DIGITAL TWIN TECHNOLOGY: CONCEPTUAL FOUNDATIONS, APPLICATIONS AND IMPLEMENTATION CHALLENGES

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Abstract

Over the past ten years, Digital Twin (DT) technology has developed from a specialised academic idea to a widely utilised operational tool across a wide range of sectors. Since its initial introduction in 2003, the idea has garnered increasing attention from academics and business due to developments in cloud computing, artificial intelligence, and the Internet of Things. The purpose of the study is to review the literature in order to present an organised picture of the state of technology today. Conceptual fundamentals and typologies are analyzed, including the widely cited distinction between Digital Model, Digital Shadow, and Digital Twin. Moreover, the main supporting technologies (IoT, cloud computing, artificial intelligence, extended reality), five major application areas (manufacturing, healthcare, construction, agriculture, services and product-service systems) and the key implementation challenges, are also examined. The analysis highlights that the success of DT adoption does not depend exclusively on solving technical difficulties, but equally on the organizational and human capacities of the companies implementing it. The paper highlights that non-technical implementation challenges are consistently underestimated in the specialised literature and simultaneously integrates the technical and organisational perspectives, covering five application areas through a unified analytical framework in contrast to previous syntheses.

Keywords: *Digital Twin, Industry 4.0, Internet of Things, artificial intelligence, industrial applications, implementation challenges*

JEL: *O33, O14, L86, M15*

1. Introduction

Digital Twin (DT) technology, or digital twin, has evolved in recent years from a niche technical concept to a widely used tool in industries such as manufacturing, healthcare, construction, and agriculture. A 2019 Gartner survey found that 75% of organizations implementing Internet of Things (IoT) solutions were using or planning to use Digital Twin technology by 2020 (Gartner, 2019). More recent estimates indicate that over 40% of large companies worldwide will integrate digital twins into their projects by 2027 (Gartner, 2022). The global market for this technology, valued at approximately $8 billion in 2022, is expected to grow at a compound annual rate of approximately 25% through 2032 (Global Market Insight, 2022).

This rapid expansion is supported by the convergence of several technologies that have previously developed in parallel. IoT sensors are capable of continuously transmitting data in real time, while cloud computing infrastructures store and process large volumes of data. The artificial intelligence methods are extracting useful information from this data and extended reality tools allow interaction with virtual representations of physical assets (Attaran and Celik, 2023). Together, these technologies create the framework in which a faithful and dynamic digital counterpart of a real-world object or system becomes both technically and economically feasible.

The purpose of this paper is to provide a structured presentation of Digital Twin technology - conceptual foundations, technologies that make it possible, main application areas and key implementation challenges. The paper is based on recent specialized literature and aims to provide a coherent picture of the current state of the technology and likely development directions. The methodology used, the criteria for selecting sources, and the logic for structuring the analysis are detailed in the following section.

2. Methodology

This paper is based on a narrative literature review, an approach suitable for review articles that aim to map the current state of knowledge in a field, without imposing a selection protocol as restrictive as in the case of systematic reviews (Paez, 2017).

The identification of sources was achieved by querying the Scopus and Google Scholar databases, using as main search terms Digital Twin and Digital Twins, combined with terms specific to the analyzed application areas: manufacturing, healthcare, construction, agriculture, product-service systems. The search was mainly oriented towards works published in the period 2018-2024, to reflect the current state of technology, without excluding previous contributions with reference value, in particular the founding works of Grieves (2014) and Kritzinger et al. (2018).

The inclusion criteria were: articles published in peer-reviewed journals or in the volumes of scientific conferences, papers that explicitly treat the concept of Digital Twin in relation to at least one of the aspects analyzed in this paper, and sources available in whole or in part in English. Papers in which the term Digital Twin appeared exclusively in the title or keywords, without conceptual treatment in the body of the article, as well as those that approached the technology exclusively from the perspective of a technical subdomain with no relevance for at least one of the levels of analysis pursued: conceptual foundations, supporting technologies, application areas or implementation challenges, were excluded. Sources such as industrial reports or white papers were selectively included, exclusively where they offered quantitative market data unavailable in peer-reviewed academic literature, being explicitly cited as industrial sources and used for contextualization, not to support the central conceptual arguments. The final corpus used in the analysis includes 32 papers selected based on the criteria described above.

