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Digital Twin—A Review of the Evolution from Concept to Technology and Its Analytical Perspectives on Applications in Various Fields

Miruna-Elena Iliuţă [1,*], Mihnea-Alexandru Moisescu [1], Eugen Pop [1], Anca-Daniela Ionita [1], Simona-Iuliana Caramihai [1] and Traian-Costin Mitulescu [2]

1 Faculty of Automatic Control and Computers, Automation and Industrial Informatics, National University of Science and Technology Politehnica Bucharest, 060042 Bucharest, Romania; mihnea.moisescu@upb.ro (M.-A.M.); eugen.pop@upb.ro (E.P.); anca.ionita@upb.ro (A.-D.I.); caramihai2002@yahoo.com (S.-I.C.)

2 Department 12—Ophthalmology, ENT, University of Medicine and Pharmacy Carol Davila Bucharest, 011241 Bucharest, Romania; costin.mitulescu@umfcd.ro

* Correspondence: miruna_elena.iliuta@upb.ro

Abstract: Digital Twin (DT) technology has experienced substantial advancements and extensive adoption across various industries, aiming to enhance operational efficiency and effectiveness. Defined as virtual replicas of physical objects, systems, or processes, Digital Twins enable real-time simulation, monitoring, and analysis of real-world behavior. This comprehensive review delves into the evolution of DT technology, tracing its journey from conceptual origins to contemporary technological implementations. The review provides detailed definitions, a classification of different types of Digital Twins, and a comparative analysis of their architectures. Furthermore, it investigates the application of DT technology in diverse sectors, with a particular emphasis on medicine and manufacturing, exemplified by use cases such as personalized medicine. Moreover, the review highlights emerging trends and future directions in DT technology, underscoring the transformative potential of integrating artificial intelligence and machine learning to augment DT capabilities. This analysis not only elucidates the current state of DT technology but also anticipates its future trajectory and impact across multiple domains.

Keywords: Digital Twin; Digital Twin in medicine; product–service systems; medicine; evolution; ethical aspects

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1. Introduction

The Digital Twin (DT) represents a concept that emerges from Product Lifecycle Management and has a primary role in the development of current trends related to customer requirements, design constraints, complexity, data security, and integrity. The basic idea of this technology is to examine the use of the digital replica of a physical object. A Digital Twin has been defined as a digitization platform with a role in improving, processing, and managing information at the level of physical and virtual companies. Initially, DTs were capable of monitoring and could be improved in terms of control, optimization, and autonomy capability [1]. They also enable the integration and sharing of acquired data throughout the lifecycle, resulting from a continuous learning process, and include various aspects of digital representation. By combining the notions of artificial intelligence, data analysis, the Internet of Things (IoT), virtual reality, and the foundations of modern engineering are laid, characterized by innovation and performance.

The field of application of DTs is vast; thus, DT applications are being developed for smart cities, construction, medical systems, manufacturing, agriculture, and the automotive industry. Based on the specialized literature consulted, the advantages identified following the use of DT applications are the urban planning of cities, services, increased reliability, reduced operational costs, improved performance, optimization of implemented strategies, reduction of discrepancies between projected and realized requirements, and increasing efficiency and quality control [1].

In Section 2, a literature review methology is realized, serving as a foundation for understanding the context and research directions. Section 3 explores the evolution of the Digital Twin concept, providing a detailed analysis of its transition into a functional architectural model. In Section 4, the applicability and impact of Digital Twin models in various domains are examined, highlighting both the advantages and challenges associated with their use. Section 5 presents the results obtained in the study, providing a clear perspective on its contribution. In Section 6, discussions focus on the interpretation and detailed analysis of the results, addressing relevant aspects and their implications. Finally, Section 7 gathers the key conclusions of the work.

2. Literature Review Methodology

The Digital Twin concept is in a continuous process of development, and its promising development could bring benefits in various fields. The research methodology used in this study examines a comprehensive approach, starting from the Digital Twin concept, taxonomy, proposed reference models and architectures, and addressing its current applications in various fields such as manufacturing, medicine, energy production, education, and smart cities.

In light of the multiple application areas and the ability to simulate various real-world scenarios, DT plays an important role in technological advancement and digital transformation. The databases used for this paper are the Web of Science (WoS), IEEE Xplore, Scopus, and Google Scholar.

Figures 1–3 present the number of articles obtained following a search on Web of Science, IEEE Xplore, Scopus, and Google Scholar regarding the concept of "Digital Twin" over an interval of 8 years, from 2015 and until 2023. Analyzing the evolution of the number of articles published in the period 2015–2023, a significant increase in interest for research in this field was identified. In 2015, Digital Twin was found in 21 articles published by IEEE Xplore, 85 by Web of Science, 1393 by Scopus, and 28,199 by Google Scholar.

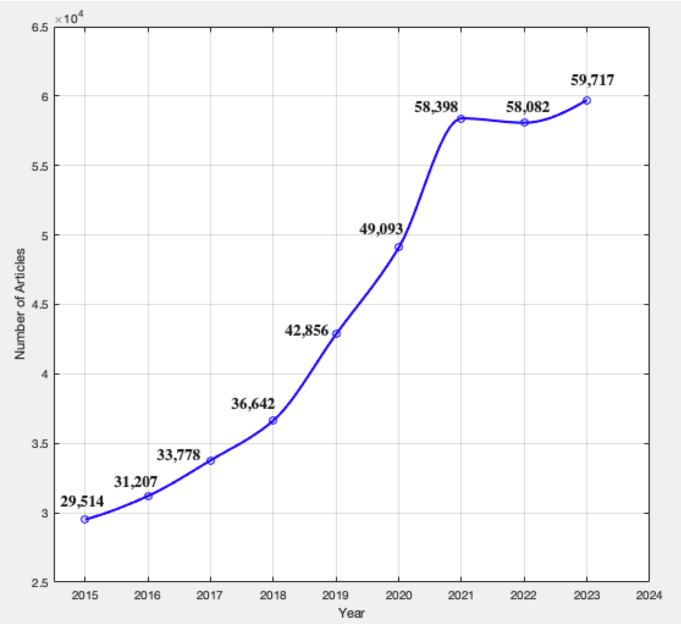
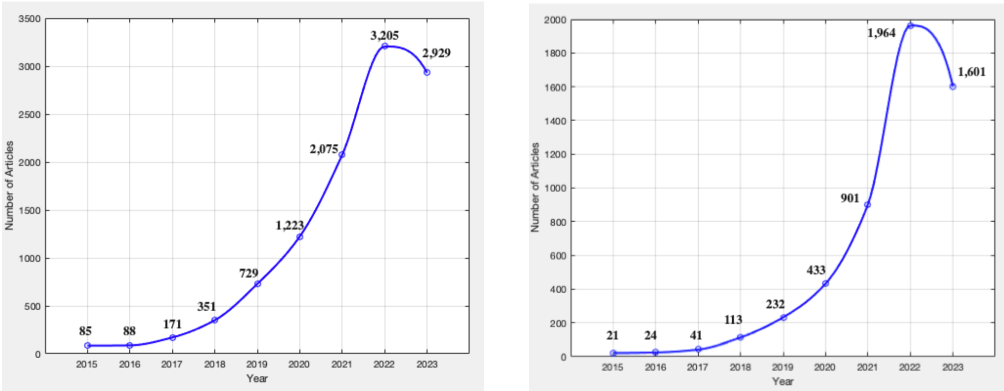
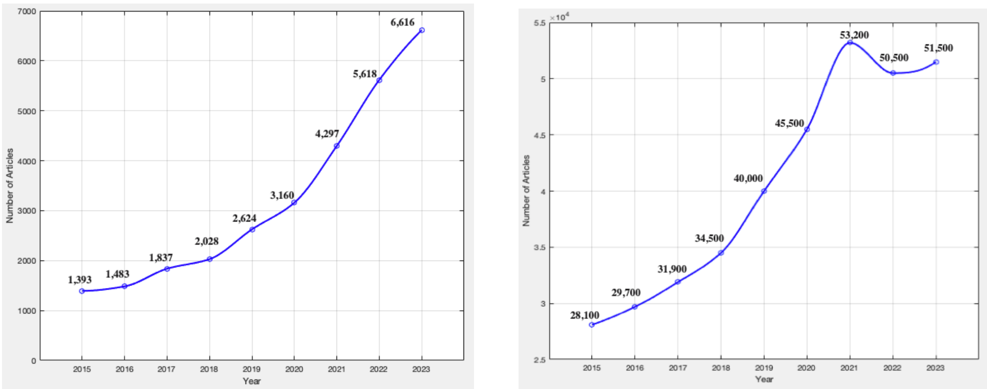


Figure 1. Number of articles about Digital Twin 2015–2023.



(**a**) (**b**)

Figure 2. Number of Articles on Web of Science and IEEE Xplore about DT. (**a**) Number of Articles on Web of Science about DT 2015–2023. (**b**) Number of Articles on IEEE Xplore about DT 2015–2023.



(**a**) (**b**)

Figure 3. Number of Articles on Scopus and Google Scholar about DT. (**a**) Number of Articles on Scopus about DT 2015–2023. (**b**) Number of Articles on Google Scholar about DT 2015–2023.

Figure 4 shows a statistic regarding the number of articles published on Google Scholar as a result of the search according to the keywords: "Digital Twin definition"—39,500 results, "Digital Twin classification"—27,100 results, "Digital Twin architecture"—31,100 results. The criteria that were the basis for the selection of the definitions were represented by the diversity and complementarity of the information that helps to identify the key functionalities, the relationship between the Digital Twin and the CPS, and the need for integration with various components. Also, the selection of a detailed classification helps to identify the technologies that facilitate the development and implementation of DTs. At the same time, this classification highlights the adaptation of DTs to various scenarios built on the basis of specific requirements, while ensuring effective implementation in a variety of fields and industries. The criteria on which the architectures were selected was relevance to the ways in which DTs can be structured and managed, ensuring interoperability, adaptability, scalability, and security of the systems. The focus has been on service delivery and adaptability in various fields such as the medical field. Among the exclusion criteria of the architectures is excessive complexity that can generate problems in the development, implementation, and management of Digital Twins, along with a lack or reduction of interoperability, scalability, flexibility, and security. The use of rigid architectures does not allow continuous adaptation to specific requirements. In the context of implementation, problems related to dependence on outdated technologies, resources, and high maintenance costs may occur.

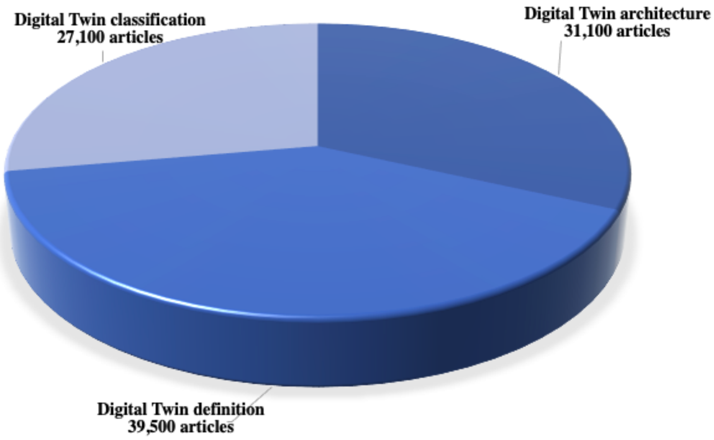


Figure 4. Definition, classification, and architecture for Digital Twin.

Figure 5 presents some fields of application of the DT such as manufacturing, medicine, energy production, education, and smart cities. Following a Google Scholar search, the largest number of articles was identified in the field of education—305,000 articles. The second-largest number of articles—273,000—was identified in the field of medicine, indicating a strong trend towards redefining existing paradigms and advancing personalized medicine.

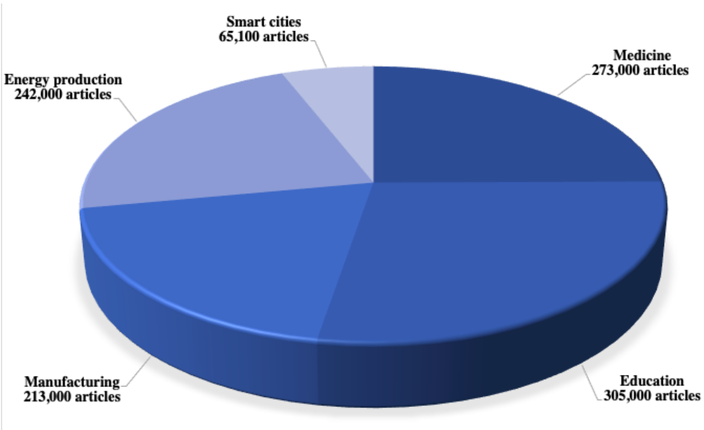


Figure 5. Number of articles about Digital Twin in various domains.

