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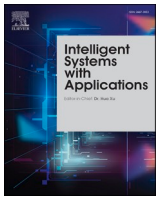

Digital twins: Recent advances and future directions in engineering fields

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ABSTRACT

Digital Twins have emerged as a powerful in silico method for the design, operation, and maintenance of real-world assets across various domains. This review paper investigates different aspects of Digital Twins, especially their application throughout the product lifecycle and across diverse engineering domains. It provides a comprehensive overview of different services that Digital Twins can deliver at each stage of the product lifecycle in collaboration with other digital technologies (e.g., Internet of Things, etc.) using a data chain (digital thread). The review begins with an introduction to Digital Twins, highlighting their fundamental principles and significance in engineering. It then explores various domains to provide cross-domain insights into the use of Digital Twins. These domains include manufacturing, healthcare and medicine, agriculture and food supply chain, aerospace, construction and building management, automotive and transportation. Each domain-specific section explores recent advancements, showcasing innovative approaches and how Digital Twins improve decision-making, while also addressing their current challenges. Furthermore, each section peers into the future, presenting a forward-looking perspective on the challenges and evolving landscape of Digital Twins in that specific engineering sector. Finally, it provides a panoramic view of the current status of Digital Twins in engineering fields, based on evaluations by a panel of experts. The expert panel assessed the Technology Readiness Level (TRL) of Digital Twins at 4.8 on a scale from 1 to 9. They identified the integration of Digital Twins with the digital thread as the most significant current challenge.

1. Introduction

Digital Twins (DTs) have emerged as a transformative technology, offering exceptional capabilities for monitoring, optimizing, and forecasting the behavior of real-world systems across various domains. Although there are different definitions for DTs, a comprehensive definition should incorporate three fundamental aspects of Digital Twins, namely, personalized product representation, dynamic real time model updates throughout the product lifecycle , and the provision of diverse services, particularly decision-making capabilities. As such, a Digital Twin is defined as a digital representation of an individual/unique physical asset that mimics the structure, context, and behavior of its real-world counterpart. It is dynamically updated with data from its physical twin throughout its lifecycle and can deliver different services especially decision-making that realizes value (X Liu et al., 2023; Tao et al., 2022; Kargin et al., 2021). DTs inform decisions that realize value by collecting and/or generating data, processing data in a virtual domain, and making decisions in real time. They are the nexus where the real world meets data science and computational engineering (Fig. 1). These three core aspects—personalized product representation, real time updates, and decision-making support—work synergistically to define DT functionality. Personalized representation creates a tailored digital model of a unique physical asset (e.g., a specific turbine or patient's organ), capturing its distinct structure and behavior. Real time updates, facilitated by sensor data and IoT connectivity, ensure this model evolves dynamically, reflecting the asset's current state throughout its lifecycle. Decision-making support leverages this live, personalized model to process data—via simulation or AI—and deliver actionable insights, such as predictive maintenance or treatment optimization.

Gartner's annually released Hype Cycle for Emerging Technologies shows the common progression for new technologies and innovation (Understanding Gartner's Hype Cycles, 2023). Gartner predicted that DTs will be at the Plateau of Productivity between 2023 and 2028. At this plateau, the practical advantages of the technology will be proven through real-world applications, leading to an increasing number of

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companies embracing its adoption. As the concept of Digital Twins (DTs) is relatively new, there are many misunderstandings about their definition, scope, and relationship with other digital technologies. In this review paper, we aim to consolidate various perspectives on DTs from different engineering fields to establish a unified definition, scope, and role for DTs. Moreover, by reviewing the recent advances and future directions, this article offers cross-domain insights, allowing stakeholders to benefit from advancements in other sectors and apply these innovations to their own use of Digital Twins. The sectors covered in this review include manufacturing and industrial processes; health and medicine; aerospace and defense; construction and building management; smart cities and infrastructure; automotive, transportation and logistics; and agriculture and food supply chain. The paper begins by defining the key concepts and scope of DTs, followed by an in-depth analysis of recent advances and future perspectives in each of the aforementioned sectors. Finally, using expert panel input, it assesses the current status of DT technology using key performance indicators, namely Modeling Fidelity, Scalability, Investment, Integration with Digital Thread, and Overall Technology Readiness Level (TRL).

This review offers several innovative contributions to the DT literature, distinguishing it from prior works. First, it provides a unified cross-domain framework by consolidating DT perspectives across seven engineering fields, namely, manufacturing, healthcare, aerospace, construction, smart cities, automotive, and agriculture. Unlike domain-specific reviews, this synthesis reveals transferable insights, such as aerospace's data integration successes informing smart city scalability, fostering interdisciplinary learning. Second, it uniquely integrates a quantitative expert panel assessment with qualitative domain analyses. The panel's ratings anchor the review in empirical maturity metrics, offering a novel benchmark for DT progress beyond anecdotal evidence. Third, by linking AI-driven material and device advancements to DT evolution, this article pioneers a forward-looking perspective. It positions DTs as beneficiaries of computational methodologies like those optimizing additive manufacturing (Purcell & Neubauer, 2023) or designing neuromorphic devices, broadening their future applicability. Together, these elements—cross-domain synthesis, expert-driven evaluation, and AI-material synergy—establish a comprehensive, actionable foundation for advancing DT research and deployment, appealing to a diverse readership.

2. Literature review methodology

The literature review method is based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) divided into three steps: literature collection, literature filtering, and literature study. Step 1: As shown in Fig. 2, literature collection is performed separately for research articles and review articles. Web of Science, Scopus, IEEE Xplore, and Google Scholar are used as databases. The literature collection spans from January 2015 to June 2024. Articles containing "Digital Twin" and the targeted application areas (e.g., healthcare, food, building, automotive, etc.) as keywords in the title or abstracts were preliminarily retained and then categorized based on the application areas. In the areas with a high number of articles per year (e.g., DTs in manufacturing), citation count was considered as a metric for novelty and contribution of the papers. Accordingly, to reduce the number of articles, the selection process focused on the top one percent of the most cited articles for each year. This approach ensured that the review paper incorporates articles that have made substantial contributions to the field and have garnered significant attention within the research community. After screening, 87 research articles and 36 review articles were preliminarily chosen.

Step 2: As shown in Fig. 2, the literature analysis and filtering step includes screening the abstract, introduction, and conclusion of all selected documents. If these three parts of the articles contain one of the DTs application's background, fundamentals, the frontiers of knowledge, and future perspective of the application, the paper is left for review, otherwise discarded. In this way, 42 research articles and 13 review articles related to the content and scope of this article were selected. Finally, in step 3, the selected articles were thoroughly analyzed to identify the trends and significant findings within the research.

3. Theories and concepts

3.1. Digital twin, digital shadow, and digital model

Digital Twin, Digital Shadow, and Digital Model are three related concepts used in the context of virtual representations of physical systems. While all three concepts involve digital representations of real-

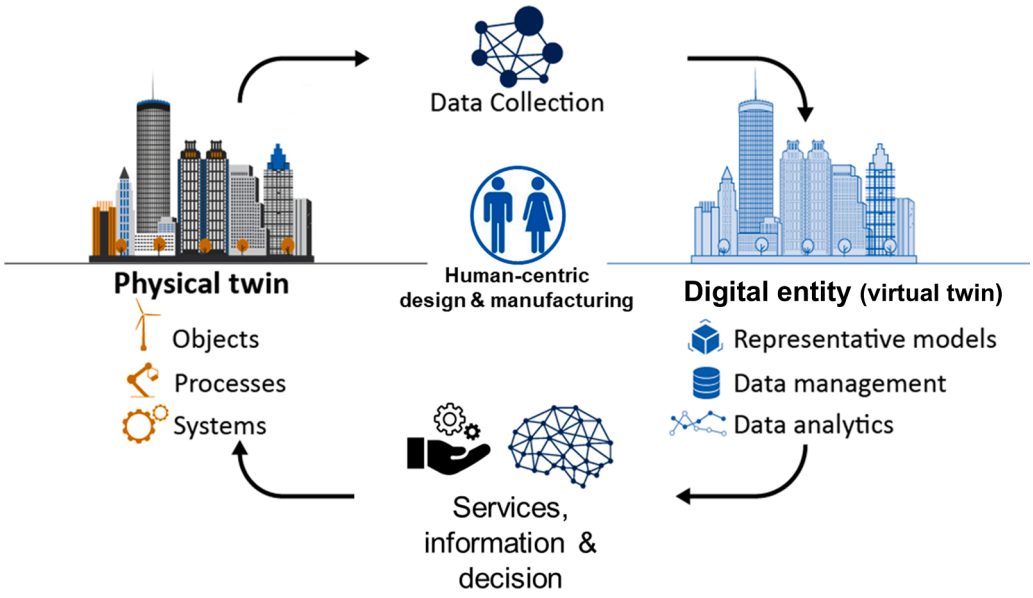

Fig. 1. Digital Twins; a digital representation of an intended or actual physical environment that collects data, processes, and makes decisions in real time. This schematic illustrates the bidirectional flow between the Physical Twin (e.g., urban infrastructure, machinery) and the Digital Entity (Virtual Twin), emphasizing human-centric design and manufacturing, data collection, and services like predictive maintenance and resource optimization.

