Digital Twin and Manufacturing

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1 Introduction

This chapter examines the concept of the DT in the context of manufacturing. The chapter's objective is to present a comprehensive review of the key enabling technologies and DT in manufacturing application domains. Therefore, the chapter focuses on the technologies that are used in the DT, DT's integration in manufacturing, and the current state of the art in the related field. Also, challenges and future directions for the DT in manufacturing are discussed.

The process of digitization was made possible by recent technological advancements and developments, including the Internet of Things (IoT), machine learning (ML), Artificial Intelligence (AI), Cloud Computing, smart sensors, and other new generation technologies. These technologies also brought new opportunities for a variety of industries. Digital technologies enable network infrastructures-based remote sensing, monitoring, and control of cyber-physical manufacturing devices and processes. This makes it feasible to connect the real and virtual worlds directly. Consequently, the digital technologies and transformation of industrial production processes from design and engineering to manufacturing lead to Industry 4.0 which refers to the fourth industrial revolution.

Industry 4.0 creates an efficient, automated, connected, and intelligent ecosystem for industry. Autonomous robots, big data, augmented reality, Cloud Computing, cyber security, IoT, system integration, simulation, and 3D printing are the nine technologies that drive Industry 4.0. Achieving digital information technology, quick design modifications, and great adaptability are all possible with Industry 4.0's sustainability and next-generation intelligent manufacturing [1]. Hence, Industry 4.0 enhances the future of industries and increases the productivity and efficiency in

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the manufacturing. Therefore, Industry 4.0 is a combination of modern information and communication technology and industrial practices [2].

In today's competitive environment, this digital transformation in manufacturing is accepted as an opportunity to reach higher productivity levels. Therefore, operations in manufacturing systems are digitized. As a result, the global manufacturing sector has undergone industrial revolutions like mechanization, electrification, and information related to this digitalization and the ongoing development of communication, information, and automation technologies [3]. Moreover, the use of digitalization technologies enabled various industrial sectors to virtually represent their products and plan their processes in manufacturing. Thus, industrial products are produced using digital technologies and machinery throughout their entire life cycle. Therefore, different types and large volumes of data are produced.

Every step of the manufacturing process involves the collection of enormous volumes of data, which are then used for real-time planning. However, this leads to low efficiency and low utilization due to the isolated nature of these valuable data [4]. Therefore, these valuable data need to be processed and analyzed by simulation-based solutions. Simulation-based solutions are applied to optimize operations and predict possible errors during the production operations. Therefore, simulation is a powerful technique for a system's early planning stages of verification, validation, and optimization [4]. The idea of the Digital Twin (DT), which is regarded as the simulation of the system itself [5], has been revealed as a result of the significance of the integration of the physical world and the digital world. Therefore, DT is used to empower the manufacturing systems and various industrial sectors.

The Digital Twin is a representation of a physical thing, process, asset, system, or service in the actual world. DT reproduces the physical entity accurately in the digital world and enables an effective monitoring, prediction, and optimization of the related physical entity throughout its life cycle [6]. For this purpose, DT uses real-world data to create simulations. In the manufacturing, DT focuses on the Asset Life Cycle Management (ALM) that is shown in Fig. 1 to optimize the life cycle of an asset. Therefore, the DT can predict how a product or process will perform in the production and how this process will progress. Thereby, each life cycle phase of the manufacturing system's operations can be optimized by DT. In addition, possible outcomes are evaluated before any cost loss occurs and problems are identified before starting the production process. Thus, efficiency is provided and higher volumes of manufacturing are ensured. In this way, DT bridges the gap between physical world and cyber world and constructs cyber-physical systems in manufacturing [7]. As a result, DT has the potential to change both the present and the future of manufacturing [8].

DT transforms the future manufacturing landscape by providing the necessary technology to create smart manufacturing that is fueled by digital twins. According to market data released in [9], the size of the global DT market is anticipated to reach $63.5 billion by 2027, growing at a rate of 41.7%. Besides, due to the COVID-19 pandemic, companies are now choosing to operate with least manpower. Also, the manufacturing has the largest share in the industry segment of the global DT market. The market research further indicates that the primary end users of DT technology

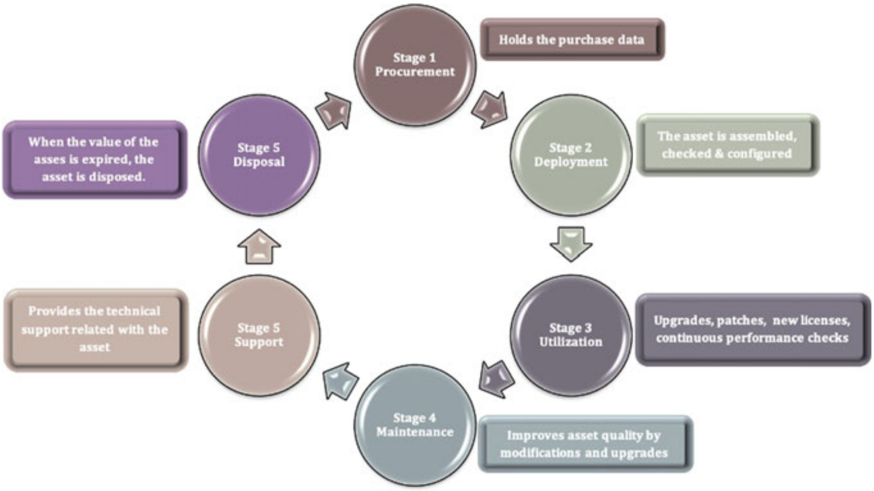


Fig. 1 Asset life cycle management

in manufacturing are the energy and power, automotive and transportation, and aerospace and defense industries. The increased demand for predictive maintenance, real-time data monitoring, real-world use cases, and improved decision-making are the prime reasons for the growth of the DT market.

The remaining parts are organized as follows. The historical context and an overview of the Digital Twin concept are provided in Sect. 2. The numerous Digital Twin components and manufacturing applications are highlighted in Sect. 3 along with its application areas. In Sect. 4, Digital Twin application examples in various industries are presented. Section 5 discusses challenges, future directions, and open problems that need to be tackled for an effective and productive adoption of Digital Twin in manufacturing. Also, conclusions are presented in Sect. 5.