Content analysis was carried out through iterative thematic reading. The categories of analysis were constructed deductively, starting from established classifications in the reference literature. In particular the typological framework proposed by Kritzinger et al. (2018) and the taxonomy of implementation challenges developed by Fuller et al. (2020), and validated by comparing the complementary or divergent perspectives of the authors included in the corpus, were used. Where the literature offered multiple definitions or classifications of the same concept, the approach that benefited from the broadest consensus in the recent literature was privileged, with explicit mention of relevant variations. The structure of the article reflects the logic of this approach: from conceptual and technological foundations, to concrete applications and, finally, to the limits and challenges faced by the implementation of the technology in practice.

3. Conceptual Framework

3.1. Origin and Evolution

The term Digital Twin was first introduced in 2003 by Professor Michael Grieves at the University of Michigan, in a course on product lifecycle management (Grieves, 2014). The concept essentially described a virtual information construct that mirrors a physical product throughout its entire life cycle (Grieves and Vickers, 2017). An early application, retrospectively invoked as a precursor to the concept, dates back to 1970, when NASA engineers used a physical simulator (a twin of the Apollo 13 command module) to diagnose and resolve a critical failure in less than two hours (Attaran and Celik, 2023). Currently, NASA continues to apply Digital Twin principles in the development of next-generation vehicles and aircraft.

Since Grieves' initial formulation, the definition of Digital Twin has been supplemented and refined by numerous researchers, reflecting the diversity of application areas. The

Encyclopedia of Manufacturing Engineering defines it as a representation of a single, active product which can be a physical device, an object, a machine, a service, an intangible asset, or a system consisting of a product and its associated services (Stark and Damerau, 2019). Fu et al. (2022) describe it as a real-time digital representation of a physical object, remotely connected to its real-world counterpart, and capable of capturing dynamic behavior beyond static CAD designs. What runs through all of these definitions is the idea of a continuous exchange of data between the physical entity and its virtual representation.

3.2. Typology: Digital Model, Digital Shadow, Digital Twin

One of the most cited frameworks for classifying virtual representations is that proposed by Kritzinger et al. (2018), which distinguishes three levels of integration between a physical product and its digital counterpart, depending on the direction and degree of automation of the data flow.

A Digital Model involves a digital representation of a physical object in which all data exchange between the two is carried out manually. Changes in the physical object do not automatically update the digital model, nor vice versa.

A Digital Shadow is characterized by a unidirectional and automated data flow from the physical object to the digital representation. The digital shadow is continuously updated based on information from the physical system, but decisions or changes made in the virtual space are not automatically transmitted back to the real system.

Digital Twin, in the strict sense of the term, involves a bidirectional and automated data flow. The physical object updates the digital representation in real time, and actions or decisions derived from the virtual model can be transmitted back to influence the physical system. This bidirectionality is what distinguishes the Digital Twin from simpler forms of digital modelling and constitutes the basis of its predictive and operational capabilities (Kritzinger et al., 2018; Saporiti et al., 2023), as illustrated in Figure 1.