The research methodology consisted of the synthesis of 115 scientific papers, providing a comprehensive vision for understanding the Digital Twin concept from different perspectives. We carried out a comprehensive analysis of the concept of the Digital Twin, starting with the identification of definitions, classifications, and the discussion of the proposed architectures. The main goal of this study was to highlight the evolution of DT in recent years, thus providing a chronological and contextualized perspective. Definitions of Digital Twins were analyzed, and detailed classification helped to highlight the diverse points of view, paving the way for a comprehensive analysis of specific implementations. The selected architectures also illustrate the ways in which digital twin models can be structured and managed to ensure the interoperability, adaptability, scalability, and security of systems. Promising areas of applicability of the DTs were selected with a focus on manufacturing and medicine, but also addressing the applicability of DTs in related fields such as smart cities, education, and the oil industry. A critical perspective, including the advantages and disadvantages of using the DTs in the above-mentioned fields, was introduced. Thus, the proposed methodology provides a holistic approach to the Digital Twin concept, addressing innovation and promising developments. Thus, a systematic review of the literature is highlighted using the Prisma framework in Figure 6.

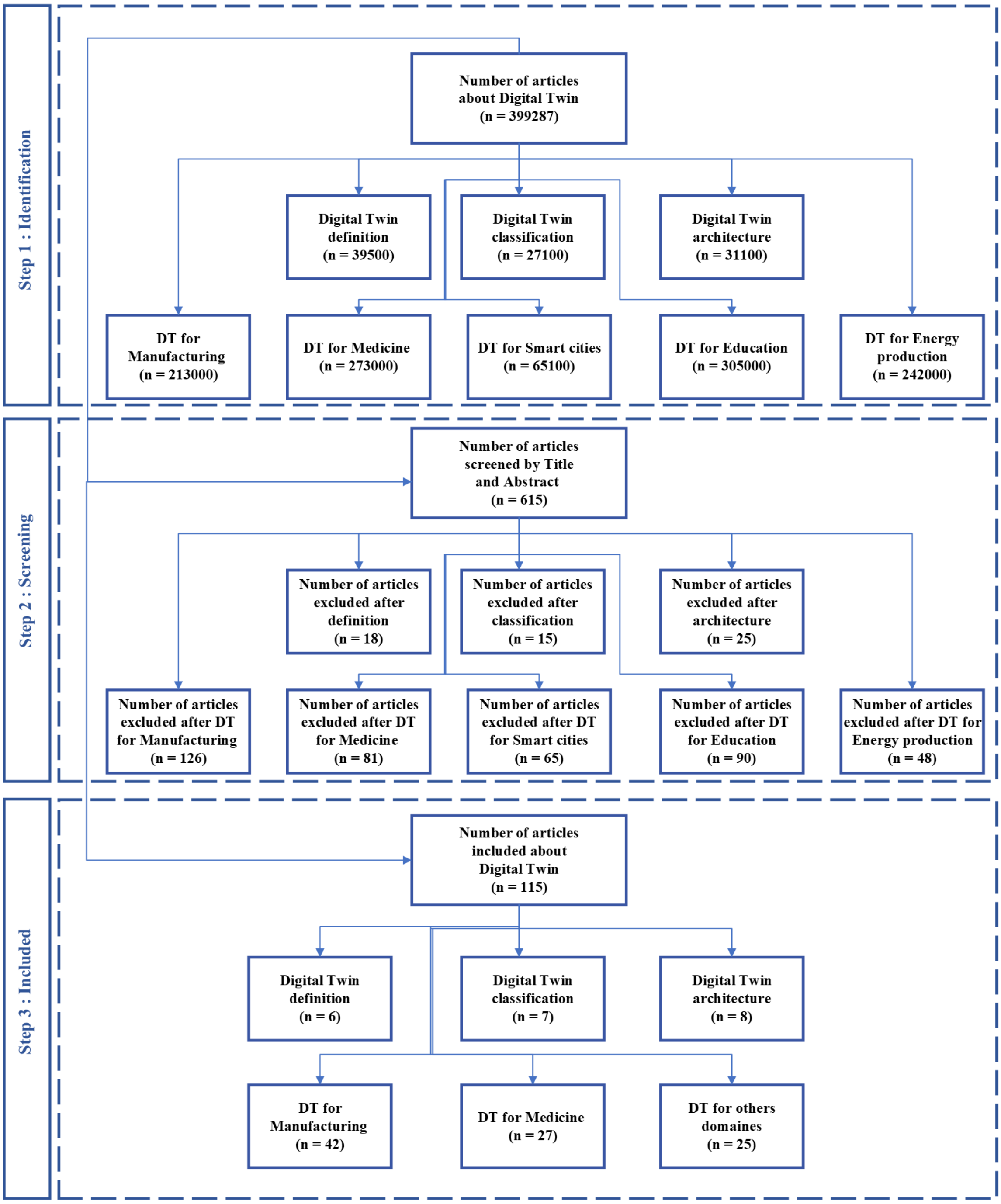


Figure 6. The systematic review using the Prisma framework.

3. Digital Twin, from Concept to Architecture Model

This section is organized as follows. First, it presents a historical perspective on the DT approach, starting from the concept, and then presents a set of classifications used in this field. Subsequently, it presents various architectural solutions proposed in this context.

3.1. The Concept of Digital Twins

A Digital Twin is a virtual model of a product, service, or process, representing one of the technologies that has a high potential for use. The beginning of DT development was marked by Grives [2], who wanted to achieve "a digital, virtual model of a physical product". In fact, the beginning of DTs was due to the National Aeronautics and Space Administration (NASA) [3], but also due to the Air Force Research Laboratory (AFRL).

Initially, regarding the implementation and use of DTs, there were limitations related to data acquisition, use of prediction algorithms, and performance. After their remediation in 2016, DTs began to be used in Industry 4.0 by Siemens, Munich, Germany. Then, Thao et al. [4,5] advanced a three-dimensional model that was originally developed by integrating two more dimensions for DT services and data.

The wide interest in this field can also be found in various definitions found in the specialized literature, which denotes a great potential in terms of development, especially the breadth of the concept. From a multitude of definitions, we highlight the following in Table 1.

Table 1. Digital Twin definitions.

Authors	Year	Definition
Grives et al. [2]	2016	"The Digital Twin theoretical model [. . .] contains three main components: (a) real environment physical products (b) virtual products in virtual space, and (c) the information and data links which connects real and virtual products."
Negri et al. [6]	2017	"The Digital Twin is a production system virtual representation which can be executed on various simulation environments, through the synchronization between the real and virtual system, using mathematical models, appropriate information. connected intelligent devices and mathematical models."
Autiosalo et al. [7]	2018	"The DT is the cyber part of a cyber-physical system (CPS)."
Boschert et al. [8]	2018	"The Digital Twin vision consists of a complex description at the functional and physical layer of a system, product or component, that integrates useful data, which can be of interest for all phases of the on-going and and subsequent life cycles."
Thao et al. [9]	2018	"Full DT should integrate five components: services, data, connections, virtual component and physical component."
Zeng et al. [10]	2018	"DT represents an integrated system which is able to monitor, simulate, regulate, compute and control the system's process and status."

Depending on the scope, Digital Twins can exhibit different characteristics [11]. Based on the specialized literature consulted thus far, the common characteristics are as follows:

- *High degree of accuracy:* From the appearance, functionalities, and content point of view, the DT must be an accurate copy of its physical counterpart. Thus, the higher the precision, the actions and simulation scenarios should achieve the same behavior both in the physical and virtual environment.
- *Dynamic:* Communication between the physical product and its virtual twin must be continuous and bidirectional, and any change made to one must be reflected in the behavior of the other.
- *Self-evolving:* Throughout the life cycle, the DT follows the changes along with its physical counterpart. The DT adapts and optimizes with the aid of the data received from the physical counterpart in real time, evolving with it.
- *Identifiable:* Each real product must have its own DT. During the product life cycle, information and functional models evolve, and based on this, at any point in time, the DT can be identified in a unique mode from its physical twin [11].

3.2. Classification of Digital Twins

In ref. [11], Singh et al., realized a hierarchization of DTs, considering the moment in which it was created, the level of integration, the applications, the hierarchy, and the level of maturity. They classified DTs according to several parameters to provide a complex view of how information is stored, managed, and interpreted. Following the classification by Singh et al., it is desirable to create an ontology—Figure 7.

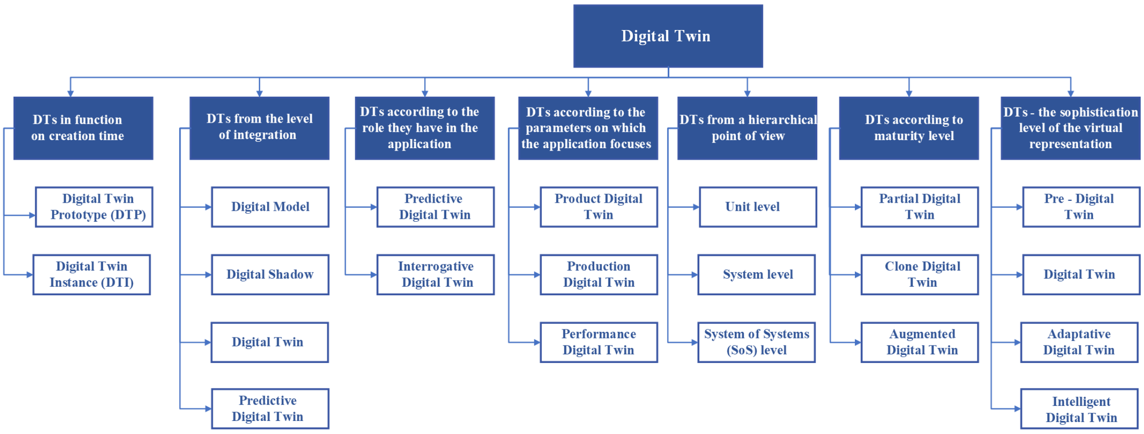


Figure 7. Classification of DTs.

Depending on the time of the creation of the DTs, Grieves and Vickers [12] proposed two categories of DTs, which were developed at different stages of the life cycle: before the creation of the prototype, that is, in the design stage, and in the production phase. These DTs were integrated and used in a Digital Twin Environment (DTE).

- *Digital Twin Prototype (DTP):* The DTP is the DT that contains the essential information for creating a physical copy of a virtual version. The product cycle will be initiated upon achievement of the DTP, which undergoes several tests before the physical twin is created. Once the DTP is realized and validated, its physical counterpart can be produced in the real environment. The simulation accuracy determines the physical twin quality.
- *Digital Twin Instance (DTI):* The DTI originates in the production phase and is a DT that is strongly correlated, throughout its life cycle. After building the physical system, real space data are transmitted to digital space and, reversely, to predict and monitor the system behavior.

From the application point of view, Grieves and Vickers [12] classify DTs according to their roles, implicit prediction and query:

- *Predictive DT:* DT predicts the behavior and performance of its physical counterpart.
- *Interrogative DT:* The DT is used to query the status of its counterpart.

Depending on the integration level, Kritzinger et al. [13] structured DTs into four categories, as follows:

- *Digital Model:* The data between the physical and virtual object are manually changed by the user. Any change to the state of the physical object is not reflected in the virtual object, and any change to the state of the virtual object is not reflected in the physical object.
- *Digital Shadow:* The data of the physical object is automatically transmitted to the virtual object, so there is one-way communication between the two objects.
- *Digital Twin:* This DT category involves a two-way data transmission between the physical twin and the digital one, and any modification made to both the physical and the digital object will be reflected in the behavior of its counterpart.
- *Predictive Digital Twin:* Like the normal Digital Twin, it is characterized by continuous, real-time communication between the two components. The novelty brought by the Predictive DT consists of the fact that the digital twin also contains cyber security components and artificial intelligence algorithms that increase the accuracy of the simulation results and allow predictions to be made.

According to [12,14], a division of DT can be made according to the parameters on which the application focuses, such as the product, process, and performance:

- *Product DT:* DT is used for prototyping, and various conditions are analyzed, which helps to confirm that the physical product behaves according to the desired standards.
- *Production DT:* DT is used before actual production and has a role in process validation, simulation and analysis. It also helps develop efficient production methodologies.
- *Performance DT:* This DT can include both actual product and production performance and is used for decision-making processes by receiving, integrating, and analyzing product data. It also optimizes operations based on resource availability, providing the opportunity to improve product and production DT through a feedback loop.

From a hierarchical perspective, DT can be structured on three levels.

- *Unit level:* Represents the smallest unit participating in production and examines the functional, geometric, behavioral, and operational model of the physical counterpart unit level.
- *System level:* Represents a collaboration of unit-level DTs, and each unit-level DT represents a component of the new system.
- *System of Systems (SoSs) level:* Represents the connection of multiple system-level DTs to form a system of systems. The system-of-systems DT also includes various phases throughout the life cycle of a product.

Depending on the maturity level, a classification of DTs was proposed in [15] as follows:

- *Partial DT:* May contain parameters (pressure, temperature, humidity) and is used to determine the DT functionality and connectivity.
- *DT Clone:* It is used to make prototypes that are made by means of the relevant data about the product/system. The data are contained in this DT.
- *Augmented DT:* It has the role of making a correlation between current data and past data based on algorithms and analyses.