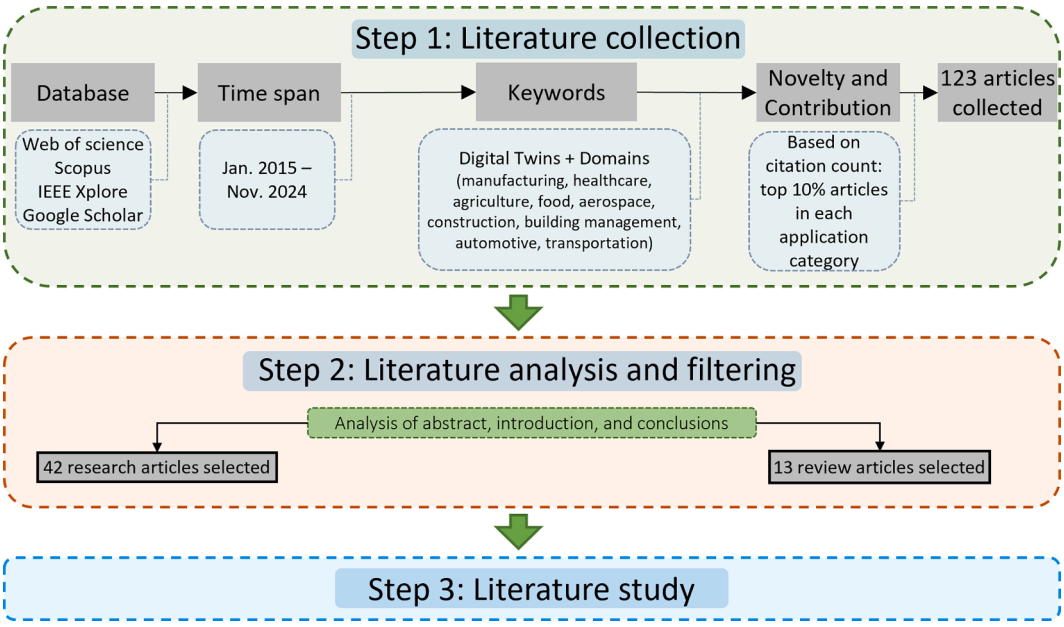

Fig. 2. Literature selection methodology.

world entities, they differ in their scope, purpose, and connection to the physical entities. The main difference between these terms is the level of automation and data flow (i.e., synchronization) between digital and physical objects (Yildiz et al., 2020; Mauro & Kana, 2023). While a Digital Model is disconnected from the physical object and requires manual validation, a Digital Shadow involves one-way automatic data flow from the physical object to the Digital Model (Fig. 3). A Digital Twin, on the other hand, involves a fully automated data flow between digital and physical objects (Figure 3). The capabilities of Digital Twin, Digital Shadow, and Digital Model in performing different functions are compared in Table 1. Note that the purpose of Digital Twins is not replacing Digital Models or Digital Shadows. These are different representation levels of the physical entities that should be employed based on the required data integration level for decision-making (Aheleroff et al., 2021). It is worth mentioning that although these are powerful tools to analyze and predict the behavior of physical systems, they are all models and hence limited in accuracy. Therefore, DTs also need validation, verification, and uncertainty quantification.

Table 1
Comparing the capability of Digital Twins, Digital Shadow, Digital Model in performing different functions.

Functions	Digital Model	Digital Shadow	Digital Twin
Automatic data flow; from physical object to digital model.	☒	☑	☑
Automatic data flow; from digital model to physical object.	☒	☒	☑
Predictive analysis; Testing scenarios in a virtual environment before applying them to the physical system.	☑	☑	☑
Real time monitoring of its real-world counterpart.	☒	☑	☑
Decision-making; Real time analyzing the data, testing predictive scenarios and making decisions.	☑	☑	☑
Control; Real time interaction and optimization of the behavior of its real-world counterpart.	☒	☒	☑

3.2. Application-oriented three-level digital twins; a model-based asset management method

In the physical space, entities can be classified into three levels (Qi et al., 2018): a unit (e.g., a component or product in manufacturing, a component of a building in the construction field, or an organ in a body in health), a system (e.g., a production line, heating system of a building, or blood circulatory system of a body), and a system of systems (e.g., an entire shopfloor, a building, a body). Accordingly, to describe the above entities in different levels, DTs fall into three types, including the unit-level DT, system-level DT, and system of systems-level DT. At the product level, Digital Twins enable designers to create virtual replicas of individual assets, incorporating detailed specifications and performance characteristics. This allows for efficient prototyping, optimization, and customization of products, leading to improved design quality and reduced time-to-market. Moving beyond the product level, Digital Twins can also represent larger systems and systems of systems. This enables a

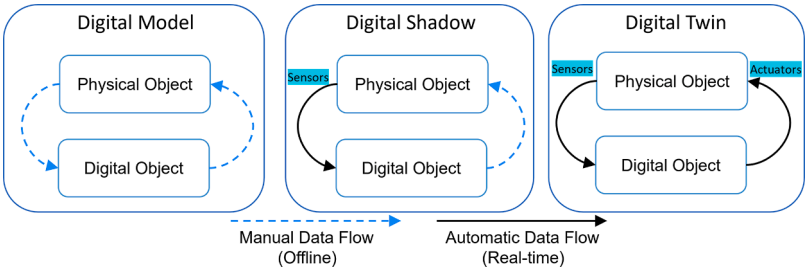

Fig. 3. The differences between Digital Twins vs. Digital Shadow vs. Digital Model.

holistic understanding and management of complex interconnected assets.

3.3. Building and implementing a digital twin

To implement DTs for different manufacturing applications, a five-dimensional DT model is proposed by Tao et al. (F Tao et al., 2019). The traditional three-dimensional DT was first proposed in 2003 by Grieves in his product lifecycle management (PLM) course at the University of Michigan, and then it was extended to 5-dimensional by Tao et al. The five-dimensional DT contains three parts: (1) a physical entity in physical space, (2) a virtual entity in virtual space, and (3) a connection of data and information that ties the physical and virtual entities together, (4) Twin data which can fuse all related data from both physical and virtual aspects, and (5) services.

In this regard, creating a Digital Twin requires different expertise and resources such as:

- Modeling and simulation (physics-based and/or data-based models); to create accurate digital representations of the physical system.

Artificial Intelligence (AI) and machine learning for Digital Twins; to develop algorithms that can analyze data from both the physical system and the Digital Twin, and use machine learning techniques to identify patterns, create reduced order models (ROMs), make predictions, and enable the system to learn from its interactions with the environment and adapt its behavior accordingly (Reinforcement learning).

- Laboratories and experimentation; to analyze the physical system by integrating sensors and collecting data, which is essential to validate and train the models.

Fig. 4 shows a detailed map of tools, methods, and expertise areas for developing and implementing a Digital Twin.

In its simplest form, a model captures the characteristics of an entity, while a simulation demonstrates its behavior. As discussed in the previous section, a DT comprises three fundamental components: physical twin, virtual twin, and twin data (Fig. 4). In this context, the virtual twin is represented by a Digital Model, which can be either physics-based (known as 'white box') or data-driven ('black box'). The Digital Model serves as a prerequisite for simulation. The twin data, produced by simulation and collected from sensors, are processed in the data processing unit to support decision-making. Therefore, modeling and simulation are considered the core of a Digital Twin as they play a vital role in supporting decision-making unit by predicting system behavior accurately. In this regard, DTs are seen as the next stage in modeling and Cyber-Physical Systems (CPS) integration and researchers consider them as the fourth wave of simulation and modeling in system development (Fig. 5) (X Liu et al., 2023; Boschert & Rosen, 2016).