2 An Overview of Digital Twin

The Digital Twin provides a digital representation of a physical object. As a result, the DT develops a living model of the physical product throughout its existence and enhances decision-making by offering data on dependability and maintenance. In order to prevent issues before they arise and to plan for the future using simulations, the physical and virtual worlds are combined.

The DT has gained significant importance due to Industry 4.0 and technologies such as machine learning, IoT, and Artificial Intelligence. The emergence of DT is a result of the development of the concept of "digital production" and the Industrial IoT [10]. The idea of DT is not new. The DT technology is based on the existing technologies such as simulation and digital prototypes. DT is stated as the next wave

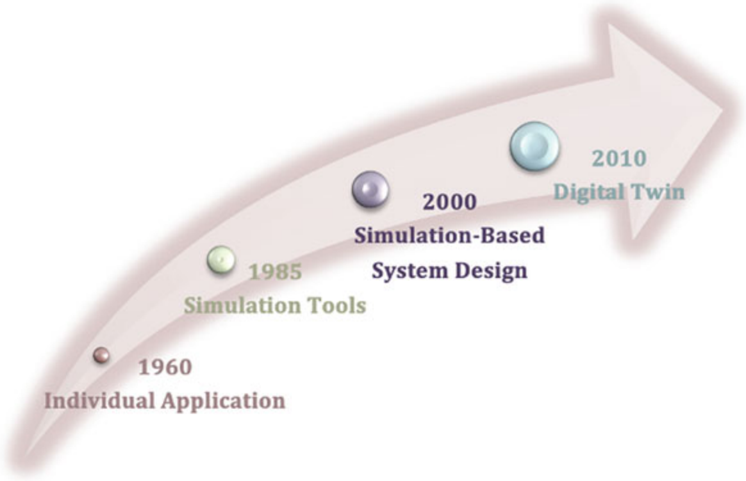


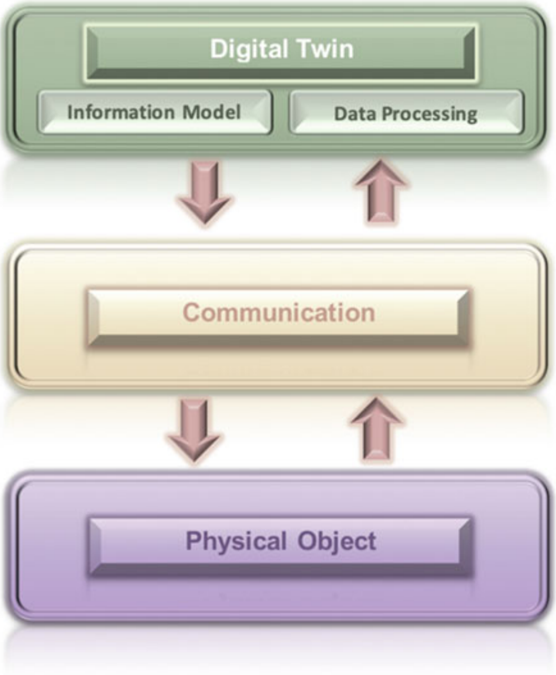
Fig. 2 Digital twin as the next wave in simulation

of the modeling and simulation technologies [11] as shown in Fig. 2. Today, the DT is a more important topic and has become more widespread. Therefore, it is applied to various fields, such as manufacturing, healthcare, retail, and supply chain. As companies are now digitizing their operational processes, the market size of the DT is increasing in worldwide. The size of the global DT market was estimated at USD 3.1 billion in 2020, and by 2026, it is expected to have grown to USD 48.2 billion [12]. Hence, the DT is considered to be one of the ten most promising technical advancements for the coming 10 years [13]. Also, the DT is predicted to have a major role in the future for the defense and aerospace industry [14].

The first use of the DT concept dates back to 2003. In 2003, the DT is introduced by Michael Grieves at his Executive Course on Product Life Cycle Management (PLM). Later, Grieves classified the DT into three subtypes: (i) the DT prototype, (ii) the DT instance, and (iii) the DT aggregate [15]. In 2014, Grieves indicated three main parts for the DT in a whitepaper [16]: (i) a virtual product, (ii) a physical product, and (iii) a connection of data and information that ties the virtual and real products. Also, the development of the DT technology needs three components that are shown in Fig. 3 [8]: (i) an information model, (ii) a communication mechanism, and (iii) a data processing module. The data processing module uses information from heterogeneous multi-source data to create the live representation of the physical object, while the information model abstracts the physical object's specifications and the communication mechanism transmits bidirectional data between a DT and its physical object. These components must work together to construct a DT [8].

The five-dimension DT model is proposed in [17]. The proposed model improves the aspects of production, operations, and business processes. As shown in Fig. 4, the five-dimensional conceptual model of the DT consists of virtual models, data, physical entities, services, and connections [17].

Fig. 3 Components of digital twin [8]



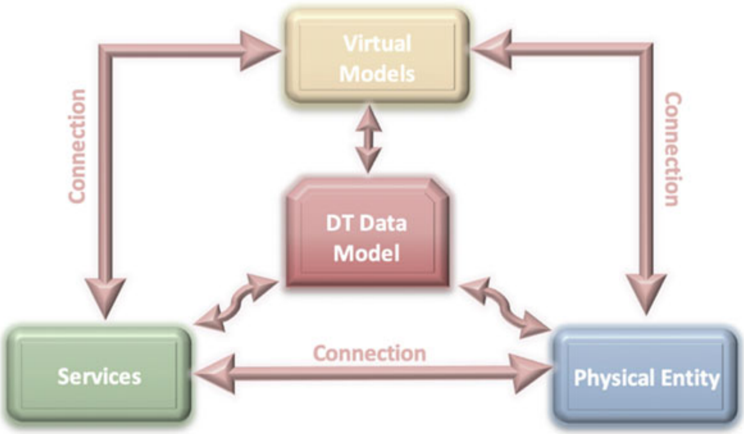


Fig. 4 Five-dimensional conceptual model of digital twin

The physical entities represent a physical object that is tangible and visible. The DT creates the virtual model of the physical entity. Physical entities provide the collection of various parameters through sensors. Thus, the collected data is used to create the virtual state of the physical entity.