According to [16], Madni et al., proposed a classification of the DT not only according to the level of maturity of the data but also according to the level of complexity of the virtual model as follows:

- *Pre-Digital Twin:* In this stage, the DT is created before the physical object and is used in the process of decision making, referring to the prototype to reduce the risks that may arise.
- *Digital Twin:* It represents the second stage, and at its level, the data of the physical product are incorporated. It is applied in the design and development decision-making phases of the product life cycle, and data transfer to it is realized in both senses.
- *Adaptive Digital Twin:* The DT offers a dynamic interface between the DT itself and the physical object. It has the ability of priority learning and can maintain the human operators preferences with the help of supervised machine learning process. Operation's real-time decision-making and planning are also noted as advantages.
- *Intelligent Digital Twin:* Unlike the Adaptive DT, this DT offers unsupervised machine learning functionality, increasing its autonomy. It also provides higher accuracy and efficient system analysis.

Table 2 shows the classification of DTs according to the previously mentioned criteria together with the corresponding bibliographic references.

Modeling the information regarding a device, production unit, or plant, generally called an "asset", across it's lifecycle, through digital representation, has been used by industrial manufacturers, but still it has no Digital Twin significance.

Table 2. Classification of DTs adapted from [11].

Classification Criteria of DTs	Types of DTs	Selected References
Depending on the time of creation	• Digital Twin Prototype (DTP) • Digital Twin Instance (DTI)	[12]
Depending on the integration level	• Digital Model • Digital Shadow • Digital Twin • Predictive DT	[13]
From the application point of view	• Predictive DT • Interrogative DT	[12]
According to the parameters on which the application focuses	• Product DT • Production DT • Performance DT	[12,14]
From a hierarchical point of view	• Unit level • System level • System of Systems (SoSs) level	[12,14]
Depending on the level of maturity	• Partial DT • DT Clone • Augmented DT	[15]
Functional sophistication level of the virtual representation	• Pre-Digital Twin, • Digital Twin • Adaptive DT • Intelligent DT	[16]

Nowadays, Digital Twin's added value, which extends the capabilities of information models, is mainly related to digital technology improvements, architecture development, standardization, new use cases, interactions, and business models facilitated by the Digital Twin (Table 3).

In many Digital Twin use cases, it is required to store data externally, for example, in the Cloud, so it is necessary to have high-speed and reliable connectivity to the manufacturing processes, assets, and operators. Adequate security capabilities are important for data acquisition, exchange, control, and management.

Some processes and products offer the possibility of realizing their digital twins, as an isolated solution. However, many use cases rely on interactions between several digital twins offered by different companies. These points highlight the necessity of Digital Twins interoperability and related data management, synchronization, and exchange.

Based on these technologies, digital twins can enable new use cases such as real-time simulation of production systems, information exchange across the manufacturing chain, predictive product design, efficient commissioning of devices and plants, analytics, and manufacturing [17].

Table 3. An overview of Digital Twin capabilities, technologies, and features.

Digital Twin Capabilities	Technologies	Features
Data acquisition	IoT Sensors	Data format, enrichment, configuration
Information access API	Monitoring, interactions, engaging, control of the physical devices	Information access and processing, upon request
Deployment/simulation	Cloud Computing	Cloud-based DTs of manufacturing machines
Information model	Virtual/Augmented Reality	Optimization, quality assurance, testing
Security	Cyber-security	Role-based access control for authenticated users
Interoperability	5G, wireless connectivity	DT various information format
Synchronization	DT replicas correlated with adjacent architectural tiers	Data transmission between architectural tiers

3.3. Digital Twin Models, Frameworks, and Architectures

Several DT models, frameworks, and architectures have been proposed in recent years in order to structure different perspectives and facilitate common understanding. Taking into account the application domains, different approaches (some of which are presented below) can be identified. DT models can be analyzed from the perspective of a combination of models and algorithms; therefore, certain aspects can be treated differently.

Yuqian et al. [18] proposed a reference model based on physical objects, the Digital Twin, and implicitly the level of communication between the two parties. Alam et al. [19] demonstrated that peer-to-peer data transmission between a physical and virtual counterpart can be achieved through CPS, and Bevilacqua et al. [20] presented a reference model of DTs for risk reduction in processing facilities. Being in a continuous development process [21], ISO 23247-2 [22]focuses on providing a general architecture for the entities and domains of the DT reference structure in the production area [23].

Table 4 shows a comparison of the results proposed in [18,19,23] based on a set of characteristics and criteria.

An architecture model containing a general description of the levels defining the Digital Twin was proposed by the German Association of Electrical and Electrotechnical Manufacturers [23] and aims to develop a general framework that defines business models and products [21]. The reference architecture addresses the fundamental structure of the process, including the design, development, and implementation phases, and can be used in Industry 4.0 applications. In Figure 8, a unifying model is presented. The model is based on the reviewed architectures, following the guidelines from [23]. Digital Twin components are highlighted, and the relation between the physical entities is detailed.

The first level is represented by the level of abstraction within the Digital Twin (the physical, communication, digital, and cybernetic layers of the application). The physical layer contains real-world objects. The communication layer contains elements that enable communication between physical and digital entities. The digital layer contains an abstraction from the real world. Data security elements were included at the cyber layer level. The application layer contains elements that favor connections with other Digital Twins. In addition, elements have been introduced that highlight the service process evolution life cycle. It contains iterative improvements that are brought to the process/service throughout its life at various levels. For example, for a product/service, improvements can be made during the life cycle at the cyber layer to secure and encrypt the data. The Agile methodology is used to introduce these small improvements, which are carried out at short time intervals.

The integration dimension of the Digital Twin is brought to the fore (Digital Shadow, Digital Model, Digital Twin, or Predictive Digital Twin). The Digital Model involves making a digital copy of the physical object; between the two entities, there is only an offline synchronization of behaviors. In the case of digital shadows, the digital component reflects in real time the changes that occur on the physical object, but it can only influence the offline behavior of the physical object. The characteristic of the Digital Twin is that the two entities influence each other in real time. The novelty introduced by the predictive Digital Twin is that the virtual model is a more complex one, including elements of data security and artificial intelligence, among others.

Table 4. Comparison of architectures adapted from [18,19,23].

Characteristics	Yuqian et al. [18]	Alam et al. [19]	Aheleroff et al. [23]
Application Field	Smart manufacturing, convergence of digital and physical space	Cloud-based cyber-physical systems, telematics application	Industrial transformation, mass individualization
Technologies and methods used	Technologies for data processing and information model	Cloud computing, Bayesian network, fuzzy logic	Cloud computing, Internet of Things, augmented reality, ThingWorx, Vuforia
Key aspects	Data-driven smart manufacturing, smart decisions at every manufacturing point	Telematics-based driving assistance	Real-time monitoring, Remote controlling, Prediction
Architecture model	Proposes a reference model for DT in the context of smart manufacturing	Reference model for C2PS architecture	Adopts RAMI and an agile model for integrating different levels of DT
The relationship with Industry 4.0	Integrating DT in smart manufacturing operations	Integrating cloud computing and physical sensor level control	Use of Industry 4.0 technologies
Data source	Capturing information from physical devices and their integration into the manufacturing process	Capturing information from physical devices	Integration of data from various sources
Adaptability	Adaptability to varied production needs	Adaptability to environmental changes	Adaptability in deployment and integration
Security	Implementing security measures and controls in the context of smart manufacturing	Implementation and compliance with security strategies for data in Cloud	Use of security technologies in DTaaS
Interoperability	Compliance with ISO standards and compatibility with existing systems	Integration with other systems and compliance with standards	Agile approach for different levels of integration
Challenges and future research directions	Standardization of communication protocols, real-time data processing, timeliness and accuracy of models, reliability	Scalability and the realization of interactions between systems, integration with Blockchain and artificial intelligence	Integration levels, mass individualization, resilience of the Digital Twin

One of the tools with a high degree of generality that can be used in the modelling and simulation of Digital Twins are represented by the Discrete Event Dynamic Systems formalism. It can be used by setting certain thresholds of the variables inside the model (whose values are tracked), thresholds that, once reached, become events that change the model.

The advantages of the proposed reference model [23] are as follows.

- The integration of different perspectives to achieve a complex framework regarding the use of the Digital Twin in Industry 4.0.
- Addressing requirements according to production paradigms that make the transition from mass production to customized production.
- Decomposition of a process into sub-processes, which can be approached and adapted with respect to the vertical axis.
- Integration of relationships between different levels, which is achieved through the iterative and incremental process.

In ref. [19], Alam et al., highlighted that the cyber-layer of a cyber–physical system should integrate cloud technologies that ensure the scalability of storage, calculation, control, and communication capacities. Thus, the Digital Twin can continuously provide a feedback loop with a role in improving the services provided by physical systems. In addition, to achieve this objective, a reference architecture was proposed including operational modes, the fusion module for sensors at the physical level and the fusion module of the Digital Twin services at the cyber level, thus facilitating the integration of the sensor–service fusion module.

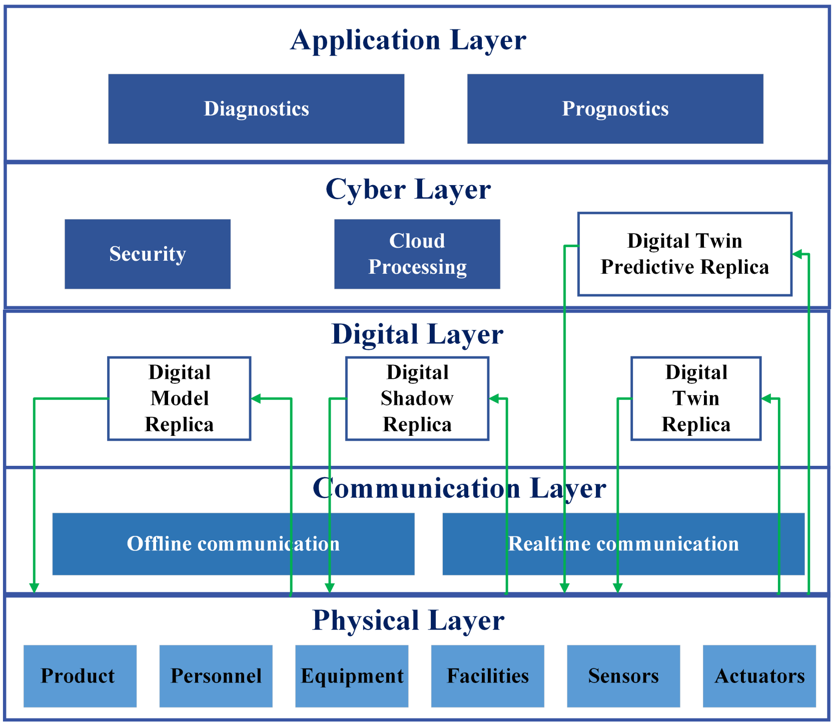


Figure 8. Unifying concept of DT.

In ref. [24], Kontar et al., proposed the use of methods to ensure the progress of Digital Twins by building a global model through which the common characteristics of the systems and the intrinsic relationships at the data level are identified. The proposed approach contributes to the improvement of the prediction accuracy of the DT model accuracy. Based on the global model, a personalized model can be developed, using the multi-tasking learning principle. This principle's benefits have been extensively presented in [25]. The meta-learning model examines the adaptation of the global model using the principle of "fast learning" through the use of a reduced quantity of training data. This principle is presented in [26]. Using the meta-learning model does not ensure performance at the system level but provides advantages in relation to specific tasks.

Another model of the life cycle presented in [10], assumes the structuring of the DT on three components: physical space, the data processing layer, and the digital space (as shown in Figure 9).

In ref. [10] an application framework is presented. The physical space represents a dynamic environment of production that comprises people, machines, materials, and rules. The physical space, in turn, is composed of two elements: resource level and connectivity level. The resource tier includes objects connected with product design, production, and development; computing clusters with high performance; and software capabilities. Objects are separated and distributed in different locations with the goal of being connected through the IoT. Then, the data from the physical space are used for optimization, following their collection and integration. The processing information layer is the link channel between real and virtual spaces. It contains three main functional modules that play roles in data mapping, storage, and processing. The information that must be stored represents data from both the physical and virtual spaces. Physical space data include production, equipment, and material data. Virtual space data refer to the evaluation, simulation, decision, and prediction data.

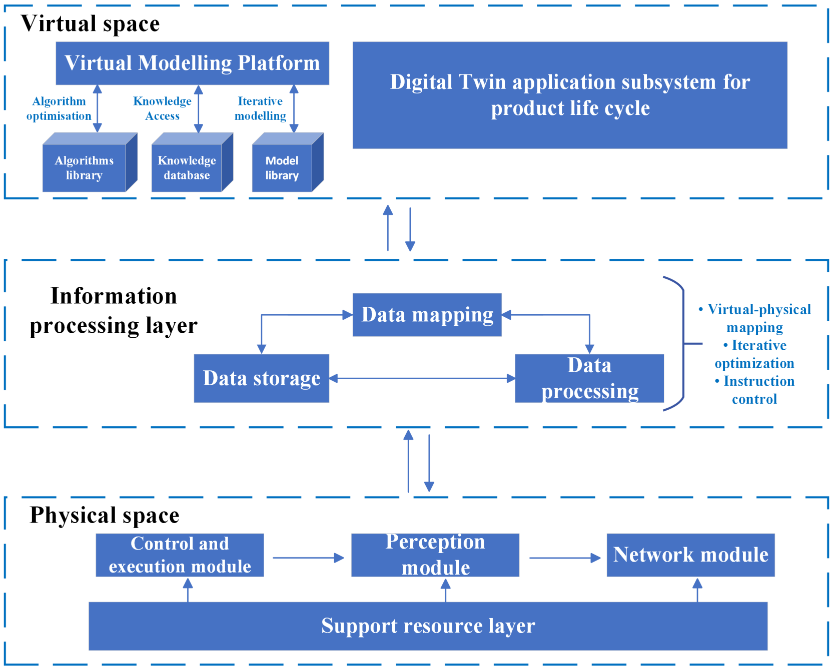


Figure 9. Application framework adapted from Zeng et al. [10].