Physics-based modeling in engineering involves constructing mathematical representations of systems using knowledge derived from experimental observations of physics. Despite the complexity of systems, creating a single high-fidelity model that captures all physics is currently impossible except for very simple systems. Therefore, engineers utilize multiple models, each focusing on different physical processes and scales, to represent the system comprehensively (Wagg et al., 2020). Hence, an important challenge includes combining multiple models to form a complete Digital Twin and creating task-specific models for efficiency. On the other hand, when the underlying physics is complex or uncertain, data-driven (black box) models come into play. Depending on the specific application and requirements of the Digital Twin, a combination of both modeling approaches may be employed to achieve the desired level of accuracy and insight into the system's behavior.

Recent progress in artificial intelligence (AI) has further catalyzed computational methodologies for discovering novel materials and devices, amplifying the potential of technologies like DTs. AI-driven approaches now enable rapid design and optimization, surpassing traditional trial-and-error methods. Advancements such as those described in Rathore et al. (2021); Pan et al. (2023) underscore AI's role in DT implementation, from modeling and simulation to real time decision-making, broadening the technology's appeal across materials science and engineering disciplines.

3.4. Applications of digital twins during the product lifecycle; servitization

Digital Twins offer a wide range of services throughout the product

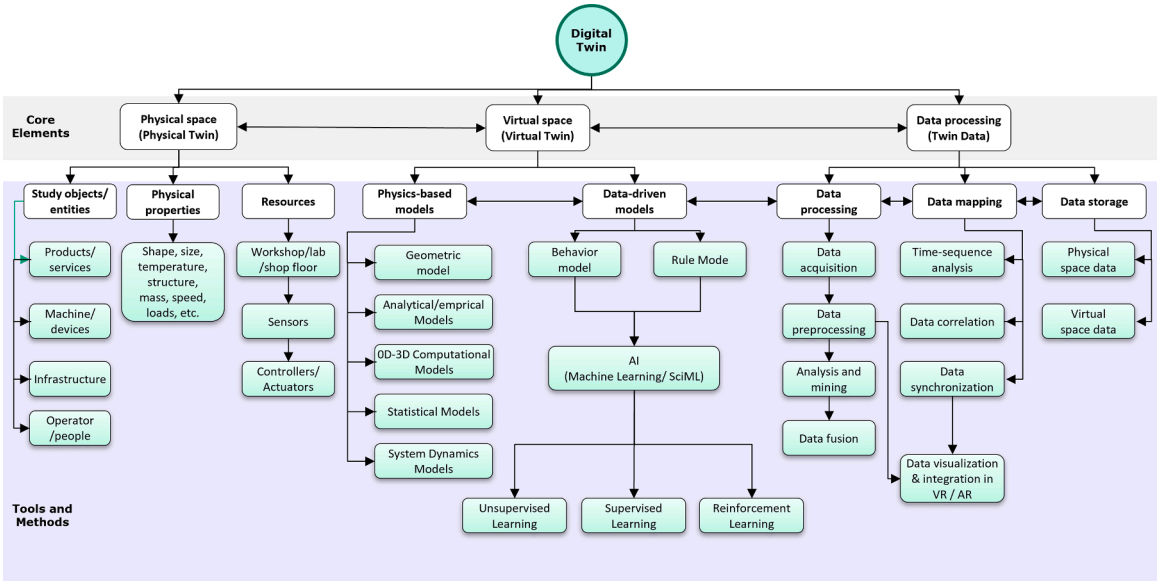

Fig. 4. Tools and methods for developing and implementing a Digital Twin (DT), illustrating the interplay between physical space (Physical Twin), virtual space (Virtual Twin), and data processing (Twin Data) to enable DT functionality across engineering domains. This schematic highlights key study objects (e.g., machines, infrastructure), tools (e.g., sensors, actuators), and methods (e.g., physics-based models, machine learning), emphasizing AI-driven techniques like unsupervised, supervised, and reinforcement learning, as well as data processing steps such as acquisition, mapping, and visualization, with applications in manufacturing, healthcare, and smart cities, while addressing challenges like fidelity and scalability. Modeling and simulation; the core of a Digital Twin.

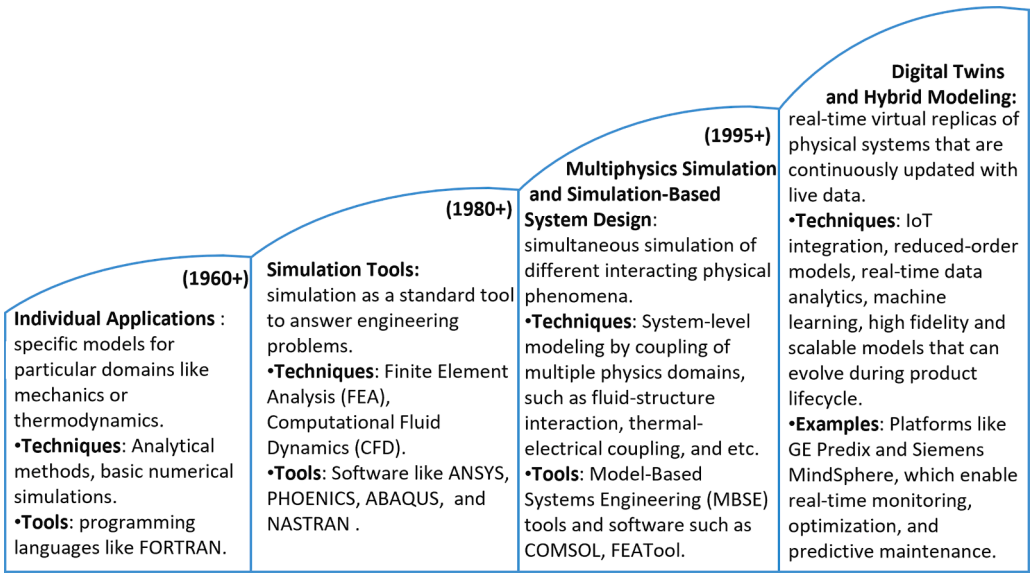

Fig. 5. The waves of simulation in system development; inspired from Boschert and Rosen (2016).

lifecycle, revolutionizing the way businesses design, develop, and manage their products (F Tao et al., 2019). These services enhance efficiency, reduce costs, and enable data-driven decision-making at every stage. Fig. 6 provides a comprehensive overview of different services that DTs can deliver at each stage of the lifecycle of a product in collaboration with other digital technologies (e.g., IoT, AI, etc.) using a data chain (digital thread). These services cover the three stages of the product lifecycle, namely: the beginning of life (BOL), middle of life (MOL), and end of life (EOL). This architecture reveals the potential of DT-driven management, as novel method for products and services management.

DTs exchange data with the digital thread, which provides a powerful tool for stakeholders to make decisions by monitoring, analyzing, optimizing, and predicting in real time during the product lifecycle (Fig. 6). These services are described in Table 2. It is important to note that the implementation of a complex DT is not always necessary to provide the full spectrum of services. DTs rather serve to complement and enhance the functionalities of the intended services. Therefore, a DT, Digital Shadow, or Digital Model can be employed depending on various factors, including the specific product, requirements, and type of service desired.