The virtual model is the digital model of a physical entity. An efficient IoT infrastructure is needed to increase the accuracy of virtual assets and to ensure the compatibility of virtual and physical assets.

The DT deals with large, multi-source, multi-temporal, multi-dimensional, and heterogeneous data [17]. This incoming data is used by various algorithms to make decisions. The data model can be obtained from multiple data sources, physical and virtual assets, services, and knowledge that is extracted from domain information.

Services include all functions of the DT. Functions that are provided by the DT are presented through interfaces. The main feature of services is to receive data from sensors and process these data. The DT offers users platform services, third-party services, and application services. Application services include simulation, verification, monitoring, and optimization (such as customized software development, and service delivery) [17].

Virtual entities, physical entities, and services connect with each other to form the structure of the DT concept. For this purpose, information flow is established between physical entities, virtual entities, and services by connections. This connection between, virtual entities, services and physical entities is crucial for accurate analysis in the DT process.

3 Digital Twin for Manufacturing

Manufacturing refers to transforming raw materials into finished goods. Manufacturing also enables more complex products to be produced by selling basic goods to manufacturers. Thus, manufacturers can produce these complex products such as cars, airplanes, or household appliances. In recent years, global competition in manufacturing has accelerated as a result of technological advancements, product diversity, and the increase in market needs. Thus, the intensification of global competition has enabled manufacturing to evolve from traditional production processes to smart production processes. Further, several sectors in manufacturing aim to reach qualified products, efficient and effective services at less cost and in less time by integrating new technological developments. Therefore, the DT is a key concept for smart manufacturing as it enables interaction between the virtual and physical worlds. The benefits of the DT technology make DT the most powerful and intelligent consultant in the industry [18]. The major utilities of the DT are given in Fig. 5 [18]. Therefore, the DT can be used to train employees, plan the innovation, identify errors and avoid them, utilize optimization and risk management, and also provide a virtual platform for learning.

Digital Twin technology enables manufacturers to better understand and analyze their products in product design, real-time simulation, tracking, and optimization. In

Fig. 5 Major utilities of the DT [18]

the real world, performing tests on complex products is costly and difficult, whereas using DT allows the product to be easily tested before presenting it to the physical world. The DT also reduces the operational costs and potential capital costs, extends the life of assets, optimizes the operational performance, and improves the optimization and preventative maintenance over the changing conditions. The product design, real-time monitoring, quality management, predictive maintenance, and production planning enable DT to improve operations in manufacturing.

3.1 Product Design

In the design and product development processes, the DT is commonly used. The DT enables to create virtual prototypes during the design phase. Thus, it is used to test different simulations or designs before investing in the final product. Therefore, deficiencies of the product are being determined before the production by analyzing whether the product designs are efficient or not, especially for a product with a complex manufacturing process. Consequently, possible results will be evaluated without any cost. Moreover, any problems that may occur will be detected before starting the production. Hence, DT saves time and money by reducing the number of iterations that are required to put the product into the production process, iteratively modeling changes, testing components and their functions, and troubleshooting malfunctions. Also, Digital Twins and XR technologies can be combined at the product modeling phase to produce high-quality designs. This makes it possible for all stakeholders, including managers and customers of digital twins, to monitor each stage of the product design process in detail and find solutions rapidly.

3.2 Real-Time Monitoring

Digital Twin is a real-time virtual representation of a product and an operational process. Instant data flow is provided to the DT through sensors that are placed on physical objects. The production is monitored in real time with this instant data flow. Therefore, problems in the production life cycle can be identified, and strategic decisions can be made by directly intervening in the production. Thus, monitoring the DT production performance in real time helps pre-planning and optimizing workflows. In addition, the DT can also be used to analyze data retrospectively to make predictions on future productions.

3.3 Quality Management

Quality management is an essential factor in the manufacturing process. Monitoring IoT sensor data and responding to them are critical issues for maintaining quality and reducing bottlenecks during production. The usage of DT enables real-time analysis of data that comes from sensors. Thus, the product quality is improved at decreased costs by detecting the quality control problems immediately. Moreover, the DT data can also be used to detect reasons of the related problems. Therefore, in order to improve the quality of the production, the DT is used to model each part of the manufacturing process to determine which materials or processes can be used.

3.4 Predictive Maintenance

The DT determines variances that indicate the need for preventative repair or predictive maintenance before a serious problem occurs in the manufacturing process. In traditional approaches, processes of determining the malfunctioning of a machine/equipment, decision-making, and taking an action result in time loss. For this reason, the production volumes of enterprises decrease. Periodic maintenance of machine equipment can help prevent malfunctions, but it does not guarantee that the equipment will not malfunction. However, the DT collects real-time data via sensors to create a virtual representation of the machine. Thus, the status of the machine can be monitored in real time, and accurate forecasts can be done regarding the status of the machine. Also, the DT is used to optimize the load levels, tool calibrations, and cycle times of machines. Therefore, using DT enables enterprises to detect problems with machines that may arise and to implement predictive maintenance.

Businesses can predict when and where potential service breakdowns might happen and respond to them in order to stop any service interruptions by having robust predictive maintenance solutions in place. In machine learning and Artificial Intelligence, predictive maintenance refers to the ability to use a vast quantity of data to forecast and address future issues before they lead to operational breakdowns. Predictive maintenance uses sensor data to determine when maintenance is required in order to minimize downtime. Data collected initially by various sensors located on the machines are pre-processed. In a pre-processing step, significant features are retrieved from this data and used to train a machine learning and Artificial Intelligence algorithms system for predictive maintenance. Then, Artificial Intelligence (AI)-based decision support systems utilize these data. However, under normal fault circumstances, it is not always possible to collect data from field-based physical equipment. Also, equipment damage and catastrophic failures might result from allowing field failures to collect sensor data used to train AI and machine learning systems. It could be time-consuming, expensive to purposefully create errors under more regulated conditions. However, the creation of a Digital Twin of the equipment and the modeling of various failure scenarios can be used to create sensor data to address these problems. Thus, all possible fault combinations can be evaluated.

