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SEEDING THE FUTURE: LITERATURE REVIEW OF DIGITAL TWIN AND ITS APPLICATIONS

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Abstract: *With the recent development of the Internet of Things, artificial intelligence, big data and other emergent technologies intensively studied in both academia and across different industries, Digital Twin has become a promising technology that could overcome the challenges faced today in the context of the fourth industrial revolution. While the concept has been known for almost 20 years, recently it has become widely studied due to its diversity to be used in new industries and use cases. This paper aims to present a comprehensive review of Digital Twin technology and its implementation in the most relevant domains and applications.*
Keywords: *digital twin; smart manufacturing; virtual twin; information technology; digitalization.*

1. INTRODUCTION

The concept of Digital Twin (DT) was introduced by Dr. Michael Grieves in 2003 at the University of Michigan being a part of the course on Product Lifecycle Management (PLM). At that moment, the term used was “Mirrored Spaces Model (MSM)”, followed by “Mirroring Model”. The definition of DT from this period presents DT as a system of three main parts: the physical object, the virtual model, and the connection between them (see Fig. 1) [1]. The term “digital twin” was clearly defined in 2017 by Dr. Michael Grieves and Dr. John Vickers as [2]:

- “Digital Twin (DT)—the Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin. Digital Twins are of two types: Digital Twin Prototype (DTP) and Digital Twin Instance (DTI). DT’s are operated on in a Digital Twin Environment (DTE).” [3]

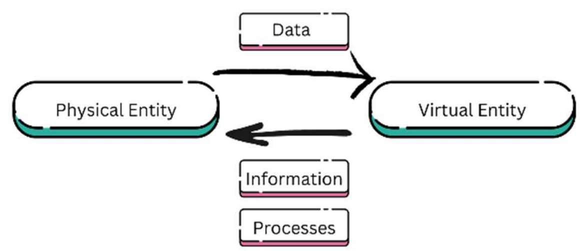


Fig. 1. Twinning between the physical and virtual entities

The origin of DT goes back to the need of improving the aerospace technology [4], mainly the aircraft simulation in different types of conditions. As a result, in 2012, NASA and U.S. Air Force Research Laboratory proposes using DT for aircraft fleet monitoring to overcome the shortcoming of the conventional approaches [5]. NASA defined DT as:

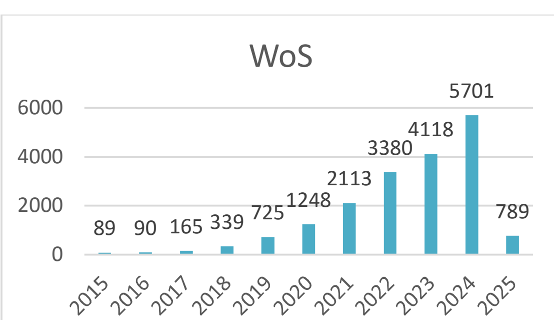
- “A Digital Twin is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.” [6]

A DT is a virtual representation of a physical entity (object or process) capable of collecting data from its physical twin to validate, represent and simulate the present and future behavior of its physical counterpart. There is no definition of what the physical entity should be, it can be a single object, a complex process, or a system of systems. The physical entity can be for example a city [7], an engine [8], a vehicle [9], the human body [10], or a nuclear plant [11]. DT is a crucial technology in data-driven decision making [12], monitoring complex systems [13], validation of new products [14], simulation [15] and management of product lifecycle management [16].

As the concept gained more attention from both academia and industries, the definition of DT diversified over the years based on the domain it was used for. For example, in 2015, Rosen et al. [17] defines DT as a large collection of digital artifacts that requires good architecture to analyze all the data collected. In 2018, Haag et al. [18] presents DT as a comprehensive digital representation that includes the properties, conditions and behaviors of a real-life object through models and data. In 2019, Madni et al. [19] defines DT as a virtual instance of a physical system (twin) that is continually updated with the physical system's performance, maintenance, and health status data throughout the physical system's lifecycle.

The rapid evolution of DT technology can be observed from the publication trends over the years (see Fig. 2).