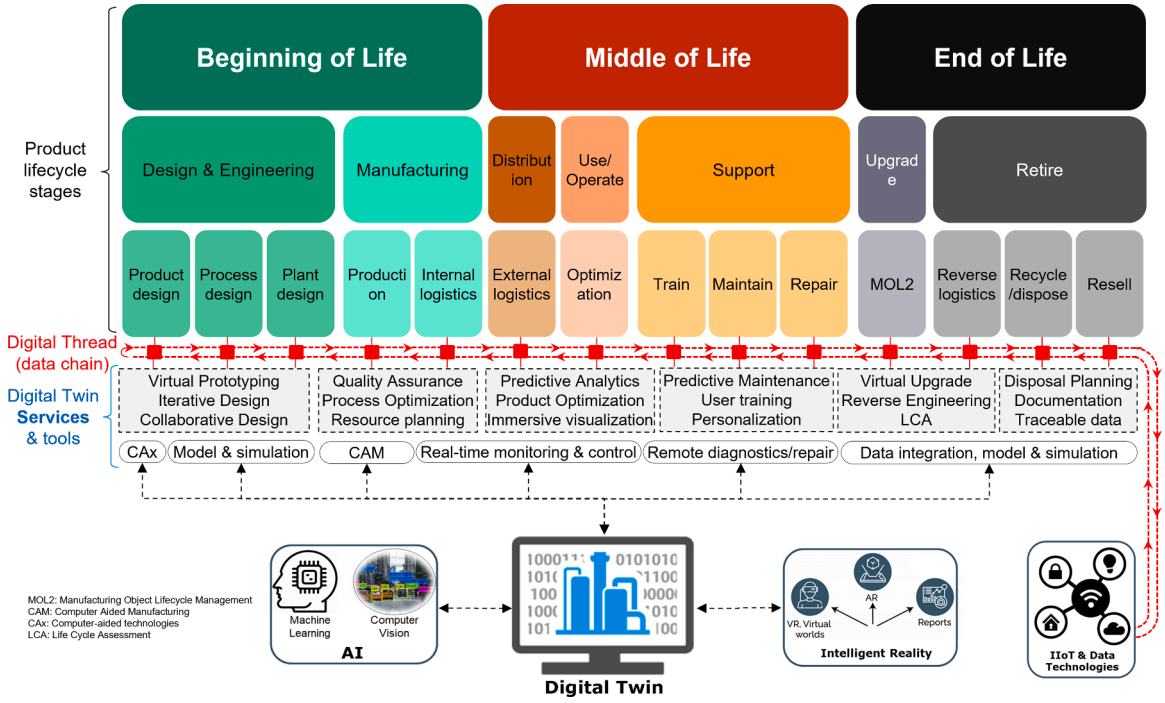

Fig. 6. A comprehensive overview of different services that Digital Twins (DTs) can deliver at each stage of the product lifecycle—Beginning of Life (BOL), Middle of Life (MOL), and End of Life (EOL)—in collaboration with digital technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing, leveraging a data chain (digital thread) for seamless integration. This schematic illustrates how DTs enable virtual prototyping, predictive maintenance, and disposal planning, among other services, by dynamically linking physical assets with their digital representations across lifecycle phases.

Table 2
Description of the services that a Digital Twin can deliver along the lifecycle of a product.

Services	Description
Virtual Prototyping	Digital Twins enable the creation and testing of virtual prototypes, allowing designers and engineers to evaluate product performance, identify potential issues, and optimize designs before physical production.
Iterative Design	Real time feedback from Digital Twins facilitates seamless iterative design, accelerating innovation and improving product quality.
Collaborative Design	DTs provide a shared platform for multidisciplinary teams to collaborate in real time, enhancing communication and coordination
Quality Assurance	Continuous monitoring and analysis of product performance through Digital Twins allow for real time quality assurance by detecting anomalies and potential defects early.
Process Optimization	Real time data from Digital Twins helps optimize manufacturing and operational processes, improving efficiency and reducing waste.
Resource Planning	Digital Twins simulate and predict resource requirements, optimizing allocation and reducing inefficiencies.
Predictive Analytics	By leveraging historical and real time data, Digital Twins perform predictive analytics to forecast performance, identify trends, and anticipate issues.
Product Optimization	Continuous monitoring and analysis provide insights for enhancing performance and reducing costs.
Immersive Visualization	DTs enable stakeholders to explore and understand product functionality and design in a virtual environment.
Predictive Maintenance	Using twin data and simulation, Digital Twins enable proactive maintenance scheduling, reducing downtime and extending asset lifecycles.
User Training	Digital Twins simulate usage scenarios for interactive training, which can be enhanced with AR and VR technologies for greater effectiveness
Personalization	Digital Twins enable product personalization by capturing and analyzing user preferences, allowing businesses to tailor products to individual needs.
Virtual Upgrade	Digital Twins facilitate virtual upgrades by simulating and testing new features or modifications before implementation, ensuring seamless integration and minimizing disruptions.
Reverse Engineering	DTs enable analysis, redesign, and replication of products in a virtual environment (in silico).
Lifecycle Assessment (LCA)	Digital Twins support LCA by providing data and simulations to evaluate and optimize the environmental impact of products throughout their lifecycles.
Disposal Planning	By simulating end-of-life scenarios, Digital Twins aid in disposal planning, assisting businesses in optimizing disposal methods, recycling, and waste management strategies.
Documentation	Digital Twins provide a comprehensive digital record of a product's specifications, configurations, and performance data, facilitating documentation and knowledge management.
Traceable Data	Digital Twins ensure data traceability by capturing and logging real time data throughout the product lifecycle, enabling transparency, audibility, and compliance with regulations and standards.

4. Digital twins application areas

4.1. Manufacturing and industrial processes

4.1.1. Recent advances

The current and future needs of the industry during the transition from Industry 4.0 to 5.0, and for reaching the United Nations Sustainable Development Goals (UN SDGs), are primarily focused on enabling a human-centric and sustainable approach to manufacturing. Improving efficiency, enhancing human-machine and machine-machine collaboration, ensuring sustainability, enabling innovation, and improving quality are the main needs that should be addressed to reach the envisaged goals in Industry 4.0, Industry 5.0, and UN SDGs (Stavropoulos & Mourtzis, 2022). To address these needs, industry and academia should focus on the Smart Factory concept by implementing advanced digital technologies, complex and precise production through additive manufacturing (i.e., 3D printing), and promoting sustainability. However, only recently has attention been devoted to the coupling relationship between cyber and physical spaces. Internet of Things (IoT), Digital Twins and Cyber-Physical Systems, Artificial Intelligence (AI), Cloud Computing (CC), and Big Data Analytics (BDA) are the advanced digital technologies or enabling tools of Industry 4.0, Industry 5.0, and UN SDGs Fig. 7. To this end, ISO 23,247–2 series (ISO, 2021) has been published that provides the overall structure of the domains and the entities of Digital Twin manufacturing reference architecture. Moreover, Aheleroff et al. (Aheleroff et al., 2021) defined a holistic reference architecture model to accomplish the most challenging Digital Twin-enabled applications. They developed a Digital Twin reference architecture and applied it in an industrial case. Shimin Liu et al. (S Liu et al., 2023) identified that current Digital Twin systems lack effective collaboration between manufacturing units, hindering dynamic optimization of processes. They propose a digital thread-driven method that uses a heterogeneous information network to model manufacturing tasks, analyze product quality, and adjust tasks based on these analyses. The method's feasibility is validated with a case study on a crank and connecting rod mechanism. DTs in smart manufacturing reduce time to market by enabling virtual process design and evaluation, cut factory commissioning time by optimizing layouts, and boost productivity through predictive maintenance and data-driven root-cause analysis. In this regard, Cai et al. (Cai et al., 2024) proposed a Digital Twin-driven method for predicting capacity in discrete manufacturing workshops. They outline a system framework and describe a mathematical model considering multiple disturbance factors. Combining Digital Twins with a Long Short-Term Memory (LSTM) algorithm, their method achieves a 91.8 % accuracy in predicting production line capacity, as verified on a commemorative disk production line. This approach enhances production control and evaluation of capacity and delivery dates. To enhance human–robot collaborative manufacturing, (Wang et al., 2024) introduced a deep learning-enhanced DT framework for smart manufacturing in Industry 5.0. By accurately detecting human operators and robots, classifying their actions, and enabling autonomous decision-making, the framework addresses safety and reliability concerns.

4.1.2. Future perspectives

The integration of Digital Twin technology with IoT, Industry 4.0 technologies, advanced analytics, and machine learning will enhance their functionality and effectiveness in optimizing processes, improving productivity, and reducing costs (Onaji et al., 2022). Hence, the future of Digital Twins in manufacturing is promising, yet several challenges persist. An important challenge is the need for high-fidelity models that accurately replicate interactions of several systems in a production line with various physics (electrical, mechanical, etc.) (Kritzinger et al., 2018; Hickey et al., 2023). A promising solution to this challenge is the use of system-of-systems modeling and object-oriented modeling tools (e.g., Modelica, SMILE, etc.), which allows for high-fidelity, multi-domain simulations (Jingjiang Wang et al., 2023). Other challenges include cybersecurity risks associated with collecting and analyzing large datasets (i.e., cybersecurity) (Brian et al., 2023), the lack of stable and sustainable technologies for implementing end-to-end collaborative Digital Twin systems, and the need to upskill the workforce to manage and interact with these advanced systems effectively.