3.5 Production Planning

Production planning cannot be handled in traditional ways due to the complex nature of the manufacturing processes. Thus, planners may overlook the actual processing conditions when designing the process. The DT enables enterprises to make production planning by simulating the operation processes in a digital environment. Thus, the efficiency of the production plan that is tested in the virtual environment can be analyzed. As a result of these analyses, production volumes and profit rates can be improved by making changes in production plans. Furthermore, production time and cost can be reduced with the results of analyses. Besides, simulations that are tested in the virtual environment include parameters such as equipment failures and lack of personnel which affect the production flow. Therefore, simulations give more efficient and accurate results than plans that are done with traditional methods. Thus, businesses achieve success in today's competitive environment and gain an advantage over their competitors by creating stronger production plans.

4 Digital Twin Applications in Manufacturing and Industry

Digital Twin is evolving rapidly with the recent scientific developments in communication technologies, sensors, actuators and connected devices, big data analytics, the Internet of Things (IoT), data fusion techniques, and Artificial Intelligence algorithms. The ongoing digital transformation and smart technologies enabled the implementation of DT technology in the industry to grow exponentially. Also, the DT has an essential role in the Industrial IoT (IIoT) concept which connects machines to other machines and optimizes productivity to make smart factories. Industry 4.0 deals with two worlds: one is the "physical world" and the other is a "digital world" [18]. Industry 4.0 aims to combine the physical and digital worlds by establishing real-time communication between them. They would be able to communicate manufacturing data in real time due to this connectivity. Therefore, the usage of DT in product development and process improvement studies has increased. In addition, the global market for DT technology is also growing due to the increased need for low-cost operations, optimized control in process systems, and the shortened product time-to-market. The Digital Factory's methodologies and models are utilized for low-cost integration, and the Digital Twin is a significant future component of the Digital Factory [19]. As stated in [19, 20], Digital Factory can avoid 70% of the planning errors, increase the planning maturity by 12%, reduce 30% of the planning time and 15% of the change costs. For this purpose, several companies in various industries use DT technology for their production systems.

The DT is useful throughout a product's life span. Four stages represent the product life cycle for successful products [21]: Development/Introduction, Growth, Maturity, and Decline. The Development/Introduction phase is the awareness stage of the product, the Growth phase is the product branding and promotion strategies, the Maturity phase is the market competition stage and in the final Decline phase the product becomes obsolete [18]. The Product Life Cycle Management (PLM) improves innovation, reduces time-to-market, provides new services for products, and supports for customers [22]. The DT has a potential to solve data-driven problems that exist in PLM, such as data sharing and big data analysis. For this purpose, the stages of detailed design, conceptual design and virtual verification are used to divide the product design process into three sections [23]. In the conceptual design, the concept, esthetics, and the main functions of the new product are defined. The design and construction of the product prototype are completed in the detailed design. Finally, the DT-driven virtual verification is the evaluation and test phase to detect design defects and their causes for a fast and convenient redesign. As a result, the DT technology offers great potential for use in product design, manufacturing, and service. In the existing literature, there are various DT solutions that have been proposed for different industry examples and real-life examples in manufacturing. In manufacturing, DT technology is generally used in applications such as manufacturing schedules and management, manufacturing control optimization, cyber-physical production system (CPPS) and layout of manufacturing lines [24]. In [19, 25], the technical production planning issues in automotive industry and the automated creation of a DT of a Body-In-White (BIW) production system are presented. Similarly, a DT approach for production planning and control is presented in [26] with a case study featuring a manufacturer that provides mechanical parts to the automotive sector.

In the automotive industry, the DT technology is used for optimization purposes in the production statistics and user experiences of the product that emerges in the vehicle production processes. For example, Tesla creates the DT of each vehicle that it sells [27]. Sensors in the car are used to provide the stream data into each car's simulation in the factory. Artificial Intelligence (AI) is used to interpret these data and determine whether a car is working as intended or if it needs maintenance [27]. Therefore, Tesla constantly learns from the real world and optimize each of its cars individually in real time by merging AI and IoT with the DT. The usage of DT technology evaluates the engine life of the vehicle, mechanical aging, damage that may occur in possible accident scenarios, errors related to aerodynamic design, and makes the necessary improvements before the vehicle reaches the end user. Thereby, Tesla ensures the continuity in its customers' vehicles by regularly downloading the recent software updates to their vehicles. Another example in automotive industry that uses the DT technology is Maserati. Maserati uses DT to increase its production capacity and maintain the tailor-made production. As a result, Maserati developed the Ghibli DT using Siemens' DT technology, which was a perfect replica of the original [28]. Processes were optimized for this reason by using data from both the real and virtual models at the same time. The result was a 30% reduction in development time and a decrease in manufacturing costs. Moreover, the DT is also used in Formula 1 to improve performances and to help in making the right strategy decision. Further, the DT helps teams to prepare and optimize their operations by practicing their driving and learning things in a car simulator before hitting the racetracks [29].

Similar to the automotive industry, DT technology has also an important role in the aerospace, defense, and space industries. The DT is used to track and monitor the vital and critical parameters of aircraft, test, and evaluate tools to check the integrity of aircraft features, and also for capacity planning, real-time remote monitoring, and process optimization. Thus, DT is a vital technique for simulating, predicting, and optimizing the product and the production system over the whole product lifetime in the associated industries. Many aerospace and defense companies have started using DTs for these reasons in order to decrease unplanned downtime for engines and other systems, mitigate damages and degradations, accurately predict how long an asset will be useful, increase operational availability and efficiency of platforms by performing proactive and predictive maintenance, extend the useful life cycle of platforms, and lower the life cycle cost of platforms [30]. For example, Boeing has adopted DT to advance aircraft manufacturing and maintenance operations in both its commercial and defense businesses, and Lufthansa Technik's AVIATOR platform uses DTs and other advanced digital tools to alert customers to possible problems before they occur and to offer technical solutions to address these problems [31].