Four stages comprise data processing: data acquisition, extraction and analysis, preprocessing, and fusion. The raw data are collected and then preprocessed; this procedure also involves rule-based data filtering, primary clustering, and structuring. Thus, the data consistency, quality, and accuracy increase, and by means of oriented data analysis, the frequent patterns that will be used throughout the life cycle are extracted.

Data mapping includes three main parts: real-time transmitted data analysis, synchronization, and correlation. Using the sequential data mining algorithm, a time-sequential data model was built, revealing the procedures of manufacturing data evolution. The correlation of data is performed by means of rules for correlating different data between digital and physical objects. Two types of data synchronization can be conducted: synchronization in real-time and asynchronous, which is not achieved in real time.

Real-time synchronization connects the physical controller to the simulation model. Thus, the physical controller can be validated with the aid of a virtual test system.

The VMP ensures different DT virtual models, such as the workflow and simulation models. In the virtual space, physical object modeling is performed by obtaining characteristics from the database of the virtual model while the 3D model behavior feedback is stored in the database. In DT, a synchronous combination of real-time data from historical data, virtual models, and physical product data was performed.

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Regarding DT, as in physical object real mapping, a complex system simulation of complex systems is performed. When behavioral uncorrelations occur within a physical system, virtual models can be verified in real time, making predictions that can relay information back to the physical environment.

4. Analyses of the Applications of Digital Twin Models

The digital transformation process for real-world entities is illustrated in Figure 10. There are three types of real-world entities: those related to the human component, those related to technology, and those related to the process. Through digital transformation, human components create digital clones, the process component is abstracted in the form of a Digital Thread, and the elements of technology are associated with the Digital Twin. The Digital Twin processes the received data sent over time by its counterpart in physical space, and the simulation is based on mathematical models. With the aid of artificial intelligence, Digital Cloning and Digital Threads are developed to create sustainable environments. A Digital Thread covers the development cycle of a product, playing a primary role in making predictions and decisions. Through this approach, the entire system has been broken down into components that lead to building a digitally oriented organization based on scalability, autonomy, and innovation [23].

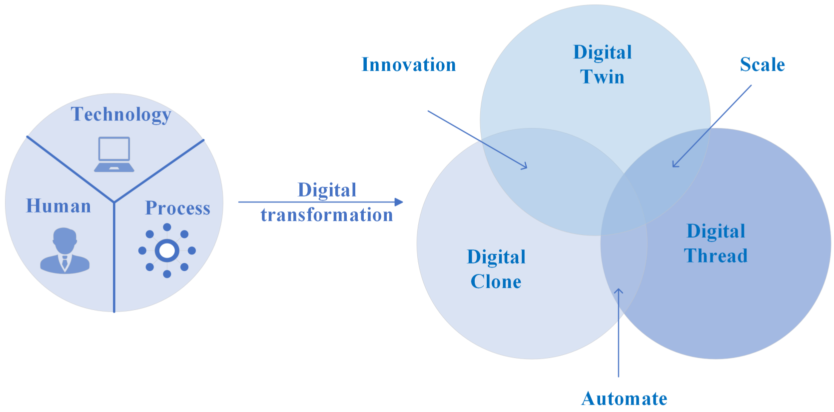

Figure 10. The process of digital transformation of real-world entities.

Digital Twins are beginning to be extensively used for applications in various domains. Important achievements identified in manufacturing and medicine are discussed in the following two sections—Sections 4.1 and 4.2. Relevant applications in other domains are discussed in the third section—Section 4.3.

4.1. Manufacturing

In the manufacturing domain, DT integration is a significant stage and is closely related to concepts such as Product–Service Systems (PSSs) and Cyber–Physical Systems (CPSs). The synergistic interconnection between DT, PSS, and CPS is envisioned to redefine how products are designed while also opening new horizons in providing personalized services and in optimization of resources.

The results of the search for the concept of "Digital Twin in manufacturing" show a minimum number of articles on IEEE Explore—1497, followed by the Web of Science—2272, Scopus—20,205, and Google Scholar—213,000. The number of articles highlights the fact that the applications of DT in manufacturing are a field of interest.

4.1.1. Application and Adoption of Digital Twin in Manufacturing

Starting from the study conducted in [27], traditional production has been known as an industrial process primarily focused on converting raw materials into finished products. However, with technological advancements and increasing quality demands, there has been a shift from conventional to intelligent processes. This transition has led to the introduction of the Digital Twin concept in production, facilitating seamless communication and interaction between the physical and digital realms. Moreover, recent technological strides have enabled the automation of production processes, with the Digital Twin aiding in visualizing real manufacturing processes and comparing physical products with their virtual counterparts. This fosters collaboration and real-time information gathering about products under production. In ref. [28], Rosen et al., demonstrated how Digital Twin technology contributes to transforming cyber–physical production systems into autonomous ones. Additionally, in ref. [29], Park et al., illustrated the implementation of a Digital Twin that aids in addressing personalized production challenges and issues encountered in distributed production systems.

The Digital Twin contributes to process optimization and asset management, supporting interaction between humans and robots. In the context of dynamic production planning with the aid of the Digital Twin, through the integration of real-time sensor data, data obtained from simulation processes, and via Enterprise Information Systems (EISs), Tao and Zhang [30] highlighted how this technology facilitates the adaptation of production plans to changes in the manufacturing environment. In this context, the Digital Twin enhances the efficiency and adaptability of manufacturing processes, with a wide range of industrial applications. Following a detailed analysis, Liu et al. [27] concluded that the Digital Twin is personalized, reflecting the behavior of the physical twin with a high degree of fidelity. Additionally, the authors emphasized the importance of multi-physics aspects and continuous updating of the model throughout the product lifecycle. Another characteristic of the Digital Twin is controllability, whereby changes at one twin level control the other, thus closing the loop between digital and physical twins and facilitating the convergence between digital and physical environments.

Integrating the concept of Product–Service Systems (PSSs), with the concept of Digital Twins throughout the life cycle of a product facilitates the creation of real-time physical–virtual and virtual–physical connections. The combination of a multitude of frameworks, methods, tools, and models can be achieved using the analysis—evaluation validation process.

In ref. [31], the authors presented a solution for the use of DTs in the PSS field, including both models in which connections could not be made between P2V (Physical to Virtual), V2P (Virtual to Physical), and their counterparts, as well as case studies that have been based on various notions related to Digital Twin, Product Avatar, and Digital Thread. The use of DTs can be achieved in each stage of a product's life cycle: design, manufacturing, and end-of-life.

At the beginning of life (in the product design stage), as mentioned in [32], DTs can be used to pre-identify customer requirements and correctly interpret the data based on some design parameters, using the results obtained by following the interaction with the product. Acting as a "shadow" and being defined as a proposal for PSS, [33] details the advantage of using DTs in the design phase of PSS to better understand business systems and the relationships between all their components.

Similarly, in the design phase [34], knowledge from transversal domains can be integrated into a unitary database of knowledge to achieve a robust thinking mechanism and high autonomy in the PSS system design process. The focus is on methods of data collection, storage, transmission, and analysis, with the aim of updating the requirements of intelligent PSS, turning its perspective towards sustainable production. In Ref. [35], a method to evaluate the product life cycle with the aid of DTs was proposed, where real-time data exchange between the virtual and physical components is not necessary.

From the point of view of the production stage, real-time monitoring using DTs is presented in several works, including [36–39], with the last two also referring to the concept "Digital Thread" (the information stages and their sequencing that characterize the life cycle of the PSS). Similar information related to the production step was provided in [27] for the scope of manufacturing.

Regarding the final phase of the PSS, Ref. [40] presented how the DT can be used to anticipate the faults that may occur in a city, with the aim of avoiding them as much as possible or at least mitigating their impact. In ref. [41], the information collected from the DT during the previous phases of the PSS life cycle was applied to offer recommendations for their improvement or reconditioning. From the perspective of recycling, in [36,42–44], the authors present how Digital Twin can be used to ensure that the last phase of the PSS (recycling) is also sustainable. System status monitoring is updated at well-established time intervals or can be performed manually.

A complex synthesis of the analysis, applications, and technologies used in the development of DTs in manufacturing was presented in [27]. In the authors' opinion, DT-based applications have benefits in terms of both shortening the design and cycle of a product and reducing costs. The study points out the benefits of using DTs in the different stages characteristic of the manufacturing process, namely the stages of design, production, maintenance, and decommissioning. Each of these stages is characterized by a series of activities for which the use of DTs brings benefits, which are presented in this paper. From the manufacturing stage point of view, for example, in [45], it was stated that the information provided by DTs allows designers to form a much more detailed overview of the implementation of the results of the design stage. Verification of the conformity of the specifications can be performed through DT, as presented in [46]. Storing and using the acquired data in real time confers the possibility of knowing the current state of the manufacturing process and the equipment used. As a result, DT can interchange data with the manufacturing environment to evaluate and optimize the process parameters. Regarding asset management (one of the activities of the production stage), DTs help in decision-making, asset planning, configuration, commissioning, reconfiguration, and status monitoring [47]. The Digital Twin Shop floor (DTS) paradigm proposed in [30] supports the fact that the production design is made using Enterprise Information System (EIS) data, both from sensors and simulation results.

In ref. [48], a study was conducted that illustrated the concept of a Digital Twin and its application in different industries, such as manufacturing, aerospace, smart cities, AR/VR, and the food industry, based on different customized features, modeling strategies, and methods of use. The authors structured the technical modeling methods into three types: technology-based, DT basic, main, and core technology. The core technologies of DTs examines the perception of physical entities by using sensor-based, IoT, and data transmission technologies, and DT model visualization. The main technologies ensure the accurate prediction of the performance of physical entities and monitor the changes that occur at their level. Advanced technologies, such as big data analysis, edge and cloud computing, machine learning, artificial intelligence, blockchain, mobile devices and technologies, virtual modeling processes, virtual–physical data fusion, data analysis, and simulation, can also be streamlined.

Jia et al. [49] proposed a complex Digital Twin (DT) modeling method based on model division, assembly, and standardized processing. The first stage of the process is represented by dividing the complex model of the DT into different models according to context, composition, code, and modules in the 4C (Composition–Context–Component–Code) architecture. Four characteristics of complex digital twins were also specified: interoperability, extensibility scalability, and fidelity. Composition and context have the role of influencing the digital twin to consider, in a specific scenario and scale, effective elements, and components. The digital twin-associated code was developed in standard-based modularization. The next stage is the assembly of simple DT models into high-complexity models through a knowledge graph, ontology, and analysis of multi-context scenarios. Efficient data update methods are used to achieve information fusion as static data, which are updated only when the DT is initiated, or real-time updated and dynamic data. The knowledge graph realizes structural correlations among the various scales of simple DTs and records the necessary attributes of the physical entities.

Cyber–Physical Systems (CPSs) are systems that use sensors and execution elements in connection with physical processes, acquire and analyze recorded data, and actively and reactively change information with the physical and virtual world, according to [50]. In ref. [51], the idea was circulated that a Digital Twin can be used to safely monitor and control human–robot assembly operations, performed in a collaborative mode, and ensure this interaction at a distance. In Refs. [52,53], DT was used for HRC modeling, reconfiguration, and collaborative assembly. By realizing the robot CPS-based digital twin and the human operator, it is possible to control the real robot or verify the movement of the real robot, as well as to compute the real-time safety distance.

Following a study carried out by Oracle [54], several elements were identified that increase the value of objects/processes through the use of DTs, among which we mention the following:

- Remote control and monitoring in real-time: the digital twin can be monitored and controlled at any time from any location.
- Increased safety and efficiency: integrating quantitative data and performing complex analyses in real time.
- Predictive maintenance and planning, achieved by continuously analyzing data and taking measures so that the impact of failures is minimal or eliminated.
- Assessment of risks through simulations to take place at the level of the digital twin and finding methods to mitigate risks highlighted from a primary phase of the life cycle.
- Rapid and continuous customization of products and services according to current trends and customer requirements.

In ref. [55], Qi and Tao identified how Digital Twin and big data technologies complement each other, bringing synergy and helping promote intelligent manufacturing. The advantages discussed are product design, production planning, and predictive maintenance. In addition, by means of simulations carried out at the level of digital models, the elements that contribute to the improvement of operation, adaptability to change, and estimation of the product's life span can be identified. The Digital Twin not only helps to accurately identify design defects in the virtual environment, but also to adjust the manufacturing process to achieve optimal production that ensures non-functional requirements such as precision, stability, high efficiency, and quality. Among the challenges mentioned by Qi and Tao, comprehensive studies on the application of Digital Twins in smart manufacturing have a high level of complexity. It is also recommended to carry out exhaustive research to ensure the accuracy of models in manufacturing, as a result of data integration, fusion algorithms, existing models, and platforms.