4.2. Health and medicine

4.2.1. Recent advances

Digital Twins have become a recent focus in medical research. Applied to medicine and public health, Digital Twin technology can drive a much-needed transformation of traditional electronic health records (focusing on individuals) and their aggregates to make them ready for a new era of precision medicine and public health (Kamel

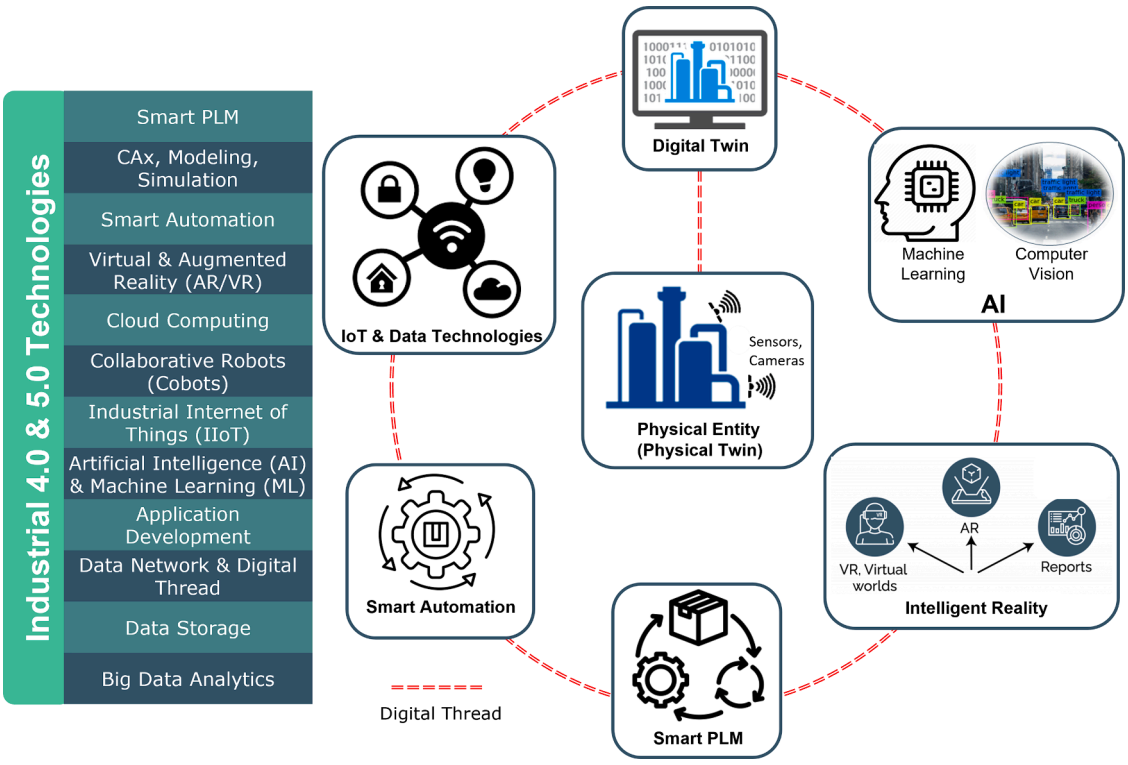

Fig. 7. Spotting Digital Twins (DTs) in a smart factory or smart processing architecture, illustrating their role as a bridge between physical systems (Physical Entity/Physical Twin) and advanced digital technologies employed in Industry 4.0 and 5.0, such as Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and cloud computing, interconnected via the digital thread.

Boulos & Zhang, 2021). Digital Twins are being explored in an increasing range of applications (Subramanian, 2020) describes a Digital Twin of the liver created by integrating the knowledge and understanding gained about various liver functions, diseases, and the effects of drugs, using a mathematical framework of ordinary differential equations. The resulting virtual liver can effectively reproduce normal liver function and simulate the evolution of disease and the impact of drug treatment (Kamel Boulos & Zhang, 2021; Lehrach & Ionescu, 2016) proposed an individualized care and disease prevention system for Europe through the use of 'virtual twins', which are intended to model the biology of European patients and their disease states using data collected on a wide range of domains that characterise the included individuals. With computing resources and big data technologies becoming more cost-effective, they envisioned that it would become increasingly easier to create personalized Digital Models where physicians can test all possible treatments and measures before prescribing them to real patients (EL Azzaoui et al., 2021) presented a framework for managing the COVID-19 pandemic at the city (population) level using Digital Twins integrated with blockchain technology, which makes it very difficult to tamper with recorded data.

4.2.2. Future perspectives

Although medical Digital Twins have seen significant progress, major challenges remain, including insufficient patient data and limited mechanistic understanding of many diseases (Laubenbacher et al., 2024). Another challenge that must be addressed is related to the models underlying medical Digital Twins, which in many cases will be multi-scale. For example, most drugs have mechanisms of action at the intracellular level but have effects at the organ or organism level. Models are likely to be hybrid, combining blood flow through an artery (modeled by a partial differential equation) with intracellular signaling in the endothelial cells lining the artery (modeled by a system of ordinary differential equations or a Boolean network). These characteristics pose challenges to most of the established model-building and analysis tools available, as well as mathematical control approaches (Laubenbacher et al., 2024). Digital Twins can be seen as a social equalizer that can potentially deliver significant benefits to society, by helping us formulate better precision public health interventions. On the other hand, Digital Twin technology for personalized medicine may not be accessible to every individual or community, creating another form of digital divide between individuals and populations. Furthermore, patterns identified across a population of Digital Twins might result in unacceptable segmentation and discrimination. Governance mechanisms should therefore be introduced to safeguard individual rights, ensure data privacy and protection of personal biological information, and promote transparency and fairness in data usage and derived benefits at both individual and societal levels.

4.3. Aerospace and defense

4.3.1. Recent advances

The aerospace industry faces extremely long product lifecycles spanning over 40 years, reinforcing challenges in lifecycle management, cost control, and profitability, which are hard to overlook amid innovation and international competition. Unlike e.g., automotive industry, aerospace systems' New Product Development (NPD) periods are still growing strongly with the increasing product complexity (Gharbi et al., 2018). In combination with the high sensitivity to uncertainties impacting the global economy and other state of emergencies, efficiency of manufacturing and operation can only be ensured with optimization of Maintenance, Repair and Overhaul (MRO) and other improvements to reduce per-flight costs (Li et al., 2022). Similar challenges occur in the defense sector, which relies heavily on technological advancements and robust systems amidst tight budgets and high competition. It also faces a fast pace of innovation and the need to adapt quickly. Nevertheless, both the aerospace and defense industries must act exceedingly safety conscious and risk averse due to the serious consequences of a system failure (Zimmerman et al., 2019). Digital Twins in the aerospace

industry are addressing those challenges with applications approaching design, assembly, manufacturing, operation, and maintenance (Bachelor et al., 2020) presented an aircraft deicing system to prevent icing on critical components using a Digital Twin with a combination of models of the mission profile, the atmosphere, the ice accretion dynamics, and the ice protection system to ensure operational safety (Shi et al., 2021) proposed an intelligent assembly integration platform for aerospace products, which uses a Digital Twin to monitor and troubleshoot equipment, optimize logistics path and inventory while controlling and optimizing assembly lines (Zakrajsek & Mall, 2017) developed and utilized a Digital Twin for aircraft tire touchdown health monitoring which addresses precise maintenance and operation optimization. In the defense sector, many steps have been taken for aircraft but applications are not limited to them. For example, (Shangguan et al., 2020) made a Digital Twin-based approach for the fault diagnosis and health monitoring of satellites with a data-driven maintenance decision algorithm. The US Defense Advanced Research Projects Agency started in 2010 the adaptive vehicle production program, which aims to shorten R&D cycle for weapons by carrying out all included processes in cyberspace. A similar concept is followed by the Turkish Aircraft Industries Corporation which signed an 11-year contract for a Digital Twin application for production of the National Fighter Aircraft Project (Mendi et al., 2022).