Industry 4.0 promises an improved productivity, increased flexibility, customization, and better quality in manufacturing [32]. In this context, manufacturing systems are updated to an intelligent level from knowledge-based intelligent manufacturing to data-driven and knowledge-enabled smart manufacturing [32, 33]. An important prerequisite for smart manufacturing is cyber-physical integration [33]. The cyber-physical system (CPS) is the integration of the physical world with the digital

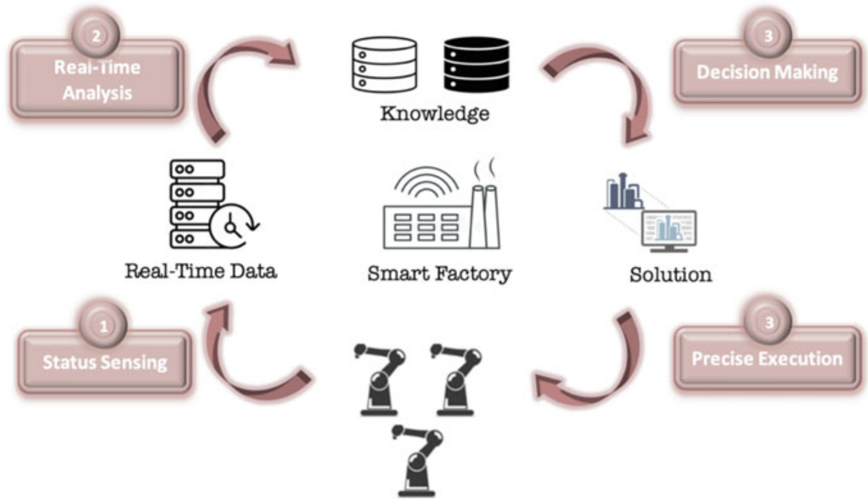


Fig. 6 CPS and DT for smart manufacturing [38]

world [18]. As seen in Fig. 6 [33], CPS and DT transform the existing manufacturing systems and enable smart manufacturing applications. The CPS consists of autonomous and collaborative parts and subsystems that are linked based on context within and across all production levels, from processes via machines up to production and logistics networks [34]. Smartness, connectedness, and responsiveness are the three main characters of the CPS. Hence, CPS is considered as a key feature of the Industry 4.0 [35], and the DT technology is accepted as a key enabler for realizing a CPS. A detailed discussion on the correlation and the integration of CPS and DT is presented in [33]. An information modeling approach to integrate various physical resources into CPPS via DT and AutomationML is proposed in [36]. In [37], the integration of CPS and DT is proposed, and a systematic framework is offered as a set of principles for quick system configuration and simple DT-based CPS runtime.

The DT-based approaches are used in various process manufacturing industries. For example, a framework is proposed in [38] to construct a DT-based approach for the petrochemical industry. For manufacturing simulation and control, the suggested DT architecture enables convergence between the physical and digital worlds. Similarly, the DT technology is also used in the energy sector for performance improvements, preventive maintenance, and repair works. Additionally, the cutting-edge DT solutions allow for changes in energy users' behavior to attain the necessary level of energy efficiency. A content analysis of the most recent energy research is offered in [39] with the goal of increasing energy efficiency. Furthermore, new generation power systems and the adaptation of the DT technology for power supply systems are presented in [40–43]. Also, energy forecasting studies based on the DT technology are proposed in [44–47] to ensure rational energy consumption and provide smart energy management system.

As a result, there are many actual instances of smart manufacturing facilitated by the Digital Twin. By fully utilizing cutting-edge information and manufacturing technology, smart manufacturing strives to optimize production and product exchanges [32]. Additionally, the use of intelligent sensors and devices, communication technology, data analytics, and decision-making models can facilitate the complete product life cycle. As a result, the DT enables real-time analysis of the past to forecast the future, enabling smart decisions to be made at every stage of manufacturing activities. This is the setting in which the DT plays a crucial role in smart manufacturing [8]. Thus, the effectiveness of the production and the quality of the goods and services will be increased, while production time and running expenses will be decreased. Besides, environment-friendly services for users are facilitated, and the market competitiveness of the manufacturing enterprises is improved [48].

5 Future Directions and Conclusion

The use of DT is anticipated to increase tremendously in the coming decades [49]. Also, the DT has enormous potential for changing the current manufacturing paradigm to one of smart manufacturing. Consequently, the DT is referred to as the leader of Industry 4.0 [39]. In this context, the DT enables to dynamically adapt to the changing environment, optimizes the production to respond changes in a timely manner, and improves economic benefits [38]. Thus, the DT technology is being recognized as a game changer in the manufacturing industry with the recent digitization process of manufacturing. Figure 7 presents the Strengths, Weaknesses, Opportunities and Threats (SWOT) of the DT in manufacturing.

The DT is an emergent technology, and the widespread implementation of the DT technology is increasing in various domains. Manufacturing is one of the main application domains among the DT applications. The DT technology is crucial in converting the conventional manufacturing system into a smart manufacturing system. The DT has the potential to develop into a significant technology for both research and application in the future, despite the fact that it is still in its early stages. Besides, the DT provides a substantial motivation for the future agenda of researchers and practitioners.

In today's dynamic environment, the DT is a promising and innovative approach for smart manufacturing. Moreover, the DT technology has an essential role in Industry 4.0 and the digitalization in manufacturing processes. The digital transformation in manufacturing reduces the production costs, increases the flexibility, and improves the productivity, the quality of products, and the efficiency of production process. The usage of the DT in manufacturing along with the advanced technologies such as smart sensors, decision-making models, data fusion techniques, big data analytics, simulation, Cloud Computing, Artificial Intelligence, and the IoT enables to facilitate of the entire product life cycle. Thus, manufacturers can monitor and optimize the production. The DT also offers special opportunities for value co-creation by assisting decision-making [50]. For this purpose, the DT reasons

Fig. 7 SWOT analysis for the DT technology

why something might be happening, evaluates different alternatives, predicts the possible future outcome, and decides the action based on the objectives and preferences [51]. Thus, the DT improves the automated production planning, predictive analysis, real-time monitoring, and product optimization. Therefore, manufacturers gain an important competitive advantage against the dynamics and fluctuations of the global manufacturing market.