In ref. [56], He and Bai highlighted that the Digital Twin plays an important role in intelligent manufacturing in terms of equipment, manufacturing systems, and intelligent services. One of the advantages of using the Digital Twin in a production workshop is the real-time monitoring of the machines, products, and reflection of their behavior at the level of the digital model. Thus, the causes that lead to non-compliance of products with quality standards can be identified. In addition, the Digital Twin can contribute to optimizing the operation of devices by performing different simulation scenarios, thereby improving stability. With the help of the Digital Twin, users can be notified of the malfunctions that may occur at the level of physical assets, recommending a series of appropriate measures depending on the situation encountered. Among the limitations of the intelligent manufacturing production line as a result of the use of the Digital Twin, the realization of a large number of experiments to reduce costs and increase productivity was discussed.

Liu et al. [27] identified the advantages of using a Digital Twin in manufacturing as the design of the production system in the form of iterative organization, emphasizing the use of virtual evaluation and verification methods, redesigning existing physical objects, and improving product quality. Among the limitations is the presence of a low level of digital design to facilitate the creation of models with the help of a Digital Twin, as well as problems related to data integration.

In ref. [57], Wang and Cao presented how the Digital Twin helps identify faults in a two-speed transmission system, which leads to cost reduction and quality assurance. Initially, three types of faults were defined, and then, an anomaly detection model was trained based on the system outputs. An accuracy of 92.7% was obtained, which leads to the recommendation of training the model with the help of generating a large number of data and features on the basis of which to identify anomalies.

In ref. [58], one of the advantages discussed by Augustine regarding the use of Digital Twin in manufacturing consists of standardizing the prototype at the security level by implementing some risk prevention measures, but also in ensuring interoperability. The Digital Twin can also contribute to the development of digital models to ensure an efficient connection between different production locations, thus facilitating the efficient conduct of operations throughout the supply chain. Among the disadvantages mentioned, the emphasis is on the need to change the mindset of the staff regarding digital transformation in the manufacturing industry and to implement an organizational structure that supports the adaptation of the Digital Twin and modular testing.

Some of the CPS challenges that can be solved using digital twins may arise from the cyber-security domain. It is recommended to carry out a risk analysis to avoid the appearance of vulnerabilities that can lead to unauthorized access to the system and data manipulation, which are affected by cyber-attacks. Additionally, data protection and privacy procedures must be implemented to prevent unauthorized access and data leakage. Using large volumes of data can lead to erroneous information management and analysis, which affects the modeling process. Thus, in such circumstances, the behavior of the system in the physical environment cannot be accurately reflected by the Digital Twin. In addition, when different equipment and technologies are used, their interoperability and integration can be complex, and problems can occur. The lack of digital twins and CPS interoperability during update operations can also cause problems that affect their adaptation and maintenance processes.

Xu et al. [59] presented an approach for identifying CPS anomalies using a Digital Twin (Adaptive Technologies for Integrated Industrial Networks—ATTAIN). The advantage of this approach is that it obtains a large amount of real-time data from physical assets, which leads to the rapid training of the error prediction algorithm. The performance of this approach is higher than that of detection methods such as SWAT (Smart Workflow Automation Technology), WADI (Wireless Automation and Digital Integration), and BATADAL (Blockchain-Augmented Technologies for Advanced Data Analytics and Logistics). Among the challenges and limitations noted are the high level of complexity in establishing communications between the Digital Twin and the corresponding CPS to obtain real-time operating data, as well as the high probability of attacks occurring during the start-up phase of a CPS.

In Ref. [60], Stary et al., pointed out that the development of Digital Twin models allows horizontal and vertical integration of CPS components. Various parameters, such as depth, connectivity, validation, and variability of implementation in the context of human-based modeling, were considered in the proposed traffic management case study. Consequently, the use of Digital Twins in the context of CPS enables the dynamic allocation of physical and virtual entities based on operational conditions, leading to organizational and technological innovation.

Steinmetz et al. [61] proposed an ontology for DT modeling in the context of CPS, by which simulation, monitoring, and management were identified as benefits. Different rule-based simulation models were created on the simulation side. Monitoring is performed with the help of a communication interface that allows the exchange of data between physical and virtual assets to make decisions and update the status of the devices. In addition, a management system can be created at the DT level to ensure continuous monitoring of access, authentication, security of stored data, and information obtained using the prediction algorithms used. As a challenge, the lack of semantic models was identified as a starting point for the design of an ontology, but also for the design models of the Digital Twin.

In ref. [62], Son et al., proposed a Digital Twin-based CPS for automotive bodywork production lines, thus having the possibility of checking whether production could be carried out according to the plan. In addition, through the Digital Twin, various changes were proposed in terms of product ordering, verifying both the degree of adaptability to the abnormal scenarios that may occur and the monitoring of the behavior of the production lines. Although the Digital Twin ensures the interoperability of the entire system, some challenges are also mentioned. Among these, he mentioned the development of a Digital Twin to facilitate general production, not just for body production lines.

4.1.2. Benefits and Challenges of Digital Twins in Manufacturing

In the following, the advantages and disadvantages identified as a result of the use of DT in manufacturing will be presented. Also, factors related to the integration of Cyber–Physical Systems (CPSs) in manufacturing will be highlighted.

- *Benefits*

Among the benefits of using Digital Twin in the field of operational efficiency are the implementation of continuous simulation and testing processes in the virtual environment, predictive maintenance, resource optimization, and cost reduction. Regarding planning and scheduling processes, these can be improved by creating an overview of the production chain, taking into account continuous changes in specifications, customer requirements, and market needs.

The use of Digital Twins contributes to ensuring production quality and compliance with appropriate standards. However, the main advantage of using Digital Twin lies in accelerating the development and innovation process, which facilitates the simulation, development, and testing of products in the virtual environment. Thus, errors that could occur on physical production lines can be avoided, leading to cost reduction.

Another benefit of using Digital Twin is that it allows real-time monitoring of CPS, playing an essential role in identifying potential failures. Additionally, the use of Digital Twins contributes to optimizing resource consumption, thus increasing their efficiency. In this context, Digital Twin helps reduce manufacturing and maintenance costs. The development of efficient solutions, based on anticipating and avoiding functional and testing problems, can be achieved through simulations and experiments conducted in the virtual space, without using the physical space. Therefore, the efficiency of CPSs in terms of innovation, rapid development, and technology implementation, as well as their adaptability to variable requirements and environmental conditions, can be improved.

By continuously acquiring data from physical assets and processing stored information, decision-making algorithms can be developed and improved. This allows for increased efficiency and precision in production and maintenance processes, while also ensuring adaptability to the constant changes in the market and technology.

- *Challenges*

In the manufacturing domain, significant challenges associated with the use of Digital Twin can be caused by the complexity of the modeling process. Creating a Digital Twin for an entire industrial process or for sub-processes relies on the specifications and operating mode of the equipment, as well as the understanding of the process by all stakeholders. This aspect requires effective collaboration and communication between engineers, operators, and managers to ensure that all relevant aspects are captured and correctly integrated into the digital model. Additionally, another challenge can be the emergence of significant cost issues related to the acquisition of necessary hardware and software resources, as well as employee training.

Implementing a Digital Twin requires considerable investments not only in technology but also in personnel training to efficiently utilize the new tools and techniques. Moreover, it is essential that all employees understand the functionality and benefits of using Digital Twin to fully exploit its potential.

In the manufacturing field, strict regulations regarding data management, protection, confidentiality, and compliance with standards are necessary. In this regard, organizations must ensure that sensitive data are protected against unauthorized access and security breaches. Organizational culture is a key factor in the use of Digital Twins, as it will be necessary to implement management change procedures. These procedures must include effective communication strategies and continuous training to facilitate the transition and ensure the acceptance of new technologies by all members of the organization.

Regarding the interoperability between Digital Twin and CPS, identified challenges include issues related to cybersecurity and managing large volumes of transmitted and processed data. Cybersecurity is a primary factor in protecting sensitive data and preventing cyberattacks, which can compromise the integrity of the entire system. Additionally, handling and analyzing large amounts of data require robust data infrastructures and advanced algorithms to ensure that relevant information is efficiently extracted and used.

4.2. Medicine

The Digital Twin applicability in medicine has become a subject of interest in recent years, the proof being represented by the number of articles published in this field. Thus, the DT can contribute to the development of personalized medicine by continuous monitoring of the patient's health and identifying pathologies from the incipient phases. Also, different pathological scenarios or treatment suggestions can be simulated. The results of the search for the concept of "Digital Twin in medicine" show a minimum number of articles on IEEE Explore—114, followed by 161—Web of Science, 307—Scopus, 273,000—Google Scholar. Thus, the presence of a total number of 273,582 articles suggests a tendency to coagulate interests in personalized medicine.

4.2.1. Application and Adoption of Digital Twin in Medicine

One of the fields that benefit more and more from the use of DTs is the medical field through the existence of smart portable devices that monitor people's health in real time and by combining engineering and medical knowledge and integrating data laid the foundations of a connected health system [63]. In ref. [64], the authors envisage DT as a digital model of the dynamic characteristics of the individual, namely the evolution over time of the molecular state, physiological state, and lifestyle. A review of the latest engineering achievements in the Organ-On-a-Chip (OOC) domain was presented in [65,66]. This is based on the effect of different drugs on human tissues but replaces the need for human testing with DTs to obtain the same information. By combining several OOC technologies, an overview of the entire organism can be generated, a technology known as Body-On-a-Chip (BOC). Along with communication and cybersecurity technologies, Virtual Reality (VR) and Computer-Aided Modeling (CAM) represent essential elements in the field of remote surgery [67–69].

Through Digital Twins and the implementation of emotion recognition systems, patients' emotions can be identified, and intelligent systems can be built to detect stress and depression in its early stages; thus, medication can be administered in advance. Building ER systems also involves technical limitations, such as limited datasets, high implementation costs, identification of salient features, occlusion and illumination problems, and false classification of emotions. In ref. [70], the authors built a custom Emotion Recognition (ER) system that gathers and processes web camera images. In addition, an end-to-end architecture was proposed by combining the ER system with a Digital Twin with a supporting decision-making role based on emotions. The predicted results can be processed, analyzed, and tested, offering the best-personalized treatment.

The Digital Twin concept emerges as a solution aimed at improving life expectancy and reducing healthcare costs, benefiting both patients and healthcare professionals. Serving as a virtual representation of an individual, it utilizes real-time monitored data to reflect the person's current health status. For example, in [71], researchers proposed a model for classifying heart rhythms using Electrocardiogram (ECG) data, employing neural networks and machine learning algorithms to diagnose circulatory system pathologies, particularly heart-related issues. The integration of IoT into daily life through smartphones, smart buildings, and wearable health monitoring devices has significantly enhanced healthcare systems. These advancements enable real-time health monitoring, assisting medical professionals in analyzing health data, identifying disease predispositions, and ultimately reducing mortality rates. Additionally, studies like the one conducted by Elayan and Aloqaily, structured in three stages, monitor patient health status in real time, allowing doctors to promptly prescribe appropriate treatments and adjust them as needed, thereby improving treatment accuracy and patient outcomes. These algorithms, including MLP

(Multilayer Perceptron), LR (Logistic Regression), CNN (Convolutional Neural Network), LSTM (Long-Short-Term Memory network), and SVC (Support Vector Classification), are pivotal in processing and analyzing patient data for various medical applications, such as heart rhythm classification and disease detection.

In the processing and prediction phase, patient data acquired from portable sensors are transferred to a cloud database in real time, facilitating predictive analysis using machine learning algorithms. Medical staff utilize the results to provide personalized advice and medication during the monitoring and correction phase, contributing to continuous model improvement. The comparison phase involves real-life scenarios, enabling collaboration among patients with similar conditions to enhance Digital Twins and healthcare systems. With governments and organizations supporting the digitization of healthcare, especially amidst the COVID-19 pandemic, continuous sensor monitoring aids in identifying symptoms and potential health issues, allowing for timely interventions and personalized treatments tailored to individual patient data, in alignment with the principles of personalized medicine.

Following the report of the Digital Patient Roadmap [72], computational medicine includes technologies for modeling and simulation, targeting the creation of a digital element called a virtual patient used in prevention, diagnosis, and treatment planning. The virtual patient integrates knowledge from mathematics, computer science, bioengineering, and biomedicine. Because people differ, building a model requires collecting, integrating, and analyzing data from many patients to increase the accuracy of the model. Virtual patient acquisition technology should be completely autonomous.

Philips [73] created a personalized "HeartModel" digital twin by combining Computed Tomography (CT) images before surgery with an X-ray information layer during the medical intervention for surgeon assistance and for providing 3D images in real time to suggest the correct choice and positioning of the devices used.

In ref. [74], a model using a Digital Twin built based with the aid of intelligent algorithms for the diagnosis of chronic congestive heart failure, as well as tests for treatment, is presented. The electrical signals of the heart were simulated using electrolytes, and the models were based on Magnetic Resonance Imaging (MRI) and ECG measurements.