4.3.2. Future perspectives

Digital Twins provide a promising way to increase robustness of defense systems and prevent cyberattacks by detecting anomalies in the system. It is also expected that Digital Twins can help human operators make better decisions with machine data collected over time. The potential for technological advances of military equipment by use of Digital Twins includes all containing areas (Mendi et al., 2022). By covering the entire lifecycle of products and production plants, Digital Twins are expected to reduce costs and time in the development and operation of aerospace and defense products while enhancing safe operation. The rising complexity of aerospace and defense systems requires tools to manage and oversee all included factors for efficient products, a process facilitated by Digital Twins. The aerospace industry including big companies active in development and in operation has recognized the potential of Digital Twins since the beginning of research in this methodology. As a result, significant progress has already been made, such as developing frameworks for various applications, which facilitates future work and can serve as examples for applications in other industries.

4.4. Construction and building management

4.4.1. Recent advances

The implementation of DTs in construction and building management has demonstrated significant potential in addressing specific industry challenges. For instance, a significant challenge in building construction is ensuring the structural integrity of concrete under varying weather conditions, which can affect its temperature and, subsequently, its curing process. To address this, DTs have been applied to monitor concrete temperature in real time using sensors, allowing for predictive measures to maintain optimal conditions (Madubuike et al., 2022). Another significant challenge is ensuring indoor safety, where DTs have been employed to simulate various scenarios such as illegal intrusions, overcrowding, and fire. These simulations enable better preparation and response strategies, improving overall safety management (Ammar et al., 2022). Additionally, the integration of DTs with Building Information Modeling (BIM) has addressed the challenge of accurate and dynamic modeling, enhancing site survey precision and reducing the risk of misalignments and rework (Deng et al., 2021). Overall, these advancements highlight how DTs are improving construction practices by enhancing accuracy, safety, and efficiency (Deng et al., 2021; Yitmen et al., 2021; Almatared et al., 2022).

4.4.2. Future perspectives

Looking ahead, DTs still need to tackle several persistent challenges in construction and building management. These challenges include the need for standardized data protocols and improved interoperability between different systems and tools (Shahzad et al., 2022). This is critical for achieving seamless data exchange and integration across various stages of construction projects. Additionally, ensuring data security and ownership remains a significant concern, necessitating robust cybersecurity measures and clear definitions of data access and permissions (Ammar et al., 2022). Another major hurdle is the financial uncertainties and substantial investment required for DT technologies, which pose barriers to their widespread adoption in this sector (Madubuike et al., 2022). By overcoming these hurdles, DTs can unlock new levels of operational efficiency, predictive maintenance, and lifecycle management of building assets, driving the construction industry towards a more sustainable and technologically advanced future. The integration of comprehensive Digital Models with real time data will not only enhance current practices but also pave the way for innovative applications in smart city planning and building lifecycle management (Madubuike et al., 2022; Kor et al., 2023).

4.5. Smart cities and infrastructure

4.5.1. Recent advances

While Digital Twins have been successfully implemented in many industrial sectors, their application in smart cities is still in an early stage (Ramu et al., 2022). Digital Twins are envisaged as the cornerstone of the next generation of smart cities by providing a framework, that not only enhances efficiency and intelligence of urban systems, but also fundamentally changes the interaction between physical city infrastructures and their digital counterparts. The main reason for the lag in Digital Twin adoption in smart cities is the lack of trust and privacy concerns regarding the sharing of sensitive data. Therefore, (Ramu et al., 2022) proposed combining Federated learning and Digital Twins for smart cities. This approach preserves data privacy in the end-user environment by transmitting only updates after local training on edge devices, ensuring raw sensitive information is not communicated over the network (Deren et al., 2021) presented a flood monitoring service using big data analysis and AI technology, which can provide real time simulation of flood monitoring in urban areas. Another application for smart cities based on Digital Twin is the smart city traffic brain Deren et al. (2021) introduced a system which realizes traffic big data management based on real time traffic data flow. The smart city traffic brain is able to detect and assess congestion, as well as provide solutions to support decision-making mechanisms for traffic departments. The increasing size, diversity and complexity of data being spatiotemporally generated every day from city infrastructures and human activities requires a shift in how everything is managed in smart cities (Mohammadi & Taylor, 2018) saw the problem in a lack of insights into interdependencies due to missing visibility and analytics. They proposed an approach where the spatiotemporal fluctuations are integrated into a single analytics platform to enhance visibility on an urban scale.

4.5.2. Future perspectives

The integration of Digital Twins into smart cities will drive significant advances in urban planning, management and services, ultimately leading to more resilient, sustainable and intelligent urban environments. Security and privacy issues are a major challenge in real time implementation and deployment. The decentralized feature of blockchain-based secured technology would enhance the security, reliability and efficiency of a system. Hence, blockchain can improve the efficiency of smart cities through high transparency and traceability. In addition, Digital Twins could predict the number of vehicles a country will need to meet its transport needs. They could also enable safe autonomous driving by transmitting environmental details and driving states to servers in real time, while ensuring that no external parties can

access or manipulate the data. To optimize Human-infrastructure-technology interactions the spatiotemporal fluctuations of a city have to be integrated into an analytics platform. Additionally, that platform must be expanded in a way that enables interdependent visual and numerical analytics of cities. That will enhance the visibility of urban scale analytics which could empower infrastructures and humans to take actions that maintain and sustain the health, safety and vitality of cities.

4.6. Automotive, transportation and logistics

4.6.1. Recent advances

Recent advancements in Digital Twins within the automotive, transportation, and logistics sectors focus significantly on optimizing performance, enhancing maintenance strategies, and improving safety (Schwarz & Wang, 2022). In the automotive industry, Digital Twins simulate real-world conditions to optimize vehicle lifecycle management, significantly reducing downtime and maintenance costs (Piromalis & Kantaros, 2022) discuss how the integration of IoT and AI with Digital Twins provides real time monitoring and predictive maintenance, which are crucial for enhancing vehicle reliability and operational efficiency. In transportation, Digital Twins are instrumental in managing traffic flow and infrastructure planning (Wang et al., 2022) detail how these systems utilize extensive data analytics to optimize traffic patterns and reduce congestion, thereby enhancing the efficiency of urban transportation networks. For logistics, Digital Twins simulate networks to enable scenario planning and resource optimization (Sahal et al., 2021) emphasize the integration of blockchain technology, which secures data exchanges across Digital Twins, enhancing the reliability and trustworthiness of these complex systems. Adding to this, (Mauro & Kana, 2023) illustrate how Digital Twins, initially developed for industries like manufacturing, are being adapted for the maritime sector, highlighting a shift towards integrating digital solutions in traditional industries that involve complex assets like ships.

4.6.2. Future perspectives

Looking forward, the role of Digital Twins in automotive, transportation, and logistics is poised for significant expansion (Sahal et al., 2021) predict an increased adoption of blockchain to further secure and verify the vast data flows within Digital Twin networks, ensuring integrity and enhancing system resilience. This development is crucial as Digital Twins become increasingly central in managing complex logistics operations and autonomous vehicle networks. Additionally, as discussed by Martínez-gutiérrez et al. (2021), the automotive sector is expected to leverage Digital Twins more extensively in vehicle testing and design processes. This approach reduces the need for physical prototypes, accelerating the pace of innovation and bringing advanced vehicle technologies to market more quickly (Bhatti et al., 2021) highlight that electric vehicles, in particular, will benefit significantly from Digital Twins. These systems are capable of real time monitoring of battery performance and optimizing energy consumption, which is essential for the sustainability and efficiency of electric mobility. Moreover, the integration of Digital Twins with smart city infrastructures presents an opportunity to enhance the quality of urban living. By managing and optimizing everything from traffic and public transport to emergency services and energy distribution, Digital Twins can make cities more livable and resilient. As these technologies mature, their ability to handle real time data and provide actionable insights will be instrumental in transforming how cities and transportation systems operate (Mauro & Kana, 2023) also point out the importance of addressing the design and decommissioning phases in the maritime industry, suggesting a broader application of Digital Twin technology across various sectors to foster sustainability and efficiency. In conclusion, Digital Twins are set to revolutionize the automotive, transportation, and logistics industries by enabling more efficient, secure, and sustainable operations. Their role in facilitating real time data integration, enhancing predictive analytics, and fostering an environment of continuous improvement will be pivotal in navigating the complexities of modern transportation networks and logistics systems. The future of these sectors will increasingly rely on the sophisticated capabilities of Digital Twins to drive innovation and efficiency at every level.