Several cloud service providers, such as Amazon, IBM, Microsoft Azure, provide "Container-as-a-Service" solutions for the development of Digital Twins. An Internet of Things (IoT) platform called Azure Digital Twins enables you to construct a digital representation of things, places, people, and business processes that exist in the actual world. Azure Digital Twins enables the creation of twin graphics based on digital models of all environments such as buildings, factories, farms, power networks, railways, stadiums, and even entire cities. These digital models provide better products, improved operations, reduced costs, and improved customer experiences. The "device twin" model is a component of the device management strategy used by Microsoft Azure IoT. The Device Twin is a JSON file that represents the device and provides information about its state. It changes practically quickly using data from the real system. When a device is connected to the Microsoft IoT hub, a device twin is automatically created. Azure IoT Hub is hosted in the cloud that serves as a central messaging hub for interactions between IoT applications and the connected devices. AWS IoT TwinMaker is a different Digital Twin platform that makes it simple for developers to generate digital twins of real-world systems like factories, industrial machinery, buildings, and production lines. Building Digital Twins can help optimize building operations, boost output, and enhance equipment performance. AWS IoT TwinMaker gives users the tools to do this. Customers can import pre-existing 3D models into AWS IoT TwinMaker to develop 3D representations of the physical system, which can then be overlaid with knowledge graph data to produce the digital twin. The Digital Twin is a JavaScript Object Notation (JSON) file that contains data, metadata, timestamps, and other essential information to clearly identify the connected device and is frequently referred to by Amazon as a device shadow. MQ Telemetry Transport, Representational State Transfer (REST) calls, or Message Queue Telemetry Transport (MQTT) architecture might all be used to provide near real-time communication. Also, the IBM Digital Twin Exchange is a platform that enables sharing of digital resources as Digital Twins between manufacturers, OEMs, and third-party content suppliers [52]. IBM is now targeting this business as a way to introduce intelligence, agility, and efficiency to a variety of sectors in light of the growth of digital twins. In order to digitize the real world, the new IBM Digital Twin exchange aims to bring together businesses and a variety of service and tool suppliers to build an app store. Industries with a high concentration of assets are the focus of the IBM Digital Twin Exchange, including manufacturing, oil and gas, civil infrastructure, automotive, etc. Customers may browse, buy, and download Digital Twin materials using IBM Digital Twin Exchange, a first-of-its-kind Exchange. The user interface on the Exchange isn't all that far from a standard e-commerce purchasing experience. The IBM Digital Twin Exchange's quick integration with ERP and EAM systems is a key benefit for customers.

On the other hand, various threats arise during the implementation of the DT. The DT is continuously fed with data via sensors to optimize performance, predict errors, and simulate future scenarios. Therefore, the automated process for physical asset data collection requires an efficient and robust IoT structure. A robust IoT infrastructure enables the DT to provide greater efficiency and more accurate results. Besides, the DT needs a noiseless and continuous stream of data to produce accurate results. Insufficient, inconsistent, and incomplete data cause the DT to produce incorrect results. Consequently, this also causes the results of the analysis to be inaccurate. Therefore, data quality has a significant role in the DT technology.

Further, privacy and security issues are the main challenges for the DT technology. The DT in manufacturing deals with large amounts of data that is provided by the IoT infrastructure. Besides, risks related to security, compliance, data protection, and regulations arise with the growing connectivity [53]. Also, the rise in cyber-attacks on critical infrastructures and sensitive data raises security concerns. Therefore, the relevant IoT infrastructure must meet the security requirements and be compatible with the recent privacy regulations. Another challenge is the lack of a standardized concept and approach in DT modeling systems. The lack of a standardized approach for the implementation of the DT concept causes the implementation process to be more complex. Universally shared use of digital twins throughout the entire product life cycle requires a standardized coherent framework that encompasses data flows, interfaces, etc. Thus, this is also an important research topic for future research in DT technology.

The concept of the DT has been around for a long time since it is introduced by Michael Grieves. However, in recent years DT technology has become a strategic technology trend in digital transformation. Moreover, the DT technology is working in integration with other technologies such as IoT, Cloud Computing, and Artificial Intelligence. Therefore, the DT is impacting several industries from many different areas. In smart manufacturing, manufacturers use DT to create products' designs, prototype their products, simulate their operations, and analyze production data and results. The DT enables interconnecting the physical and virtual worlds. For this purpose, the DT gathers all the interrelating data sources from an asset's entire life cycle [53]. Thus, operational processes and products that are risky and expensive in the physical world can be simulated in digital environments and analyzed and implemented in the physical world. Therefore, manufacturers improve their operational performance and business processes, save production costs and time. In addition, the Digital Twin will help to reduce IoT device development costs by accelerating the development of IoT devices. Thereby, IoT devices can be prototyped, the performances of these prototyped devices can be tested, and designs can be reshaped with the virtual world created by the DT.

Over two-thirds of businesses that have adopted IoT will have deployed at least one DT in production by 2022, predicts Gartner [54]. Furthermore, it is estimated that by 2028, the size of the global DT market would be USD 86.09 billion [55]. Additionally, the COVID-19 has accelerated the adoption of DTs in particular end-use industries and given DT adoption a boost to be better prepared for any future crises of this nature [55]. Figure 8 shows the global market size of the DT [53, 55]. Energy, automotive, transportation, aerospace, and defense industries are indicated as key industries among the end users of the DT technology [53].

