84,117], there remains a notable absence of standardised approaches for models, data formats, connections, syntax interfaces and semantic ontologies, and associated services. Other DT standardisation initiatives (ISO, Digital Twin Consortium, Industrial Digital Twin Association, European Telecommunications Standards Institute, etc.) also face challenges in deploying DT capabilities, standardising digital asset representation for interoperability, and defining reference architectures for machine-to-machine communication [23]. These limitations hinder DT development, integration, and interoperability across different platforms and systems. To address these challenges, efforts are focusing on developing unified processes for constructing generic reference models and developing DT maturity standards to assess existing realisations and guide iterative upgrades. Developing comprehensive standards for DTs, including data, models, communication protocols, and cross-system interoperability, is crucial for promoting DTs in design.

Accounting for these standardisation challenges in engineering design means transforming fragmented and proprietary systems into an interoperable framework that supports every phase of the design process. This requires developing smart standards for data formats, models, and communication protocols that ensure generic reference models and reliable interoperability and interfaces for plug-and-play integration of design tools.

6.2.8. Verification and validation

DTs comprise various data, models, and processes, requiring verification and validation at both individual and system levels. The lack of established methodologies for the V&V of DTs presents a significant challenge that is not covered enough by current research and existing standards. To overcome these challenges, it is crucial to develop clear, standardised V&V methodologies specifically tailored to DTs, and metrics or KPIs to assess the accuracy and trustworthiness of DTs. These metrics are crucial for DT implementation and acceptance while providing a systematised framework for V&V evaluation. Furthermore, establishing and choosing metrics for V&V will depend on the specific use case, highlighting the need for adaptable approaches. The research field of V&V of DTs requires new collaboration agreements between public, industrial, and business partners in terms of ensuring appropriate availability of open and private data and models for the DT research community to study different levels of verification and validation.

Taking these challenges into account in engineering design implies establishing standardised frameworks that ensure that every DT is rigorously tested and trustworthy. For current design practices, it requires developing methodologies and metrics to verify the accuracy and reliability of the models and simulations at both component and system levels and the impacts of uncertainties on the data and model quality. Moreover, uncertainty regarding human involvement and decision-making in DT design and implementation needs to be also considered and quantified.

6.2.9. Software and platforms

Gil et al. [71] examined 14 open-source DT frameworks and identified both benefits and drawbacks. The limitations include insufficient documentation, simplistic examples, lack of public case studies and long-term support, useability, restricted scalability to other domains, and insufficient integration with other tools. In contrast, commercial software offers more stability, out-of-the-box functionalities, and support, although they may create dependencies on software developers. If designed based on standards, open-source and commercial software can offer greater flexibility and long-term reliability, thereby streamlining the development and integration of DTs and DT eco-systems. DT frameworks based on AAS and ISO 23247 are in the early stages of development, necessitating further research and implementation efforts.

Ensuring that DT software can interface smoothly with existing design tools is critical. Inadequate interoperability can lead to slower product development cycles, constrain the design process at every stage, hinder collaboration, and increase the need for counterproductive manual interventions.

6.3. Future research

Building upon the identified challenges in DT-enabled engineering design, this section presents potential research opportunities structured across key themes. These themes span multiple facets, from advanced design methods and tools to human-centred approaches and educational opportunities, providing a framework for integrating DTs into engineering design practices.

6.3.1. Advanced methods for design

DT development requires advanced design methods that address complex modelling challenges, optimise iteration cycles, and integrate AI into design workflows while maintaining high fidelity. Consequently, future research efforts should focus on the following objectives:

- Develop hybrid modelling approaches for complex components, products, and manufacturing systems across their lifecycle with sufficient DT fidelity and confidence. This could involve combining models of different fidelity and integrating digital tools like PLM, CAD, and CAE.
- Establish DT-based methodologies for risk and uncertainty management in product and system models, especially during the early design stages.
- Use high fidelity and multi-scale DT modelling to design and optimise sociotechnical and manufacturing systems, balancing detail and computational efficiency.
- Implement exploration and optimisation tools in the design process to potentially enhance new product designs by leveraging AI technologies as part of DT to derive insights from previous product generations.
- Develop rapid modelling and simulation approaches using simple, lightweight (surrogate) models that preserve DT simulation accuracy through model simplification, reuse, and migration.
- Develop automated design approaches to achieve a self-adaptive design driven by data and algorithms, in accordance with requirements and real-time data

6.3.2. Digital platforms for engineering design

Implementing DTs effectively requires advanced digital infrastructures capable of integrating diverse models, data, and emerging technologies within interoperable, composable architectures. Hence, future research efforts should focus on the following priorities:

- Develop composable and interoperable architectures that integrate data, models, and advanced digital platforms with DT capabilities. This will enhance the flexibility and reusability of products and processes in complex system design.
- Deploy interoperability and standardisation in the use of AR/MR/VR and AI techniques in design, allowing these technologies to seamlessly work together within DT and connect DT with traditional design tools.
- Develop knowledge graphs, ontologies, and data fusion to support DT-based decision-making processes in design, enabling engineers to access, integrate, utilise, and adapt diverse data sources.
- Develop efficient communication methods to enable seamless collaboration in virtual spaces, allowing designers, manufacturers, and engineers to communicate and collaborate on product designs and testing within the virtual environment.