Another representative example of personalized medicine was presented in [75]. Siemens Healthineers Turkey is in a continuous process of developing DTs for organs (especially the heart and brain) through 3D images. As a result of using this technology, the efficiency of operations increases. DTs are used to highlight pathologies from an early age, and the same company made a demonstration at TURKRAD 2019 that helps specialists identify and correct congenital heart defects in infants.

From the desire to see the aging progresses at the cellular level and combat it, researchers have tried to find the correct treatment [76]. The focus has fallen on the development of the virtual patient, for which the digital twin corresponding to the physical patient uses the DNA genetic code for personalization and individualization. The virtual patients can also be used to provide guidance on exercise and diet choices that lead to an improved quality of life [77].

Until the development of DT technology, the vast majority of tests regarding the effects of certain drugs on certain organs were performed in animals [78]. The shift to simulation through DTs has opened the way for research in the field of personalized medicine [79], noting advantages such as observing the hearth complex structure in detail in the model of this organ and taking tissue mobility into account [80].

To capture information from patients, wireless equipment can be used to transmit real-time data, such as heart rate, blood pressure, and breathing [81]. Based on the data, predictions can monitor activity analysis to avoid depression or other neurological and psychiatric disorders. Devices have been developed that simulate the brain's electrical signals, with the patient having an electrode placed on each temple that transmits an electronic signal to the brain. The symptoms of depression can be reduced until they are eliminated. To collect real-time data from patients [82], applications have been developed where they can enter data, such as their mood and feelings, which can be stored in a database that the doctor can access at any moment. Based on the data, simulations can be carried out, and treatments are established with modifications of the treatment.

Regarding the changes that may occur in the skeletal and muscular systems, through DTs using muscle activation and Electromyography (EMG) technologies, mobility deficiencies, paralysis, and imbalances in patients can be detected. The company Myontec, through an application [83], obtains information from patients by wearing pants that transmit muscle activity and health status in a digital environment, where the muscles behavior threshold is computed, realized, and analyzed post-exercise [80].

Physiotherapy is another field of DT application. For example, for people who have had accidents, real-time data can be captured to determine if they are responding to treatment by monitoring their health. Time can be saved and, at the same time, expensive treatments that will not have a positive impact on the patient can be avoided.

Another representative example in the area of personalized medicine is organ transplantation, where the DT can predict the probability of acceptance of a new organ by the body.

The development of 5G technology together with DT can also come to the aid of military teams that send data about the state of health of soldiers, examining the methods of intervention in which to act through sensors embedded in clothes [80].

In ref. [84], Tianze et al., conducted a state-of-the-art analysis on the impact of Digital Twins in medicine. This technology shows promising advancements in patient health monitoring, accurate diagnosis, and precise treatment. For instance, in the treatment of malignant tumors, a Digital Twin was created for the patient, which utilized genotype data and applied various computational algorithms and bioinformatics principles to predict the effects of anticancer drugs. Consequently, Digital Twin assists medical staff by suggesting the most suitable treatment options and benefits patients by improving survival rates and quality of life. However, the study also identified several limitations and highlighted ethical and technological risks associated with the use of Digital Twins in medicine. These include concerns about data confidentiality and unanticipated issues in the physical space during surgical interventions that were not detected in the digital model.

In ref. [80], Tolga et al., emphasized the benefits of Digital Twins in enhancing hospital operations. Using Digital Twin technology, predictions were made to optimize both costs and resource utilization in a radiology department, including work hours, CT (Computed Tomography) or MRI (Magnetic Resonance Imaging) scan times, and patient waiting periods. For resource management at the hospital or departmental level, various test scenarios and simulations can be performed to improve planning and organization. However, one of the weaknesses identified in [80] is the potential for errors in medical devices transmitting data to physical assets. These errors can result in the Digital Twin model being trained with inaccurate data, leading to incorrect diagnoses and inappropriate treatments.

In ref. [85], Moztarzadeh et al., developed a Digital Twin for breast cancer detection and monitoring, as well as predicting medical parameters. Utilizing datasets, Artificial Intelligence, and various machine learning techniques, they proposed creating robust prediction models based on data from medical consultations and blood tests. This approach allows for the simulation of breast cancer progression to identify potential complications. The discussion in [85] also addressed limitations related to patient data management, such as ensuring confidentiality, data encryption, compliance with GDPR and ISO 27001 standards [86], and monitoring platform access. Another challenge involves the need for large datasets for model training, model accuracy, and result interpretation by non-experts.

In ref. [87], Ali Vahdati developed a Digital Twin model of the cornea to identify pathologies such as keratoconus. This approach utilized in silico modeling and simulation, providing an efficient method for the identification, diagnosis, and simulation of surgical interventions. Additionally, the evolution of corneal parameters was demonstrated through simulations of laser-assisted in situ keratomileusis and photorefractive keratectomy surgeries.

In another study on the application of Digital Twin in ophthalmology, Iliuţă et al. [88] illustrated how this technology aids in the early diagnosis of glaucoma, incorporating systems medicine and predictive medicine concepts. They showed that the Digital Twin not only facilitates the early detection of glaucoma but also identifies correlations among various parameters such as age, gender, and race. Based on these correlations, personalized treatment plans can be developed, enhancing the patient's quality of life. However, one limitation identified in the process of monitoring glaucoma progression [88] is that it requires the assistance of medical staff during periodic ophthalmological consultations. This limitation is due to the lack of sensors or medical devices capable of real-time intraocular pressure measurement, a crucial parameter for tracking this condition.

In ref. [89], Armeni et al., proposed the initial development of a static model of the eye. This model aims to illustrate the structural and functional behavior of the human eye, enabling medical staff to identify various pathologies, provide personalized treatment, and simulate surgical interventions. For the construction of a comprehensive eye model, data will be collected from ophthalmology consultations and medical imaging techniques such as OCT (Optical Coherence Tomography), confocal microscopy, gonioscopy, and ultrasound. The integration of data from ophthalmological consultations, medical imaging, specific biomarkers of various eye diseases, and the application of prediction algorithms presents a significant challenge due to the difficulty in ensuring model accuracy. Additionally, the functionality of visual acuity testing using Digital Twins could lead to legal issues if mispredictions occur, particularly in situations where visual ability is a determining factor, such as in disability claims or the granting or revocation of driving privileges.

4.2.2. Benefits and Challenges of Digital Twins in Medicine

Digital Twins provide a number of advantages in medicine, but challenges may also be encountered, which will be mentioned in the following.

- *Benefits*

The use of Digital Twins in the medical field can support innovations in prevention, diagnosis, and personalized treatment processes. With the help of wearable sensors and the Internet of Things (IoT), continuous patient monitoring can be achieved, and in exceptional situations, medical staff can be notified, thus facilitating continuous communication between doctors and patients. This allows for rapid interventions and real-time adjustments to treatments, thereby improving medical outcomes.

Additionally, through the processes of organ simulation and modeling, as well as the functions of the human body, the accuracy of diagnoses increases, allowing the identification of pathologies at early stages. Detailed organ simulations enable the identification of pathologies in early stages, providing the possibility for timely and efficient interventions. For example, virtual modeling of the heart or other vital organs can help doctors observe anomalies that would otherwise be difficult to detect.

The application of Digital Twins in systems medicine aids in personalizing treatment by creating a virtual model of the patient. Thus, medical staff can visualize patients' reactions to different drugs, considering the genetic and individual factors that influence the progression of diseases. Moreover, the Digital Twin plays an essential role in optimizing and planning medical procedures, such as reducing the time spent in the operating room. Simulation of surgeries can support increased precision, eliminating or reducing the risks associated with interventions and enhancing the accuracy of surgical procedures (Precision Medicine).

Digital Twin can also be used for designing and testing various medical devices, facilitating the creation of dental or corneal implants by simulating the body's reactions in such situations.

Other benefits of using Digital Twin include the development of interactive platforms that help medical staff improve their professional training through simulations. Additionally, virtual consultations, facilitated by telemedicine capabilities, allow patients to receive medical care remotely, reducing the need for travel and ensuring access to specialized medical expertise, regardless of location.

- *Challenges*

One of the challenges related to the use of Digital Twins in the medical field is that patients' medical data are stored in databases that can become targets for cyber-attacks, generating significant ethical risks. Protecting these data against unauthorized access and security breaches is a major concern, given the sensitivity and confidentiality of medical information.

Additionally, obtaining patients' consent for the acquisition, storage, and processing of the data necessary for the pathology diagnosis process and personalized treatment recommendations is a significant challenge. Patients must be fully informed and understand how their data will be used, which may require additional time and effort from medical staff to ensure transparency and compliance with data protection regulations.

Another challenge may be the refusal of medical staff to use Digital Twin, even though it is considered just a tool that facilitates the pathology identification process, with the final decision still belonging to the medical staff. This refusal may be caused by reluctance to change, lack of familiarity with new technologies, or fear of losing control over the diagnostic process.

The high costs associated with implementing Digital Twin in individual practices are also an important concern. These costs include not only the acquisition of the necessary technology and equipment but also the training sessions for staff and the regular maintenance of the entire system. Ensuring that medical staff are well-trained and that systems are maintained in optimal conditions requires considerable financial resources, which can be an obstacle for many medical institutions.

4.3. Digital Twin in Other Domains

The variety of DTs and their applicability in different fields such as Smart Cities, Energy Production, Oil Industry, and education highlights the impact of this emerging technology, which contributes to development. Within this section, an example of the applicability of DTs is presented in the previously mentioned areas, starting from the modeling of urban infrastructures, optimizing energy production, reducing gas emissions, and exploring innovation in education. Figure 11 presents the number of articles specific to each domain due to the search for the concepts of "Digital Twin in Smart Cities", "Digital Twin in Energy Production", "Digital Twin in Oil Industry", and "Digital Twin in Education" in the databases.

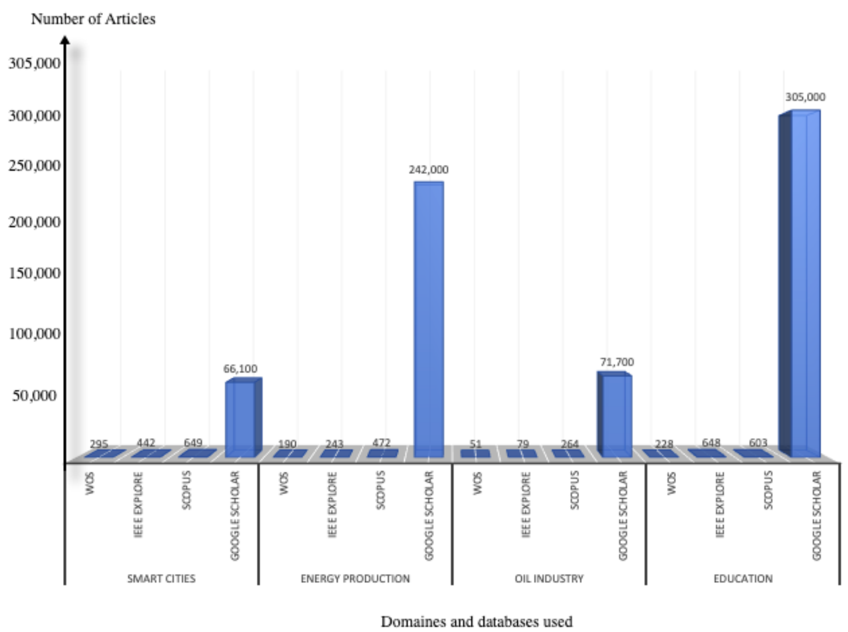

Figure 11. Digital Twin in various fields.

From the point of view of education, with the pandemic generated by the emergence of COVID-19, the transition from traditional to online education was achieved, and with the help of artificial intelligence and DTs, configured learning frameworks were proposed, these being available in [90–92], based on the concepts of e-learning, mobile learning (m-learning), ubiquitous learning (u-learning), and smart learning (s-learning).

In ref. [93], Arantes et al., highlighted the integration of the Digital Twin in the educational context, emphasizing the differences between technology-driven customization and human-centered personalized learning, given the promotion of a personalized learning policy in K–12 educational environments. The advancement of Digital Twin integration in the educational domain has coincided with the development of the Metaverse. Technology-driven customization, achieved through Digital Twin integration, supports quantification and power forms based on reference environments, generalizability, and standardized testing. In contrast, human-centered personalized learning does not involve standardization and generalization of involvement, being quantifiable and measurable. The use of the Digital Twin in personalized learning negatively affects the recognition of human relational involvement by teachers. Regarding the datasets provided by the Digital Twin, measures to reduce costs compared to organizing classes in the classroom have been discussed, a phenomenon that amplifies socio-economic disadvantages in the implementation of educational policies.

In ref. [94], Chen et al., developed an innovative pedagogical method through the integration of the Digital Twin, avatars, and generative Artificial Intelligence, considering this approach as a complement to traditional teaching. Thus, the focus has been placed on developing platforms that encourage constructivism and collaborative learning, also adopting a problem-solving oriented method. The experiment to validate the new method was conducted with the participation of medical students who attended learning sessions in the metaverse. The learning sessions were facilitated by a real teacher (in the form of an avatar), a digital clinical instructor, and an AI teacher, aiming to provide students with an efficient educational experience, taking into account both human–machine interaction and problem-solving abilities.