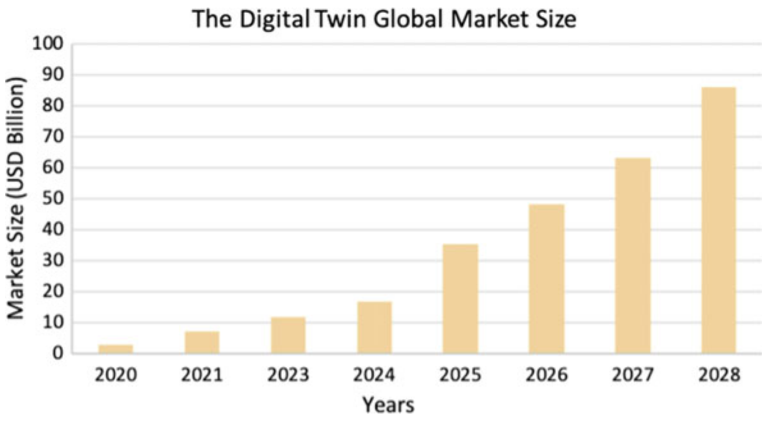


Fig. 8 DT global market size

Today's digitalizing world is reshaping the manufacturing industry. The use, operation, and maintenance of products after the sale are all being altered by the digitization of production. Additionally, the management of the manufacturing supply chain is changing as a result of digitization, as are the operations, procedures, energy footprint, and management of factories [56]. In this digitalization process of manufacturing, DT is a powerful tool for manufacturers to improve production lines, downstream operations, and to gain advantages in the global manufacturing competition. The DT technology, however, is still in its infancy. The DT faces several constraints and difficulties that must be overcome in order to realize its full potential, including financial burdens, the complexity of the information, a lack of standards, upkeep requirements, and regulations, and communications and cybersecurity-related problems [57]. Therefore, the DT concept provides new opportunities and motivation for future research initiatives. In this chapter, the fundamentals of the Digital Twin are discussed, along with how they apply to manufacturing. Additionally, a comprehensive analysis of the advantages, difficulties, and potential applications of DT technology in manufacturing is presented.

References

1. He, B., & Bai, K. J. (2021). Digital twin-based sustainable intelligent manufacturing: A review. *Advances in Manufacturing, 9*(1), 1–21.
2. Haag, S., & Anderl, R. (2018). Digital twin–proof of concept. *Manufacturing Letters, 15*, 64–66.
3. Cheng, J., Zhang, H., Tao, F., & Juang, C.-F. (2020). DT-II: Digital twin enhanced industrial internet reference framework towards smart manufacturing. *Robotics and Computer Integrated Manufacturing, 62*, 101881.
4. Liu, M., Fang, S., Dong, H., & Xu, C. (2021). Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems, 58*, 346–361.
5. Negri, E., Fumagalli, L., & Macchi, M. (2017). A review of the roles of digital twin in CPS-based production systems. *Procedia Manufacturing, 11*, 939–948.
6. Editorial. (2021). Digital twin towards smart manufacturing and industry 4.0. *Journal of Manufacturing Systems, 58*, 1–2.
7. Zhou, G., Zhang, C., Li, Z., Ding, K., & Wang, C. (2020). Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing. *International Journal of Production Research, 58*(4), 1034–1051.
8. Lu, Y., Liu, C., Wang, K.I.-K., Huang, H., & Xu, X. (2020). Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer Integrated Manufacturing, 61*, 101837.
9. Research and Markets. 2021. Global digital twin market by type, by application, by industry, by regional outlook, industry analysis report and forecast, 2021–2027, 297 pages.
10. Liezina, A., Andriushchenko, K., Rozhko, O., Datsii, O., Mishchenko, L., & Cherniaieva, O. (2020). Resource planning for risk diversification in the formation of a digital twin enterprise. *Accounting, 6*(7), 1337–1344.
11. Boschert, S., & Rosen, R. (2016). *Digital twin-the simulation aspect, mecatronic futures, Chapter 5* (pp. 59–74). Springer.
12. Tansley, E. (2021). Digital twins and smart buildings—An expert's view. https://www.twinfm.com/article/digital-twins-and-smart-buildings-an-expertsview. Last Accessed: April 15, 2022.

13. Panetta, K. (2018). Gartner top 10 strategic technology trends for 2019. https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019/. Last Accessed: April 15, 2022.
14. Murray, L. (2017). Lockheed martin forecasts tech trends for defense in 2018. https://dallasinnovates.com/lockheed-martin-forecasts-tech-trends-for-defense-in-2018/. Last Accessed: April 15, 2022.
15. Grieves, M. (2005). Product lifecycle management: The new paradigm for enteprises. *International Journal of Product Development (IJPD), 2*(1/2).
16. Grieves, M. (2014). Digital twin: Manufacturing excellence through virtual factory replication. Whitepaper.
17. Qi, Q., Tao, F., Hu, T., Anwer, N., Liu, A., Wei, Y., Wang, L., & Nee, A. Y. C. (2021). Enabling technologies and tools for digital twin. *Journal of Manufacturing Systems, 58*, 3–21.
18. Pal, S. K., Mishra, D., Pal, A., Dutta, S., Chakravarty, D., & Pal, S. (2022). Digital twin—fundamental concepts to applications in advanced manufacturing. Springer Series in Advanced Manufacturing.
19. Biesinger, F., Meike, D., Kraß, B., & Weyrich, M. (2018). A case study for a digital twin of body-in-white production systems general concept for automated updating of planning projects in the digital factory. In *IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA) (*pp. 19–26).
20. Westkämper, E., Spath, D., Constantinescu, C., & Lentes, J. (2013). Digitale Produktion, Springer-Verlag Berlin Heidelberg.
21. Cao, H., & Folan, P. (2012). Product life cycle: the evolution of a paradigm and literature review from 1950 to 2009. *Production Planning and Control, 23*(8), 641–662.
22. Stark, J. (2015). *Product lifecycle management (volume 1): 21st century pardigm for product realisation (decision engineering)*. Springer.
23. Tao, F., Cheng, J., Qi, Q., et al. (2018). Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology, 94*, 3563–3576.
24. Yang, D., et al. (2021). Developments of digital twin technologies in industrial, smart city and healthcare sectors: A survey. *Complex Engineering Systems, 1*, 3.
25. Biesinger, F., Meike, D., Kraß, B., & Weyrich, M. (2019). A digital twin for production planning based on cyber-physical systems: A case study for a cyber-physical system-based creation of a digital twin. *Procedia CIRP, 79*, 355–360.
26. Agostino, I. R. S., Broda, E., Frazzon, E. M., & Freitag, M. (2020). Using a digital twin for production planning and control in industry 4.0. In B. Sokolov, D. Ivanov, & A. Dolgui (Eds.), *Scheduling in industry 4.0 and cloud manufacturing, international series in operations research and management science* (Vol. 289, pp. 39–60). Springer.
27. Coors-Blankenship, J. (2020). Taking digital twins for a test drive with Tesla, Apple. https://www.industryweek.com/technology-and-iiot/article/21130033/how-digital-twins-are-raising-the-stakes-on-product-development. Last Accessed: April 15, 2022.
28. Austin-Morgan, T. (2017). Maserati has fused cutting-edge digitalisation methods with Italian passion to meet customer demand. https://www.eurekamagazine.co.uk/content/Other/Maserati-has-fused-cutting-edge-digitalisation-methods-with-italian-passion-to-meet-customer-demand. Last Accessed: April 15, 2022.
29. Nguyen, H. (2021). Formula 1 is leading the digital twin technology. https://dt.mdx.ac.uk/?p=1427. Last Accessed: April 15, 2022.
30. Patel, N. (2019). How aerospace industry can use digital twins to improve fleet management and sustainment. https://www.einfochips.com/blog/how-aerospace-industry-can-use-digital-twins-to-improve-fleet-management-and-sustainment/. Last Accessed: April 15, 2022.
31. Careless, J. (2021). Digital twinning: The latest on virtual models. https://www.aerospacetechreview.com/digital-twinning-the-latest-on-virtual-models/. Last Accessed: April 15, 2022.
32. Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of industry 40: A review. *Engineering, 3*(5), 616–630.