With the evolution of related technologies such as Internet of Things (IoT), Big Data, multi-physical simulation, Industry 4.0, sensor networks, real-time sensors, data management, data processing and with a concept of virtual manufacturing in mind, Digital Twin is set to become one of the most powerful multidisciplinary technologies in the following years (see Fig. 3).



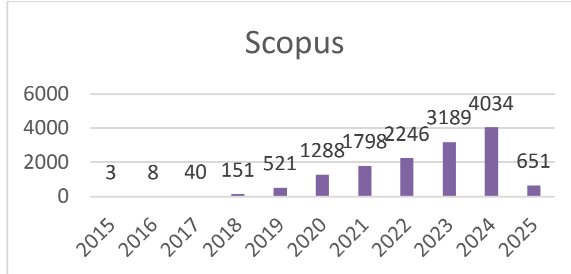


Fig. 2. Number of publications per year in Web of Science and ScienceDirect

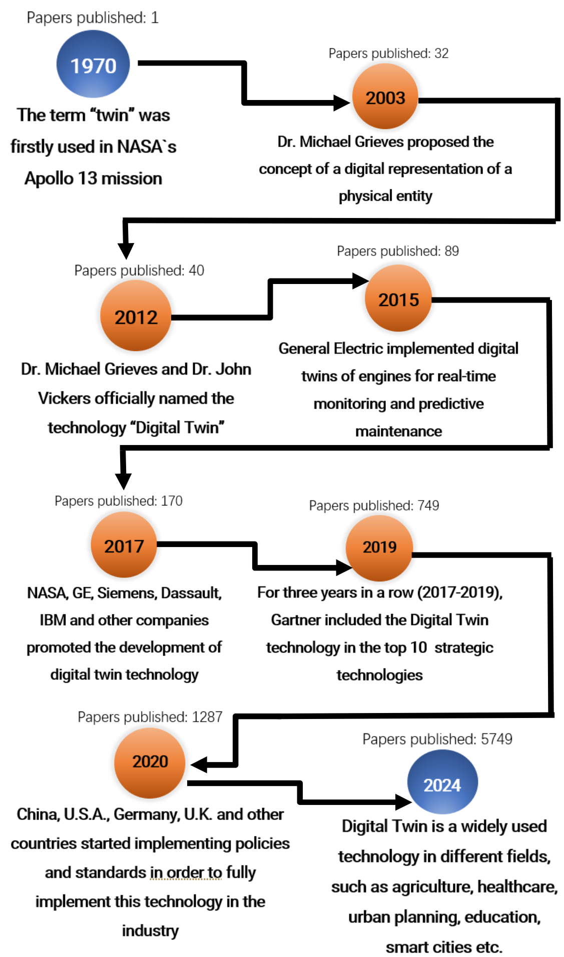


Fig. 3. Evolution of DT

2. METHODOLOGY

This paper aims to review the literature focused on DT technology. This review follows the systematic approach [20] with the scope of outlining the key aspects of DT technology, with the aim of characterizing DT and outlining the main applications of this technology in various fields.

The paper is focused on answering the following questions:
RQ1: What are the characteristics of a Digital Twin?
RQ2: What are the main applications of Digital Twin in the engineering sector?
RQ3: What are the challenges and further developments of Digital Twin?

The inclusion and exclusion criteria can be found in the following table (Table 1).

Table 1¶

Inclusion/exclusion criteria

Inclusion criteria	Exclusion criteria
Articles published between January 2020 to March 2025	Articles that were published before 2020
Articles focused on digital twin characteristics and engineering applications	Articles focused on other fields expect engineering
Type of articles: research articles	Book chapters, proceedings papers, early access papers
Articles published in English language	Articles not written in English

Extensive research is conducted by both academia and industry on the topic of DT. In Scopus, using the term "digital twins" a total number of nearly 2000 papers can be found in the year 2020 and over 9000 in the year 2024 respectively. The applications in which DT is presented as a viable technology range from manufacturing processes [21] to smart grids and education [22].

The search was focused on the years between 2020 and 2025. The databases used in this paper were Web of Science and Scopus, using the keywords "digital twin" in the Title field and "engineering" in the topics field. After collecting the relevant papers, a screening of the title and abstract was conducted in order to select the relevant papers for this literature review.