In ref. [95], Khan and Mekind emphasized that during the COVID-19 pandemic, universities with engineering programs encountered difficulties in conducting practical experiments. To address this situation, the organization of laboratory sessions was carried out by creating a Digital Twin for each experiment, using online applications and Augmented and Virtual Reality (AR/VR) technologies. Thus, the Digital Twin provided an efficient framework for laboratory experiments, offering students a synchronized 3D environment to facilitate interaction between the physical and virtual environments. Additionally, Khan and Mekind noted that the greatest challenge lay in assessing and improving students' psychomotor skills.

Also, in the realm of education, utilizing the Digital Twin and the NVIDIA Omniverse platform, Sim et al. [96] developed three modules for NTUniverse (NTU): digitalizing the NTU campus, modeling the campus train, and virtual education. Thus, the Digital Twin contributes to the digitalization of the university campus, providing users with a realistic immersive experience by integrating detailed building components and accurately simulating railway transportation and vehicle dynamics, while also allowing students to interact in safe and interactive 3D environments. Additionally, the Digital Twin enables integration with other systems for real-time display of building information and the generation of realistic simulations based on data collected from sensors. Another important aspect is the integration of STEM (Science, Technology, Engineering, and Mathematics) modules and the enhancement of user interfaces to enhance the learning experience for students. These scenarios are not only beneficial for students but also for new employees, aiding in the development of technical skills and ensuring a high level of safety in their training.

In ref. [97], Goodwin et al., presented a framework called SAMPLE (Machine-learning Predictions as Lightweight Estimates) to support decision making using the online Digital Twin, employing offline learning methods. The efficiency of this framework was demonstrated through a case study focused on disruption mitigation, highlighting its ability to improve computational efficiency and accelerate the process fourfold, using machine learning models with low predictive accuracy. The authors identified several research directions to enhance the performance of SAMPLE, such as exploring alternative models to integrate offline machine learning predictions with online simulation output and investigating other estimation methods, all aimed at improving the classification of alternatives based on their importance. Additionally, the authors suggested incorporating data from real-time simulation iterations to adjust estimates from offline-trained machine learning models in new contexts.

Another field of application of DTs is energy production. Thus, in [98], the authors presented how the modeling of a wind farm can be performed either at the individual level of the windmills, treating them as subsystems, or at the level of the entire farm using a single DT.

An example of the oil industry is [99], where the authors propose a DT based on machine learning algorithms, with a role in forecasting and data analysis to identify risks that may occur in an oil transportation system. Thus, an integrated and intelligent virtual automatic control system is created, highlighting the integration of transmission lines with the aid of wireless data networks.

In addition, Industry 4.0 standard technologies regarding oil and gas have been updated to emphasize the shift to the digital component. In Refs. [100–102], the authors presented the integration of these technologies to increase the energy efficiency in smart enterprises, aiming to reduce both production costs and gas emissions, as illustrated in [103–105].

In ref. [106], Deng et al., conducted a study on bridge health monitoring systems, which included sensor technology, computer vision technology, data preprocessing methods, noise reduction, data reconstruction, and early warning systems for abnormal data. The authors highlighted the importance of these systems in the field of civil engineering, considering the integration of satellite technologies such as InSAR (Interferometric Synthetic Aperture Radar), which supports the development of visualization platforms and risk assessment methods. In this context, by integrating the concept of Digital Twin, virtual models of bridges can be created to perform various procedures regarding their simulation, prediction, and real-time analysis of their health. By collecting, processing, and integrating data from sensors into artificial intelligence algorithms, Digital Twins can provide accurate information about the state of bridges, helping to detect problems early, optimizing not only costs and durability but also facilitating rapid interventions.

In the same field, Huang et al. [107] conducted a study to highlight the importance of detecting deteriorations in structural elements, focusing particularly on rubber bearings, essential for the proper functioning of bridges. The authors proposed an innovative method for identifying bearing deterioration, considering the limitations faced by traditional methods in this regard. The proposed method is divided into two stages, the first involving the introduction of a deterioration localization indicator, called the Mean Squared Error (MSE), which helps determine the precise location of deteriorations. The second stage contributes to estimating the deteriorations by combining knowledge of deterioration optimization with Sailfish Optimization (SFO). The method's validation was performed through experimental tests, demonstrating its effectiveness for both simple and complex structures. Integrating this method of bearing deterioration identification into the Digital Twin concept can significantly contribute to the safety and durability of bridge infrastructure. Thus, with real-time sensor-acquired data and the use of the MSE indicator, the condition of the bearings can be monitored. Using simulation and prediction methods for bearing deterioration, employing SFO, the location and severity of deteriorations can be rapidly identified, facilitating immediate interventions and reducing operational risks and maintenance costs.

In the field of Structural Health Monitoring (SHM), Zhang et al. [108] highlighted the significant impact of missing sensor measurement signals on the accuracy of deterioration identification and the assessment process of structural health. They conducted a study to examine the current advantages and limitations of methods for recovering missing data in SHM, emphasizing that machine learning algorithms provide increased precision and computational efficiency. Additionally, Zhang et al., underscored the need for in-depth research in this direction, focusing on abnormal sensor measurement signal treatment, complete response recovery, and few-shot learning approaches. They also proposed establishing standardized criteria for evaluating data recovery accuracy, considering not only computational efficiency but also model complexity. Thus, to ensure algorithm applicability, expansion to complex and varied structures such as dams and tunnels is necessary. In this context, utilizing Digital Twin involves integrating mathematical models and artificial intelligence algorithms to detect and fill in missing sensor signals. Consequently, continuous and precise system state evaluation is facilitated through machine learning algorithms and statistical inference techniques. All of these contribute to the development of robust monitoring systems for critical infrastructure.

In ref. [109], Huang et al., proposed an innovative method for nonlinear spatio-temporal modeling of temperature and Temperature-Induced Bearing Displacement (TIBD) in rigid frame bridges with a single large-span pier to reduce structural deformations and instability. This method, based on the DCNN-LSTM (Deep Convolutional Neural Network–Long-Short-Term Memory) network with elastic module fusion, utilizes monitoring data from the second bridge over the Yangtze River in Wuhan and addresses three major issues: insufficient selection of characteristic temperature values, inadequate research on the correlation between structural temperature and TIBD for bridges, and low accuracy of temperature–TIBD regression models. The authors identified positive linear correlations between temperature sensor data placed inside the box girder and measurements from the same box. Regarding the comparative study results of hyperparameters, it was observed that the DCNN-LSTM network exhibited the highest prediction accuracy, and the 2CONV+1LSTM network combination provided the best performance. By introducing elastic module data, the model's prediction capability was enhanced.

Integrating the Digital Twin concept in this context can contribute to monitoring and managing such structures by creating a virtual model of the bridge. This virtual model will use real-tim-acquired data from temperature and displacement sensors, considering the structural and functional characteristics of the bridge. The construction of the model will integrate the DCNN-LSTM network with elastic module fusion, which accurately determines bearing displacements, identifying possible structural changes caused by temperature variations. Through real-time simulations and analyses, a continuous and precise evaluation of the entire system is generated, identifying potential risks and mitigation methods. Implementing warning systems built using prediction data provided by the Digital Twin facilitates continuous communication with intervention and management teams. The data analysis capability of collected sensor data and their integration into artificial intelligence algorithms contribute to optimizing maintenance and repair strategies, extending the bridge's lifespan. The Digital Twin will be continuously updated by real-time sensor data collection and modeling, ensuring highly accurate results.

Smart city Digital Twins were addressed in [110], where the functional integration of data from Building Information Modeling (BIM) and Geographic Information Systems (GISs) was presented, as well as the realization of experiments regarding data conversion between the two systems. Data integration has been developed to achieve semantic integration, functional interoperability, and information sharing. Geographic Information System (GIS) data provide cities with geospatial data, spatial analysis, and applications that are very important for urban environment design. Building Information Modeling (BIM) involves the active application of models to the engineering, architecture, and construction industries throughout the life cycle, along with the passive presentation of micro-digital information regarding real entities. The sustainable design of smart cities can be achieved through the support of urban DT technology by combining the two technologies, GIS and BIM.

In the field of Architecture, Engineering, Construction, and Operation (AECO), Vuoto et al. [111] highlighted the need for detailed studies to implement and identify platforms that facilitate interoperability and efficient collaboration among involved stakeholders. This stems from the importance of finding a common language for data acquisition, storage, transmission, and modeling. In the preservation of Built Cultural Heritage (BCH), the authors emphasize that the integration of the Digital Twin is essential. The use of the Digital Twin involves not only the use of specialized simulation software but also the application of predictive analyses through statistical methods and artificial intelligence tools. From this perspective, the need for continuous collaboration among experts from various scientific fields to implement concrete case studies is emphasized. These studies will form the basis for evaluating and validating holistic approaches aimed at developing a complex and integrated perspective on performance-oriented management.

In ref. [112], Vuoto et al., highlighted the necessity of defining a methodological framework for implementing the Digital Twin in the conservation of Mobile Cultural Assets (BCH), aiming for its full potential exploitation. Additionally, the importance of conducting a systematic comparison between the concepts of Digital Twin and HBIM (Historic Building Information Modeling) was emphasized, thereby supporting the advancement of practical implementations in the field of structural engineering and BCH conservation. By leveraging the predictive features of the Digital Twin and adopting a predictive conservation strategy, the authors highlighted how this technology contributes to the digital documentation of cultural heritage and ensures its preservation.

In ref. [113], Zhang et al., presented how the Digital Twin can contribute to optimizing Positive Energy Districts (PEDs), a field still in its early stages and requiring in-depth studies and the implementation of methodological standards. In the construction of digital PED twins, the following key components have been identified: the virtual model, integration of sensor networks, data analysis, and a layer dedicated to stakeholders. In this context, most available tools focus on industrial applications, including existing GIS and BIM models. Recently, digital PED twins have been divided into three categories, including enhanced versions of the BIM model, the development and existence of semantic platforms for managing data flow, and the use of agents employing artificial intelligence in feedback and data analysis operations. Through the use of specialized simulation software and the application of predictive analyses, statistical methods, and artificial intelligence tools, precise computational models can be created and the structural response of historical buildings evaluated, thereby optimizing preventive management and the sustainability of positive energy districts.

Benefits and Challenges of Digital Twins in Other Domains

Digital Twins provide a number of advantages in various domains, but challenges may also be encountered, which will be mentioned in the following.

- *Benefits*

In the field of education, the Digital Twin brings numerous benefits by facilitating the transition from traditional to online learning. This has allowed for the creation of configured learning frameworks based on concepts of e-learning, m-learning, u-learning, and s-learning, offering the possibility of personalized learning, standardized testing, and cost reduction, providing an efficient alternative to traditional classroom organization. The integration of avatars and artificial intelligence has led to the development of innovative pedagogical methods that complement traditional teaching. Additionally, Digital Twin has facilitated the organization of virtual laboratory sessions through the use of online applications and Augmented and Virtual Reality (AR/VR) technologies, providing students with an interactive and immersive learning environment.

In energy production, Digital Twin offers significant benefits by facilitating the optimization of operations and cost reduction, while also ensuring more precise control over energy resources. In the oil industry, Digital Twin is essential for forecasting and data analysis, identifying risks, and optimizing oil transportation systems, thus contributing to the efficiency and safety of operations.

In structural health monitoring, Digital Twin brings considerable benefits by integrating into bridge health monitoring systems and other civil infrastructures. The use of sensor technologies, computer vision, and data preprocessing methods allows for the detection and warning of structural issues. Digital Twin facilitates the creation of virtual models of bridges, offering the possibility of simulation, prediction, and real-time analysis of their condition. This contributes to the early detection of problems, cost optimization, and increased durability of infrastructures.

- *Challenges*

One of the main limitations of using Digital Twin in education is the high cost associated with implementing and maintaining this technology. This includes not only the acquisition of necessary equipment and software but also the training of staff to efficiently use the new tools and techniques. Additionally, there is a reluctance among educational staff to adopt new technologies due to a lack of familiarity or fear of losing control over the traditional educational process. There are also challenges related to student data confidentiality. Ensuring data protection against unauthorized access and compliance with data protection regulations are essential aspects of implementing Digital Twin in education, which can generate ethical risks.

In energy production, one of the major challenges is the complexity of integrating Digital Twin with existing infrastructure. The need for large amounts of data to train the models represents an obstacle, and the accuracy of the models can be affected by errors in the data collected from sensors.

In structural health monitoring, the main difficulties are related to real-time data collection and processing. The lack of uniform standards for evaluating data recovery accuracy and the complexity of the models can affect the applicability of Artificial Intelligence algorithms. Additionally, detecting and filling in missing sensor signals requires complex mathematical models and advanced statistical inference techniques.

In summary, Table 5 shows the fields of application of the Digital Twin presented in this paper, together with the corresponding bibliographic references.

Table 5. The fields of application for DTs.

Applications of Digital Twins—Fields	References
A. Manufacturing	[27–49]
B. Medicine	[63–85,87–89]
C. Various fields—Smart cities, Energy production, Oil industry, Education	[90–113]

5. Results

The general objective of this study was to create an overview of the evolution and current status of the Digital Twin (DT) concept. This encompassed identifying definitions from specialized literature, examining the applicability of DTs in fields such as manufacturing, medicine, smart cities, and education, and presenting some of the available architectures that offer flexibility and adaptability in implementation. Another objective was to identify the advantages, limitations, and challenges resulting from the use of DTs in these fields.