33. Tao, F., Qi, Q., Wang, L., & Nee, A. Y. C. (2019). Digital twins and cyberphysical systems toward smart manufacturing and industry 4.0: Correlation and comparison. *Engineering, 5*, 653–661.
34. Monostori, L., et al. (2016). Cyber-physical systems in manufacturing. *CIRP Annals—Manufacturing Technology*, *65*, 621–64.
35. Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016). Towards smart factory for Industry 4.0: A self-organized multi-agent system with big data-based feedback and coordination. *Computer Networks, 101*, 158–168.
36. Zhang, H., Yan, Q., & Wen, Z. (2020). Information modeling for cyber-physical production system based on digital twin and automation ML. *The International Journal of Advanced Manufacturing Technology, 107*, 1927–1945.
37. Liu, C., Jiang, P., & Jiang, W. (2020). Web-based digital twin modeling and remote control of cyber-physical production systems. *Robotics and Computer Integrated Manufacturing, 64*, 101956.
38. Min, Q., Lu, Y., Liu, Z., Su, C., & Wang, B. (2019). Machine learning based digital twin framework for production optimization in petrochemical industry. *International Journal of Information Management, 49*, 502–519.
39. Onile, A. E., et al. (2021). Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Reports, 7*, 997–1015.
40. Andryushkevich, S. K., Kovalyov, S. P., & Nefedov, E. (2019). Composition and application of power system digital twins based on ontological modeling. In *IEEE 17th International Conference on Industrial Informatics (INDIN)* (pp. 1536–1542).
41. Brosinsky, C., Westermann, D., & Krebs, R. (2018). Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers. In *IEEE International Energy Conference (ENERGYCON)* (pp. 1–6).
42. Francisco, A., Mohammadi, N., & Taylor, J. E. (2020). Smart city digital twin–enabled energy management: Toward real-time urban building energy benchmarking. *Journal of Management in Engineering, 36*(2), 04019045.
43. Zhou, M., Yan, J., & Feng, D. (2019). Digital twin framework and its application to power grid online analysis. *CSEE Journal of Power and Energy Systems, 5*(3), 391–398.
44. Xie, X., Parlikad, A. K., & Puri, R. S. (2019). A neural ordinary differential equations based approach for demand forecasting within power grid digital twins. In *IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)* (pp. 1–6).
45. Kychkin, A., & Nikolaev, A. (2020). IoT-based mine ventilation control system architecture with digital twin. In *International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM)* (pp. 1–5).
46. O'Dwyer, E., Pan, I., Charlesworth, R., Butler, S., & Shah, N. (2020). Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. *Sustainable Cities and Society, 62*, 102412.
47. Nwauka, O., Telukdarie, A., & Enslin, J. (2018). Virtual power plant basic requirements for integration of distributed energy resources driven by industry 4.0. In *Proceedings of the International Conference on Industrial Engineering and Operations Management* (pp. 511–523).
48. Li, B., Hou, B., Yu, W., et al. (2017). Applications of artificial intelligence in intelligent manufacturing: A review. *Frontiers of Information Technology and Electronic Engineering, 18*(1), 86–96.
49. Singh, M., Fuenmayor, E., Hinchy, E. P., Qiao, Y., Murray, N., & Devine, D. (2021). Digital twin: Origin to future. *Applied System Innovation, 4*(2), 36.
50. West, S., Stoll, O., Meierhofer, J., & Züst, S. (2021). Digital twin providing new opportunities for value co-creation through supporting decision-making. *Applied Sciences, 11*(9), 3750.
51. Agarwal, A., Fischer, M., & Singh, V. (2021). Digital twin: From concept to practice. *ASCE Journal of Management in Engineering, Special Collection on Re-thinking the Benefits of Adopting Digital Technologies in the AEC Industry.*

52. Find a digital twin. IBM Digital Twin Exchange. (2020). Retrieved August 29, 2022, from https://digitaltwinexchange.ibm.com/
53. Markets and Markets. (2021). Digital Twin Market by Technology, Type (Product, Process, And System), Application (predictive maintenance), Industry (Aerospace & Defense, Automotive & Transportation, Healthcare), and Geography—Global Forecast to 2026. https://www.marketsandmarkets.com/Market-Reports/digital-twin-market225269522.html. Last Accessed: April 15, 2022.
54 Gartner Newsroom. (2019). Gartner survey reveals digital twins are entering mainstream use. https://www.gartner.com/en/newsroom/press-releases/2019-02-20-gartner-survey-reveals-digital-twins-are-entering-mai. Last Accessed: April 15, 2022.
55. Grand View Research. (2021). Digital twin market size worth $86.09 billion by 2028. https://www.grandviewresearch.com/press-release/global-digital-twin-market. Last Accessed: April 15, 2022.
56. Ezell, S. (2018). Why manufacturing digitalization matters and how countries are supporting it. *Information Technology and Innovation Foundation, Technical Report.*
57. Botín-Sanabria, D. M., Mihaita, A.-S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., & Lozoya-Santos, J. J. (2022). Digital twin technology challenges and applications: A comprehensive review. *Remote Sensing, 14*(6), 1335.