4.7. Agriculture and food supply chain

4.7.1. Recent advances

Regarding key challenges like resource optimization, productivity and sustainability, the use of system models and Digital Twins is receiving increasing attention in agricultural applications (Verdouw et al., 2021). Jo et al. (Jo et al., 2018) conducted a preliminary investigation of a Digital Twin for the optimal growth of agricultural livestock, through the regulation of barn systems to maintain air quality and temperature within a predefined range. Kampker et al. (Kampker et al., 2019) investigated the creation of a Digital Twin of a potato as a smart service for potato harvesters, which can be used to automatically calibrate potato harvesters to minimize potential damage to the potatoes. The system makes use of a sensor-equipped artifact, which imitates a potato, variety information and Machine Learning to determine the optimal harvester configuration. Concerning the food supply chain, O. Keates (Keates, 2024) outlines a Digital Twin for improving meat and livestock value chains by offering a method to capture and share key metrics while comparing their respective performance against a reference model. This Digital Twin can generate missing data by simulating the physical supply chain based on a reference model, enabling a better understanding of the supply chain. Overall, based on a literature review from Pylianidis et al. (Pylianidis et al., 2021), most of the Digital Twins in this topic were found for agricultural fields, farms, landscapes, and buildings. Fewer were found for living plants, animals or agricultural products and the food supply chain. However, in the food supply chain and agricultural machinery, Digital Twins have largely surpassed the Technology Readiness Level (TRL) concept level, while in agricultural products, they remain mostly at the concept or prototype stage.

4.7.2. Future perspectives

Compared to other disciplines, the investigation of Digital Twins in agriculture is delayed. This may be because agricultural researchers are more risk-averse since firms are often small and medium farms which can bear less risk than bigger companies. Also, in agriculture there is mostly a direct or indirect interaction with living subjects like animals and plants where creating a Digital Twin for such systems is harder than for non-living (human-made) systems. Nevertheless, Digital Models hold great potential in agriculture, where experimentation is crucial, as they enable quick, iterative model-based experiments to efficiently explore known and unknown phenomena. This could lead to innovations that increase productivity, sustainability, and transparency. For example, as presented by Srai et al. (Srai et al., 2019), they could support precision agriculture in water-stressed areas or introduce new approaches to enhance supply chain traceability. Jo et al. (2018) (Jo et al., 2018) highlighted the need for further research on systems and data integration, especially in complex systems where processes and entities are not well understood. This means modeling in agriculture requires in-depth inter-disciplinary collaboration and integration of multiple complex system models, which is limited in current research. Also in agricultural situations, data are often limited, and new methods may need to be developed to allow the entity's lifecycle to be learned and modeled. Purcell et al. (Purcell & Neubauer, 2023) emphasized that more research on applying Digital Twins to agricultural applications is needed. New use cases, new approaches to current use cases and the construction of frameworks for developing and implementing Digital Twins in agricultural and food supply chain applications are required to facilitate the use of this technology also for smaller companies.

5. Discussion and conclusion

Based on the aforementioned review of current status of DTs in each sector, in this section an overview of the current status of DT technology is provided. To comprehensively evaluate the current status of DTs, the following indicators are considered: Fidelity, Scalability, Investment, Integration with Digital Thread, and Overall Technology Readiness Level (TRL). Fidelity is measured by the accuracy with which Digital Models replicate real-world processes, assessed by comparing model outputs to actual data and evaluating the percentage deviation. Scalability refers to the system's ability to handle increased loads, gauged by its performance under varying user numbers, transaction volumes, and data sizes without significant performance drops. Investment captures the financial resources dedicated to DT initiatives, including technology, training, and maintenance costs. Integration with the Digital Thread is assessed by the feasibility of interoperability and seamless data exchange between DTs and different digital systems, ensuring synchronized and automated processes across the organization. Lastly, the Overall Technology Readiness Level (TRL) is determined using a scale from 1 to 9, reflecting the maturity of current DTs from basic principles to proven operational systems. To keep consistency, other indicators are also rated on this same scale. Each indicator was rated via a structured survey, with scores averaged and reviewed for consensus. To evaluate this comprehensively, we consulted a panel of nine experts, selected for their extensive experience (5 to over 10 years) in DT-related fields—spanning manufacturing, healthcare, aerospace, construction, smart cities, automotive, and agriculture—and their contributions to academic or industrial DT projects, ensuring cross-domain representation.

The result of the assessment is shown in Fig. 8. The evaluation results indicated a high level of scalability and relatively strong fidelity of the models currently used in the DTs, with ratings of 7 and 6.6, respectively. The overall Technology Readiness Level (TRL) was rated at 4.8, suggesting that Digital Twins are transitioning from lab validation to validation in relevant environments. Investment in Digital Twins was rated at 5.3, pointing to moderate performance but also highlighting the need for increased financial support for digital transformation (Sauser et al., 2023). Finally, integration with the digital thread, rated at 4.2, emerged as the most significant challenge. These ratings, derived from expert evaluations, provide a detailed insight into the strengths and areas for enhancement within the digital transformation efforts.

5.1. Limitations of digital twins: technical, ethical, and operational

While Digital Twins (DTs) offer significant potential, their implementation faces notable technical, ethical, and operational limitations that warrant consideration. Technically, achieving high-fidelity and high accuracy models remains challenging, particularly for complex multi-domain systems. For instance, in manufacturing, multi-domain interactions (e.g., electrical, mechanical) often exceed current modeling capabilities, limiting predictive accuracy (rated 6.6 by the expert panel). Accordingly, for high accuracy, high computational power is required, demanding substantial resources that strain scalability. Similarly, in healthcare, multi-scale models integrating intracellular and organ-level dynamics pose unresolved computational hurdles. Ethically, DTs raise privacy and equity concerns. For instance, DTs in healthcare and smart cities handle sensitive personal and urban data, vulnerable to breaches that could enable surveillance or widen digital divides. Privacy-preserving techniques offer solutions. Differential privacy adds noise to datasets to protect individual identities, while secure multi-party computation (SMPC) allows data analysis without sharing raw inputs. For instance, blockchain-integrated DTs leverage SMPC principles to secure data exchanges in smart city applications, though their adoption remains nascent. Cybersecurity challenges compound these risks, as DTs' reliance on interconnected IoT systems increases exposure to data breaches, unauthorized access, and system attacks—threats evident in smart cities' complex networks. Operationally, the lack of standardization across industries hampers interoperability. Moreover, DT deployment is constrained by cost and scalability. High initial investments (rated 5.3) and expertise requirements deter smaller firms. Meanwhile, scaling DTs across large systems like construction projects encounters interoperability issues (rated 4.2) due to fragmented standards. These limitations—complexity in modeling, ethical risks, and operational barriers—temper DTs' promise, necessitating advances in computational tools, robust governance, and cost-effective frameworks to fully realize their potential (TRL 4.8).

5.2. Case studies on digital twin integration with the digital thread

To further elucidate the challenge of integrating DTs with the digital thread, low rated at 4.2 by the expert panel, this subsection presents illustrative case studies highlighting both successes and persistent

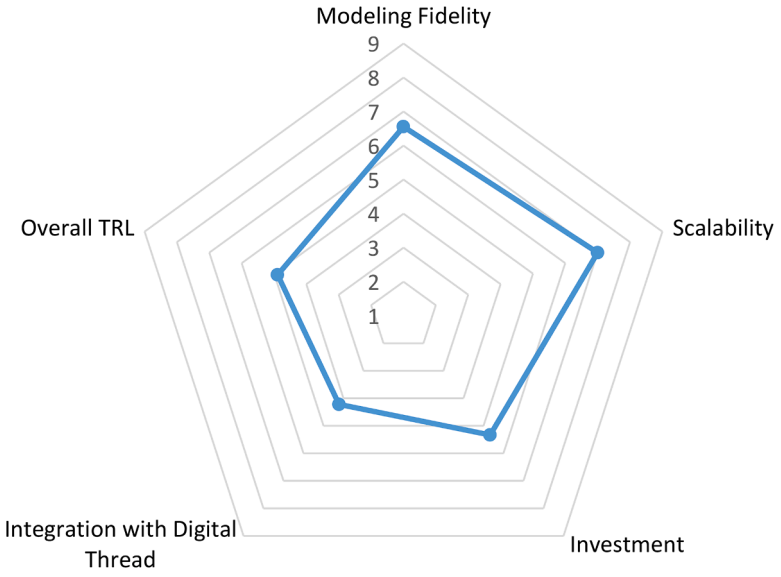

Fig. 8. Evaluation of the current status of DT technology based on inputs from expert panel. This radar diagram illustrates DT technology's transition from lab validation to relevant environment validation, highlighting strengths in scalability and fidelity, while identifying critical challenges in interoperability and investment, as validated by real-world case studies.

hurdles across engineering domains. These examples underscore the practical implications of this integration and offer cross-domain insights.