The number of articles selected can be found in Fig. 4, where a diagram adapted from PRISMA Flow Diagram [23] is presented.

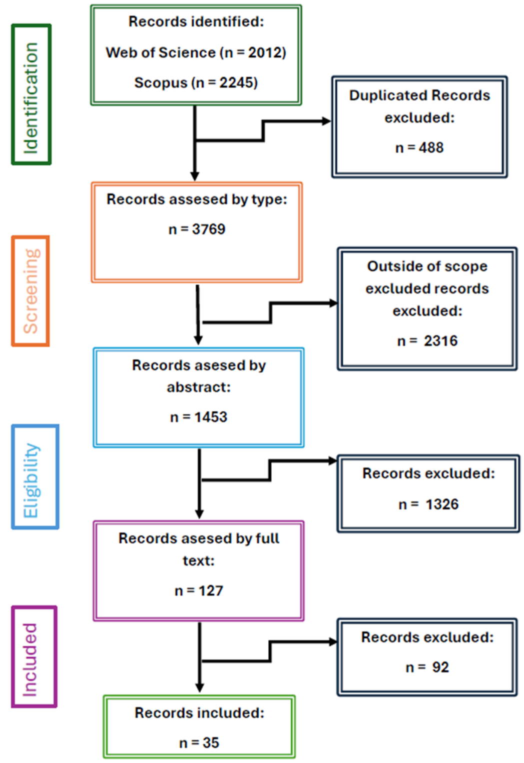


Fig. 4. Systematic review flow

3. RESULTS

In order to obtain the answers to our research questions, a two-phase methodology was approached. In the first phase, the first and second questions were addressed by selecting relevant papers to obtain an overview of DT technology and its applications. The second phase addressed the third question based on the most cited papers in DT area of interest. A total of 35 papers were selected for answering the first two research questions, and for the last research question, the papers selected were chosen based on the number of citations, without taking into consideration the publication year.

All selected papers were limited to the keyword "*digital twin*" that appeared in the title or in the abstract of the paper. Also, the research field focused on engineering applications, written in English and being open access. The most cited papers in this field were obtained from Scopus and Web of Science databases, and the result can be found in Table 2.

Table 2

Detailed view of the most cited papers (based on Google Scholar as of 12-March-2025)

Title & Reference	Authors	Journal	Publication year	Citations
Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems	Grieves, M. and Vickers, J.[2]	*Springer, Charm*	2017	3967
Digital twin-driven product design, manufacturing and service with big data	Tao F. et al. [24]	*The International Journal of Advanced Manufacturing Technology*	2018	3266
Digital Twin in manufacturing: A categorical literature review and classification	Kritzinger et al. [25]	*IFAC-PapersOnLine*	2018	3193
Digital Twin in Industry: State-of-the-Art	Tao F. et al. [26]	*IEEE Trans Industr Inform*	2018	3567
Characterising the Digital Twin: A systematic literature review	Jones D. et al. [27]	*CIRP J Manuf Sci Technol*	2020	2263
Towards a semantic construction digital twin directions for future research	Boje C. et al. [28]	*IEEE Trans Industr Inform*	2020	1168
Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues	Y. Lu et al. [29]	*Robotics and Computer-Integrated Manufacturing*	2020	1460
Digital twin paradigm: A systematic literature review	Semeraro C. et al. [30]	*Comput Ind*	2021	813
Digital Twin: Origin to Future	Singh, M. et al. [31]	*Appl. Syst. Innov.*	2021	864
Digital twin-based sustainable intelligent manufacturing: a review	B. He and K.-J. Bai [32]	*Adv Manuf*	2020	606

3.1 DT concept

Since the first definition of DT introduced by NASA, authors described DT based on its application field. Over the years, the definition of DT migrated from describing an aircraft to describing other entities such as vehicle, system, entity, process. The common part of every DT definition is a virtual representation of a physical object and the bidirectional transfer or sharing of data between the digital twin and its physical counterpart.