6.3.3. Product-service systems and lifecycle engineering

DT capabilities are evolving to encompass complex product-service systems throughout their lifecycle, necessitating iterative development approaches that align with modern software practices and societal imperatives. Therefore, future research priorities should address the following areas:

- Expand the understanding of the DT lifecycle to encompass both physical components and product-service systems. This is especially crucial for smart products and systems that combine tangible products and services.
- Develop DT-oriented methodologies and supporting infrastructure to enable iterative and rapid design, development, and validation of products in alignment with modern software engineering practices (e.g. DevOps for engineering design).
- Explore the setup, development, and operation of Digital Twin Networks to provide new advanced solutions for sustainable operations of technical systems.
- Address responsible design considerations in DT-enabled systems, including sustainability, society, and resilience.

6.3.4. Human-centred design

DT technologies when integrated with human-centred approaches enable the development of improved design

environments that enhance creativity. Accordingly, future research should prioritise the following objectives:

- Investigate the integration of AR/MR/VR and immersive interfaces into the DT design workflow to enhance designers' creativity during concept generation and evaluation.
- Develop adaptive DTs that allow for right-time customisation based on user feedback, changing requirements and supporting creativity in the design phase.
- Explore how Human-in-the-Loop (HIL) approaches can be leveraged in DT-based systems to involve designers more effectively, enabling intuitive interaction with digital models and simulations.
- Establish Cognitive DTs to allow human-oriented engineering of future sociotechnical systems.

6.3.5. Digital tools for advanced manufacturing

Manufacturing processes and systems can significantly benefit from context-adaptive DT engineering solutions, especially through real-time data integration and tailored simulation means. Therefore, advancing this field requires dedicated research in the following areas:

- Develop tools to facilitate real-time data assimilation from sensors and physical systems to DTs, thereby enhancing the design of advanced manufacturing systems and processes (e.g., additive and hybrid manufacturing).
- Develop modelling and simulation methods and tools that support the real-time twinning of complex manufacturing processes, helping to achieve efficiency and precision in the design of manufacturing processes and systems.
- Establish adaptive DT frameworks for sustainable and resilient manufacturing that operate effectively across diverse industrial contexts.

6.3.6. Standardisation, sustainability, and reliability

The successful adoption of DTs in engineering design requires foundational standards to ensure interoperable and scalable solutions, ensuring that DT deployment remains resource efficient and long-term reliable. Consequently, research opportunities should focus on the following key directions:

- Implement a unified DT software platform to facilitate information exchange throughout the product lifecycle.
- Develop a set of procedures to standardise the integration of DTs into the design process.
- Establish consistent interoperability of DT models, data representations, and interfaces throughout the design process to streamline communication between designers and manufacturers.
- Investigate resource-efficient and frugal designs of DTs to increase accessibility and reduce deployment costs.
- Research on security, privacy, and other non-functional aspects critical to DT reliability, robustness, and resilience.

6.3.7. Education and training

Finally, realising the transformative potential of DTs in engineering design necessitates strategic education initiatives and targeted professional training to equip current and future engineers with essential skills. This educational transformation will also accelerate DT adoption. Therefore, the scientific community should focus on the following areas:

- Investigate how DTs can be used in engineering design education to enhance the understanding of complex systems and provide hands-on virtual experiences, allowing experiential learning.
- Investigate how to leverage DTs to enhance existing design practices and improve design skills, thereby increasing the acceptance and adoption of DTs.
- Develop training modules to enhance professional competence in DT knowledge and applications for industry practitioners.

- Explore how DTs used in training can be dynamic to accurately represent the adaptive nature of complex products and manufacturing systems, mirroring their real-world counterparts' adaptability and operational complexity.

7. Conclusion and outlook

This paper provides a comprehensive overview of DTs in engineering design, focusing on both the engineering of DTs and engineering with DTs. By examining the defining characteristics, methods, and tools enabling their development, practical applications, and implementations, we identified critical research gaps and provided future research directions.

The future of engineering design with DTs is promising, and this paper serves as a foundation for further research and implementation efforts. As we look to the future, we envision a world in which DTs are seamlessly integrated into engineering design practices, enhancing human-centred design, and enabling the creation of sustainable products and systems that are tailored to human and society needs and preferences. As the field of DTs continues to evolve drastically, it is evident that their integration into engineering design practices will foster significant advancements and transformations. From early concept exploration to rapid virtual testing, real-time twinning, and continuous improvement of designs, the realisation of these advancements will require the integration of heterogeneous data from IoT devices, low-latency communications, immersive technologies, semantic interoperability, and effective verification and validation, and will call for model-data-driven approaches, advanced simulation platforms, and AI technologies supporting multimodal reasoning. As DTs continue to expand the boundaries of what is possible, we must remain focused on the broader societal and environmental implications of DTs and strive for responsible and ethical implementation.

Collaborative efforts from the research community, industry, practitioners, and stakeholders across various domains are essential to develop the necessary methodologies, frameworks, and technologies to facilitate the widespread adoption and effective use of DTs, and the evolution towards DTs, incorporating intelligent and cognitive capabilities, that will open new possibilities for smart, autonomous, and self-evolving sociotechnical systems in manufacturing.

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.

CRediT authorship contribution statement

N. Anwer: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **R. Stark:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **F. Tao:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **J.A. Erkoyuncu:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization.

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