In aerospace, Gharbi et al. (2018) (Gharbi et al., 2018) demonstrated successful integration by implementing a digital thread within commercial aircraft companies. This framework connected design, manufacturing, and maintenance phases via a DT, ensuring data continuity across a 40-year lifecycle. The result was enhanced lifecycle management and cost control, advancing the TRL from lab validation to operational deployment. Key to this success was a standardized data framework that facilitated interoperability across disparate systems.

Conversely, in manufacturing, Liu et al. (2023) (S Liu et al., 2023) proposed a digital thread-driven method for distributed collaboration among DT manufacturing units. Using a heterogeneous information network, they modeled tasks and adjusted processes based on quality analyses. While validated in a crank and connecting rod case study, the approach faced challenges in dynamic optimization due to insufficient real time collaboration between units. This highlights persistent issues of data silos and synchronization, critical barriers to seamless digital thread integration.

In smart cities, Ramu et al. (2022) (Ramu et al., 2022) showcased an emerging success by combining federated learning with DTs to integrate urban data while preserving privacy. This approach enabled real time analytics without transmitting sensitive raw data, a significant step forward. However, scalability remains constrained by the lack of standardized protocols, reflecting broader interoperability challenges in complex, multi-stakeholder environments.

These cases show that successful DT-digital thread integration depends on standardized data frameworks and advanced analytics, as demonstrated in aerospace. However, challenges like interoperability, real time synchronization, and cybersecurity persist across domains.

5.3. Technical aspects of digital twin implementation

Implementing Digital Twins (DTs) requires sophisticated modeling techniques, simulation tools, and data processing methods tailored to domain-specific needs. This subsection outlines examples from key fields, illustrating the technical backbone of DT deployment.

- Modeling Techniques and Simulation Tools: Bachelor et al. (2020) (Bachelor et al., 2020) employed physics-based models using ordinary differential equations (ODEs) to create a DT for an aircraft deicing system. These ODEs captured ice accretion dynamics and atmospheric interactions, enabling precise simulations of safety-critical components. This approach exemplifies the reliance on mechanistic models for high-stakes applications. Nevertheless, for a real digital twin, dynamic model and simulation are needed, enabling real time behavior prediction across engineering fields. Two primary approaches—causal and acausal simulation tools—underpin this process, each with distinct strengths and limitations, particularly for complex systems like those in manufacturing.
  - Causal Tools (e.g., MATLAB/Simulink): Widely used in DTs, MATLAB/Simulink employs a causal, signal-flow approach where outputs are explicitly computed from inputs. This method excels in open-loop systems or linear processes, such as control system design. However, for closed-loop systems like heat pumps or refrigeration cycles, causal tools falter due to their inability to efficiently handle bidirectional dependencies and algebraic loops, leading to simulation failures or reduced fidelity (rated 6.6 by the expert panel).
  - Acausal Tools (e.g., Modelica-Based tools): Referenced in the "Manufacturing and Industrial Processes" section 4.1.2, adopt an acausal, equation-based approach. Physical components are modeled declaratively, allowing solvers to resolve cyclic interactions implicitly. For closed systems—e.g., heat pumps with interdependent thermal and mechanical cycles—acausal simulation outperforms causal methods by accurately capturing multi-domain dynamics, enhancing DT fidelity and supporting system-of-systems integration. In manufacturing, where DTs optimize production lines or energy systems, acausal tools like Modelica are increasingly preferred for their robustness in simulating interconnected physics (e.g., electrical, thermal). Causal tools, while simpler to implement, struggle with the cyclic nature of such systems, underscoring a technical trade-off. This distinction highlights the need for domain-specific simulation strategies to address fidelity and scalability challenges (rated 7), as identified by the expert panel.
- Data Processing: Predictive analytics in medical DTs leverages advanced algorithms like Long-Short-Term Memory (LSTM) networks. Adapted from Cai et al. (2024) (Cai et al., 2024), who achieved 91.8 % accuracy in manufacturing capacity prediction, LSTM processes time-series patient data to forecast disease progression. This method supports real time decision-making, critical for precision medicine applications.

These technical elements—ODE-based modeling, Modelica simulations, and LSTM-driven analytics—highlight the diversity of DT implementation strategies. Their success depends on integrating domain expertise with computational tools, a synergy essential to overcoming fidelity and scalability challenges (rated 7) identified by the expert panel.

5.4. Emerging solutions to digital twin challenges

While the challenges facing Digital Twins (DTs) are well-documented across domains, ongoing research and emerging technologies offer promising solutions. This subsection highlights efforts addressing three key issues: modeling fidelity, data privacy, and scalability.

- High-Fidelity Modeling in Manufacturing: The need for accurate, multi-domain DTs, a challenge noted in manufacturing (Onaji et al., 2022; Zhang et al., 2023), is being tackled with object-oriented modeling tools like Modelica. These tools, referenced in the "Future Perspectives" subsection 4.1.2, enable high-fidelity simulations of complex system interactions (e.g., electrical and mechanical physics), improving predictive accuracy and supporting system-of-systems integration.
- Data Privacy in Healthcare: Privacy concerns in medical DTs, highlighted in the "Health and Medicine" section, are being addressed through blockchain integration. EL Azzaoui et al. (2021) (EL Azzaoui et al., 2021) demonstrated this in a city-level DT for COVID-19 management, using blockchain to secure data exchanges. This approach ensures patient data protection while enabling real time decision-making, a model adaptable to personalized medicine.
- Scalability in Construction: The construction sector's scalability and interoperability issues (Shahzad et al., 2022) are being mitigated by integrating DTs with deep learning. Kor et al. (2023) (Kor et al., 2023) proposed a framework combining these technologies to enhance Building Information Modeling (BIM), improving real time data processing and system interoperability across project phases.

These advancements—leveraging standardized modeling, secure data frameworks, and AI—demonstrate actionable paths forward. Continued interdisciplinary research and investment will be crucial to scale these solutions, aligning with the need for increased financial support (rated 5.3) and addressing the expert panel's identified bottlenecks.

5.5. Collaborative efforts advancing standardization and interoperability

Standardization and interoperability, recurring challenges across

domains like construction (Shahzad et al., 2022) and smart cities (Ramu et al., 2022), are critical to Digital Twin (DT) scalability (rated 7). Collaborative efforts by industry consortia, standardization organizations, and open-source initiatives are pivotal in addressing these issues.

- Industry Consortia: The Digital Twin Consortium, formed by industry leaders, develops frameworks to enhance DT interoperability. It promotes common ontologies and data models, enabling seamless integration across platforms—e.g., linking manufacturing DTs with supply chain systems. This aligns with the need for robust data frameworks seen in aerospace successes (Gharbi et al., 2018).
- Standardization Organizations: Standards such as ISO 23,247 (ISO, 2021), cited in the "Manufacturing and Industrial Processes" section, provide a DT framework for various domains of engineering, defining data exchange protocols and reference architectures. This standards facilitate interoperability among heterogeneous systems, addressing the synchronization issues noted in manufacturing case studies.
- Government Regulations: Policies like the European Union's Digital Strategy enforce data standards and interoperability requirements for DTs in public infrastructure. By mandating compliance, such regulations align diverse systems, addressing scalability and privacy concerns (EL Azzaoui et al., 2021).
- Academic-Industry Partnerships: Collaborations, such as those between universities and firms, drive interoperable DT solutions. Joint research on deep learning and BIM integration (Kor et al., 2023) exemplifies how these partnerships develop open standards, enhancing cross-phase compatibility. These initiatives collectively mitigate the interoperability bottleneck (rated 4.2) by fostering unified standards and accessible tools. Their adoption can accelerate DT maturity (TRL 4.8) by reducing data silos and enhancing cross-domain collaboration, a priority echoed by the expert panel.

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.

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Data availability

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

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