The key concepts of DT are (Fig. 5):

- Digital Twin
- Digital Twin Prototype (DTP)
- Digital Twin Instance (DTI)
- Digital Twin Aggregate (DTA)
- Digital Twin Environment (DTE)

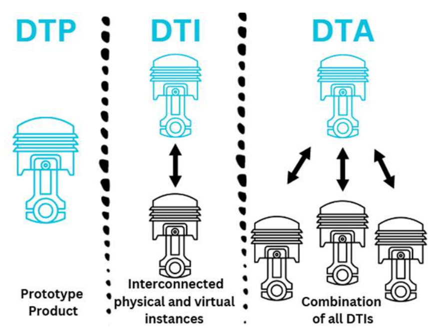


Fig. 5. Key concepts of DT

DTP represents a virtual representation of a prototype product that contains all the necessary information to create the physical twin.

DTI represents a specific instance of a physical product that remains linked to a specific product throughout its life cycle.

DTA represents a combination of all DTIs.

DTE represents an integrated, multi-domain physics application space for operating on DTs for different purposes (predictive, interrogative).

The main characteristics of DT are: Physical Twin, Virtual Twin, Physical Environment, Virtual Environment, State, Metrology, Realization, Twinning, Twinning Rate, Physical-to-Virtual Connection, Virtual-to-Physical Connection, Physical Processes, and Virtual Processes. The description of each component can be found in Table 3.

Table 3

Main characteristics of DT

Characteristic	**Description**
Physical Twin	The physical entity that exists in the physical world
Virtual Twin	The virtual entity that exists in the virtual world
Physical Environment	The environment in which the physical twin exists
Virtual Environment	The environment in which the virtual twin exists
State	The values measures between the physical/virtual twin and its environment
Metrology	Measurement of the state of the physical/virtual twin
Realization	The act of changing the state of the physical/virtual twin
Twinning	Synchronization of the states of the physical and virtual twin
Twinning Rate	The rate at which the twinning occurs
Physical-to-Virtual Connection	Data connection/process of measuring the state of the physical twin/environment and realizing the state in the virtual twin/environment
Virtual-to-Physical Connection	Data connection/process of measuring the state of the virtual twin/environment and realizing the state in the physical twin/environment
Physical Processes	The processes in which the physical twin is involved, and/or processes acting with or upon the physical twin
Virtual Processes	The processes in which the virtual twin is involved and/or processes acting with or upon the virtual twin

DT extends the use of simulation to all the phases of the product life cycle.

Simulation is the basis of design decisions, validation, and tests not only for a generic device, but also for monitoring complex systems.

In the context of Product Lyfe Cycle, DT plays a crucial role in optimizing each stage of the product`s life cycle [33].

The design phase establishes necessary product design definitions before production. It is divided into 4 main parts: task clarifications, conceptual design, embodiment design, detail design [34]. In this phase, physical products are not available (Fig. 5).

The focus turns over replacing the physical prototypes and physical tests by simulating the product`s performance under various conditions, enabling virtual testing and prototyping [35], shortening the design cycle and reducing rework costs.

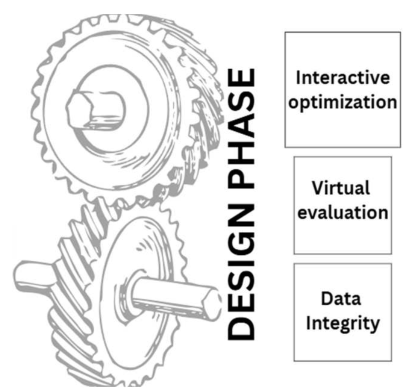


Fig. 6. DT in the design phase

Panarotto et al. [36] proposes an approach to use DT in space exploration, by using a modular platform development. As the cost of performing physical tests on a large number of radically new products is high, creating sets of DT modules that can be reused and recomposed is an efficient way to overcome these challenges.

In the manufacturing phase, the focus is to create the products based on the specifications defined in the design phase. The latest trends and developments in digital technologies have enabled a new manufacturing model (Fig. 6).

DT can monitor and adjust manufacturing processes in real-time, reducing errors and it can increase efficiency by predicting equipment failures and scheduling predictive maintenance [37].