The research was conducted in four stages.

The first stage focused on understanding the Digital Twin concept. A Google Scholar search for "Digital Twin definition" yielded 39,500 results. Starting from the definition given by Grieves (2016) [2], five more definitions were selected to provide a clear, complete, and precise understanding of the concept, highlighting aspects applicable in different industries. The selected definitions emphasized the three components of a Digital Twin: the physical product, the virtual product, and the connection between them.

The second stage involved identifying sources to classify Digital Twin architectures. A Google Scholar search for "Digital Twin classification" yielded 27,100 results. Singh et al. [13] classified Digital Twins according to several parameters, including creation time, integration level, role within the application, focused application parameters, hierarchical structure, and maturity level. This classification helped in understanding the technologies facilitating the development and effective implementation of Digital Twins, as well as their similarities and particularities.

The third stage involved a comprehensive assessment of the advantages, limitations, and challenges associated with the use of Digital Twins. By examining both the benefits and drawbacks, the study provided a balanced perspective on the potential and challenges of adopting Digital Twin technology.

The structured approach taken in this study provided a thorough examination of the Digital Twin concept, from definitions and classifications to practical applications and challenges. The insights gained are valuable for academics and practitioners aiming to implement Digital Twin technology effectively across different industries. The systematic analysis and detailed classification offer a robust foundation for future research and development in this dynamic field.

Regarding the classification of Digital Twins, six sources were cited to highlight their adaptability to various scenarios built on specific requirements, ensuring effective implementation in a variety of fields and industries.

One of the future objectives is the proposal of an architectural framework for the Digital Twin. A Google Scholar search for "Digital Twin architecture" yielded 31,100 results. Given the large number of publications, several criteria were established based on which the sources detailed in this work were selected. The criteria focused on how Digital Twins can be structured and managed to ensure interoperability, adaptability, scalability, and security of the systems.

Several reference architectures [18,19,23] were selected, emphasizing service delivery and adaptability in various domains such as the medical field. For example, the architecture proposed by Aheleroff et al. [23], Digital Twin as a Service (DTaaS), serves as a starting point for real-time patient monitoring and personalized treatment prediction. This architecture offers a flexible, secure, and modular vision that can significantly contribute to the development of personalized medicine.

The presentation of these architectures and application frameworks used information extracted from ten sources, highlighting the adaptability of Digital Twins in various industries and their interoperability with other platforms. The modular nature of these architectures allows for security measures to be implemented at each layer or across the entire system, minimizing risks and the probability of cyber-attacks. Procedures can also be introduced to protect the data involved in building models and predicting the behavior of physical assets while monitoring system-level access.

For manufacturing and PSS integration, the general objective was to identify methods, tools, and models of Digital Twins that ensure the monitoring of physical–virtual and virtual–physical connections throughout the product life cycle. The study explored the use of Digital Twins from the product design phase, pre-identifying customer requirements, analyzing data based on design parameters, extending through maintenance and fault prediction.

The study focused on identifying the concepts, technologies, and applications used in the development of Digital Twins in manufacturing, emphasizing their benefits. The analysis–evaluation–validation process identified articles that presented techniques for verifying the conformity of DT specifications and the ways in which DTs interact with the production environment to optimize process parameters. Technologies that provide accurate predictions and monitor the behavior of physical entities have been developed, facilitating effective feedback mechanisms during evaluation and validation phases.

The overall objective of integrating Digital Twin with Cyber–Physical Systems (CPS) was to identify the potential contributions of DT technology. The selected articles provided virtual representations of the physical components of CPSs, including human–robot collaborative assembly operations and remote interactions. These representations facilitated real-time monitoring and analysis based on sensor data, such as manipulating the real robot or checking its movement and calculating safety distances. The findings suggest that Digital Twin technology enhances the simulation of systems, helps identify potential problems, optimizes operations, aids in decision making, and efficiently manages resources. This analysis underscores the pivotal role of Digital Twins in enhancing the functionality and safety of CPSs.

In the medical field, the general objective was to create a comprehensive model of the human body using Digital Twin technology to simulate and monitor patients' health statuses. The study identified several aspects highlighting the real-time evolution of pathologies, considering molecular characteristics and the effects of drugs. Notably, articles discussed the development of custom emotion recognition systems through image processing and ECG heart rhythm classification models using machine learning and AI algorithms.

The research delineated the stages involved in creating a patient's digital model: data acquisition, processing and prediction, monitoring and correction, and data comparison. Various medical specializations where Digital Twin technology can be applied were identified, such as cardiology (digital heart models and chronic heart failure diagnosis), neurology (monitoring brain activity to prevent depression and neurological disorders), and rheumatology (tracking changes in the bone and muscle systems). Future directions include integrating Systems Medicine to develop a Digital Twin associated with the eye, which could identify potential hereditary pathologies (e.g., glaucoma, cataract, macular degeneration), suggest treatment plans, simulate patient reactions, and assist in medical decision making. This comprehensive approach highlights the transformative potential of Digital Twins in personalized and predictive medicine.

In the context of smart cities, the general objective was to explore sustainable design using Digital Twin technology, GIS (Geographic Information System), and BIM (Building Information Modeling). The applicability of Digital Twins extends to related fields such as education, energy production, and the oil industry. This multi-faceted approach underscores the versatility of Digital Twin technology in enhancing urban planning, resource management, and environmental sustainability.

Compared to previous studies examining the evolution of Digital Twins over several years, common elements such as DT definitions, research paradigms, and reference architectures were identified. This study, however, placed greater emphasis on highlighting the temporal evolution of DTs in research and their application across various fields, including PSSs (Product–Service Systems), CPS, smart cities, and medicine. A detailed classification of Digital Twins was sought to shape a holistic approach, focusing on identifying the advantages and limitations of DT usage from specialized literature.

This study proposed a holistic approach to Digital Twin technology across various domains (PSS, CPS, medicine, and smart cities) to provide a comprehensive view of its potential contributions. By highlighting both the advantages and disadvantages of Digital Twin technology, this analysis offers valuable insights into its role in digital transformation. The selection of reference architectures and application frameworks in medicine and other fields provides a foundation for future research aimed at developing a general architecture for Digital Twins. This holistic vision encompasses defining the concept, identifying characteristics of a general architecture, and focusing on practical examples of DT applications, enhancing the understanding of its benefits and limitations.

The integration of Digital Twin technology in the field of civil engineering, particularly in bridge health monitoring systems, offers significant advancements as evidenced by multiple studies. Deng et al. [106] demonstrated the potential of Digital Twins to create virtual bridge models that enable simulation, prediction, and real-time health analysis by leveraging sensor data and artificial intelligence algorithms. This approach facilitates early problem detection, cost optimization, durability enhancement, and rapid interventions. Huang et al. [107] introduced an innovative method for identifying rubber bearing deteriorations using Mean Squared Error (MSE) and Sailfish Optimization (SFO), which, when integrated into the Digital Twin framework, significantly boosts the safety and longevity of bridge infrastructure. Zhang et al. [108] highlighted the critical role of addressing missing sensor data in structural health monitoring, proposing advanced machine learning algorithms for accurate data recovery, essential for robust infrastructure monitoring. Furthermore, Huang et al. [109] presented a novel method using DCNN-LSTM networks for modeling temperature-induced bearing displacement, demonstrating the highest prediction accuracy through the integration of elastic module data. These studies collectively underscore the transformative impact of Digital Twin technology in enhancing structural health monitoring, enabling precise, real-time evaluation, and optimizing maintenance strategies, thereby extending the lifespan and reliability of critical infrastructure.

In the AECO sector, the integration of Digital Twin technology has been highlighted as essential for enhancing interoperability and collaboration among stakeholders. Vuoto et al. [111] emphasized the need for detailed studies to identify platforms that facilitate these aspects, focusing on a common language for data acquisition, storage, transmission, and modeling. In preserving Built Cultural Heritage (BCH), Digital Twins not only utilize specialized simulation software but also apply predictive analyses through statistical methods and AI tools, requiring continuous interdisciplinary collaboration. Additionally, defining a methodological framework for implementing Digital Twins in the conservation of mobile cultural assets is crucial for fully leveraging their potential, as noted by Vuoto et al. [112]. This approach supports advancements in structural engineering and BCH conservation by systematically comparing Digital Twin concepts with Historic Building Information Modeling (HBIM), optimizing preventive management, and ensuring the sustainability of these assets.

The results of this study present a thorough analysis of the evolution and current status of the Digital Twin concept. By integrating findings from various fields, the study underscores the significant potential of Digital Twins in driving innovation and efficiency. The proposed architectural frameworks and detailed classifications offer a robust foundation for future research, paving the way for innovative applications and enhanced system performance. This comprehensive approach ensures a deeper understanding of Digital Twin technology's impact across multiple domains, facilitating its effective implementation and contributing to ongoing digital transformation efforts.

6. Discussion

According to the analysis presented in this paper, there is a strong upward trend in research interest for Digital Twin, reaching the highest number of articles in the current year—59,717. The steady number of articles over the past three years indicates not only the maturity of the concept and its adoption by large research communities but also a consolidation of research interests followed by a focus on relevant applications. Another relevant result of the analysis is the tendency observed in numerous papers to redefine existing paradigms and support the digital transformation process.

As a result of the analysis carried out in this paper, some future research directions will be presented regarding the applicability of Digital Twin in the field of medicine, highlighting not only its innovative potential but also the perspectives that can influence its evolution.

In relation to the applicability of Digital Twins in medicine, a holistic approach to the patient emerges. The systemic approach, where each organ can be represented with the help of a Digital Twin, or each pathology can be associated with a Digital Twin, is emerging as a viable research direction. The functional and structural modeling of each organ with the help of Digital Twin and Systems Medicine offers the possibility of identifying and diagnosing pathologies and providing personalized treatments. Thus, virtual models of patients can be developed by modeling the behavior of different organs or systems by combining engineering and medical knowledge.

From the perspective of creating a Digital Twin associated with each pathology, a detailed analysis of its evolution can be carried out, and the integration of the Digital Twins associated with them could facilitate the identification of connections, correlations, and dependencies that influence the evolution of the previously represented pathologies. Thus, the behavior of the entire system, as well as a system of systems perspective, can be simulated, facilitating the identification of pathologies and the optimization of treatments.

One of the major challenges is the application of deep learning in the creation of Digital Twins. To create customized models and ensure the accuracy of the results, it is necessary to use large volumes of data; the process of collecting, processing, and transforming them into information is time- and resource-consuming. Issues related to the confidentiality and security of patient data, and the ethical risks that may arise, can also be discussed.

Starting from the previously presented models, another challenge could be the creation of a modular architecture that ensures the interoperability, performance, security, and reliability of the Digital Twin-type system with applicability in medicine, especially in ophthalmology. Such an architecture should be capable of integrating real-time data, utilizing sensor networks, and applying advanced analysis and prediction techniques, thereby providing a powerful tool for monitoring and optimizing medical treatments.

As a result of a holistic approach, the Digital Twin becomes an essential tool for the efficient and sustainable management of diverse systems and infrastructures.

7. Conclusions

The Digital Twin concept and technology are increasingly recognized as powerful tools for simulating, monitoring, and optimizing complex systems across a wide range of domains and applications, including industry and medicine. This paper aims to provide an analysis of the Digital Twin concept, exploring its evolution, current status, and future prospects. It addresses several key research questions: What is the current state of Digital Twin technology? How is it applied across different domains? What are the benefits and challenges associated with its adoption? Finally, how can existing architectures be integrated into a new proposed architecture for specific applications, such as in ophthalmology?

The study begins by examining the current state of Digital Twin technology. A comprehensive literature review reveals a significant upward trend in the number of research articles published on this topic. This trend indicates not only the growing maturity of the concept but also its widespread adoption by large research communities.

Digital Twin technology has found applications in numerous fields, including manufacturing, medicine, energy production, education, and smart cities.

The benefits of Digital Twin technology are numerous, including improved efficiency, reduced costs, enhanced performance, and the ability to simulate and predict complex system behaviors. However, several challenges need to be addressed. These include data integration issues, security concerns, and regulatory compliance. The increasing use of machine learning and artificial intelligence holds the potential for overcoming these challenges by providing more accurate predictions and enhancing the capabilities of Digital Twins.

Building on the insights gained from existing Digital Twin architectures, this paper proposes a new architecture specifically designed for applications in ophthalmology. This architecture aims to integrate real-time data from various sensors, utilize advanced analysis and prediction techniques, and ensure interoperability, performance, security, and reliability. The proposed modular architecture will facilitate the precise and personalized medical care needed for detecting and managing eye-related diseases.

In conclusion, this study provides a detailed examination of the Digital Twin concept, technologies, and architectures, highlighting their applicability across various domains and industries. The research underscores the significant potential of Digital Twin technology to drive innovation and efficiency in multiple fields. By addressing the ongoing challenges and proposing a new architecture for specific applications like ophthalmology, this study contributes to the advancement of Digital Twin technology and its integration into practical, real-world solutions. This holistic approach ensures a comprehensive understanding of Digital Twin technology's impact, paving the way for future research and development in this dynamic field.

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