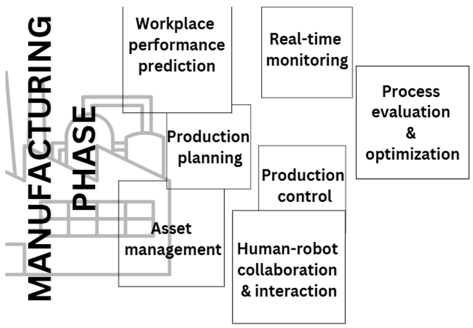


Fig. 7. DT in the manufacturing phase

In the service stage (Fig. 7), DT can track the product`s behavior and health using sensory data, predicting failures and optimizing performance [38]. It also enables remote monitoring and diagnostics, reducing operational costs [39].

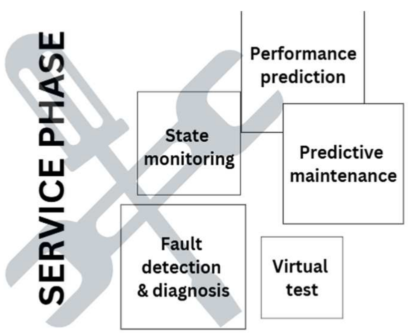


Fig. 8. DT in the after-sale service phase

In the end-of-life stage, it can facilitate recycling by providing a full history of materials and components used. It can also provide information for future designs of the same product [32]. In this way, the problems that occurred with the previous product can be avoided by using the knowledge from its predecessor.

The evolution of DT is directly proportional to the innovations in technologies such as 3D Simulations, IoT, Big Data, Machine Learning, Artificial Intelligence (AI), Extended Reality and Cloud Computing. Furthermore, DT is also the main driver of evolution in other research areas such as Virtual Manufacturing Systems [40], Model-based Predictive Control (MPC) [41], and Building Information Modeling (BIM) [42].

3.2 DT applications

The areas in which DT is used are constantly expanding. Although DT was primarily used by NASA and US Air Force for the design, maintenance and prediction of their aircraft, the concept was extended to areas such as engineering education [43] and healthcare [44].

With the evolution of the latest technologies, and with the interest shown regarding DT in both academia and industry, this technology will further develop reaching a higher level of maturity in each area of application.

The main applications of DT in manufacturing are real-time monitoring [45], production control [46], workplace performance predictions [47], human-robot collaboration and interactions [48], process evaluation and optimization [49], asset management and production control [50].

Moench et al. [51] presents several use cases in the aircraft production and Maintenance, Repair and Overhaul (MRO) in which DT can be integrated in different phases of the aircraft life cycle phases. The digitalization projects at Airbus or Lufthansa Technik could transform the industry of aircraft production and MRO.

Another paper focused on studying the damage to an offshore wind turbine. Drones were used to capture the images and then an AI model analyzed the images. After mapping the damage, DT gave an accurate representation of the structure, helping in prognostic health management and changing maintenance strategies for economic and sustainable purposes [52].

As Human-Robot Interaction (HRC) in an assembly line is quite important, Cimiono et al. [53] presented a case study in the automotive sector where a simulation-based DT is used to support HRC optimization. The aim of this paper is to enhance agility, productivity, safety and well-being of human workers in the assembly production system.

Torzoni et al. [54] presents a DT framework for health monitoring, maintenance, and management planning of civil structures. The case study presented was focused on monitoring a cantilever beam and a railway bridge. The results prove that the capabilities of DT can accurately track the health of the studied structures under different operational conditions, with relatively low uncertainty.

Djebali et al. [55] offers a deep understanding of DT in smart grid, concluding with the fact that DT technologies offer a transformative approach in understanding and managing smart grids. It enables real-time monitoring, modeling, and control, leading to higher operational efficiency, reliability and sustainability.

A model-based DT framework for space launch vehicles was proposed in 2024 by Wei et al. [56] in which presents a DT maturity matrix characterizing the different stages of creating a DT: descriptive, analytical, operational, prescriptive, cognitive and connected cognitive. This framework was then tested in a case study. The conclusion from this study is that the development of DT is incremental.

3.3 Future development and challenges

Since the introduction of DT by Dr. Grieves, no formal or widely accepted definition has been achieved, one of the main causes being the variety of focused areas within different disciplines. Also, no general methodology was developed for creating and deploying process. Based on the industry it is applied on, different methods and perspectives emerges [57]. The lack of an unambiguous reference architecture leads to developing DT using different technologies, interfaces and communication protocols, models and data.

Even though the developments in DT are rapidly growing, many pressing issues should be addressed to implement its practical use. One of the main subjects prone to the advancements of DT is a DT unified modeling method.

Nowadays, building an accurate DT can be difficult due to the complexity of a real systems and the dependence between DT and other technologies. As these technologies are currently evolving themselves, DT development is closely linked to the innovations in these related.

As all the data collected is subject to security, there is an acute need to develop standards and regulations around this technology. Currently, there are 2 standardized frameworks for working with DT, ISO/IEC 30173/2023 and ISO 23247 Series. Both standards are valuable and are a starting point for clearly defining DT, but as DT technology is rapidly advancing, some aspects (like AI-driven twins) might not yet be fully covered.

According to the literature, most of the existing research on DT is conceptual work, and the development of practical DT applications is still in its infancy stage. In 2020, the innovative project names CybeFactory#1was launched with the purpose of enhancing optimization and resilience of Factory of the Future, with results tested in industrial use-cases in eight pilot factories in Europe, in sectors as aerospace system manufacturing, industrial machine fabrication, consumer electronics and textile industry [58]. In the same year, this project won the ITEA Award of Excellence 2022 for Business Impact [59].

As most of the papers focus on DT in manufacturing, there are a few papers that take into consideration the human factor. Human interaction is the one key challenge in developing and implementing a DT framework. As there are a low number of operations that can be autonomously decided, most of the decision-making process is still human-based. Therefore, the importance of humans in DT environment has to not be overlooked.

4. CONCLUSION

Our research sought to answer three research questions. By collecting relevant data, we explored the characteristics, applications and challenges of DT technology.

For RQ1, this review shows that DT is fundamentally a virtual representation of a physical entity. The key characteristics include DTP, DTI, DTA and DTE. It enables real-time monitoring, predictive analysis, and bidirectional data exchange.

For RQ2, DT is widely used in various engineering fields, including manufacturing, aerospace engineering, automotive engineering, civil engineering, and in the energy sector. In manufacturing, it enables predictive maintenance, process optimization, and reduction of downtime and operational costs. In aerospace and automotive engineering, it supports design validation, testing, performance monitoring, and failure prediction, enabling safety and efficiency. Additionally, in construction engineering DT is revolutionizing structural health monitoring and in energy engineering, it enables smart grid applications. All these applications demonstrate the versatility of DT technology, demonstrating efficiency, cost reduction, and sustainability.

For RQ3, despite DT`s potential, several challenges emerge. Lack of standardization, the complexity of data integration, cybersecurity risks and the high computation demands are some of the key issues. Future developments should focus on AI-driven predictive capabilities, scalability improvements, and standardized frameworks for cross-industry adoption. Furthermore, ethical and regulatory frameworks to address data privacy and ownership concern should be addressed.

As DT technology continues to evolve, it can be concluded that it will play a pivotal role in shaping the future of engineering and smart systems.

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Semințele viitorului: Revizuirea literaturii de specialitate privind Digital Twin și aplicațiile sale

Odată cu dezvoltarea tehnologiile precum Internet of Things, Inteligența Artificială, Big Data și a altor tehnologii emergente studiate intens atât de lumea academică, căt și în diverse industrii, Digital Twin a devenit o tehnologie promițătoare și capabilă să depășească provocările actuale în contextul revoluției industrial digitale. Deși conceptul este cunoscut de aproape 20 de ani, acesta a devenit intens studiat datorită diversitâții sale de utilizare în diferite industrii și scenario. Această lucrare îți propune să prezinte o revizuire a literaturii de specialitate din domeniul Digital Twin pentru a oferi o imagine de ansamblu a acestei tehnologii și a domeniilor în care este utilizată.

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