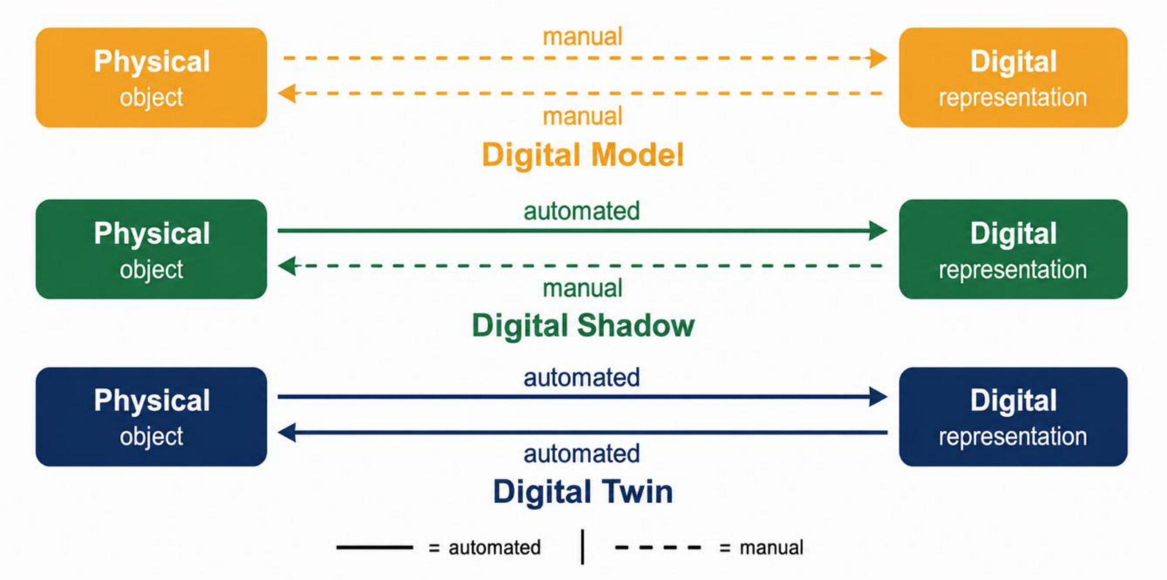

Figure 1. Integration Levels: Digital Model, Digital Shadow, and Digital Twin (adapted from Kritzinger et al., 2018)

Source: Authors' own research

3.3. Digital Twin as a Three-Component System

Most definitions in the literature converge towards a tripartite structure which includes the physical product or system, its virtual counterpart, and the connected data that links the two components (Schleich et al., 2017). This structure is consistent with early NASA formulations, which described the Digital Twin as an integrated, multiphysics, and probabilistic simulation of a vehicle or system, using physical models, sensory updates, and operational history to mirror the behavior of the physical twin (Wagner et al., 2019).

In the context of manufacturing, Saporiti et al. (2023) describe the Digital Twin as a virtual representation of physical reality, modeled to capture the physical system itself, external influences from the environment surrounding it, and the processes through which the system manifests itself in that environment. This broader perspective is important because it differentiates the Digital Twin from simple monitoring tools. The virtual model is not just a register of sensory readings, but a computational representation capable of estimating past, present and future behaviors and supporting the decision-making process through simulation (Saporiti et al., 2023).

The distinction between the three levels of integration has direct practical implications. A Digital Model may be sufficient for certain design or documentation tasks. A Digital Shadow allows for historical monitoring and analysis. Only a complete Digital Twin, with its bidirectional data loop, supports real-time intervention, predictive maintenance and closed-loop optimization (Kritzinger et al., 2018).

4. Technologies Underlying the Digital Twin

A Digital Twin is not a stand-alone technology, but a system that becomes functional through the integration of several complementary technologies. Attaran and Celik (2023) identify four main technologies that make it possible to collect and store data in real time, generate valuable information, and create a digital representation of a physical object: the Internet of Things (IoT), Artificial Intelligence (AI), Cloud Computing, and Extended Reality (XR). The extent to which each of these is used varies depending on the type of application, but all are present, in one form or another, in any functional implementation of a digital twin.

4.1. Internet of Things (IoT)

The Internet of Things (IoT) is a vast network of interconnected devices, machines, and sensors that can communicate with information systems and with one another (Attaran, 2017). IoT is the fundamental technology that underpins all applications in the context of Digital Twin: sensors affixed to real-world objects gather information in real time and send it to the digital representation, guaranteeing the virtual model’s constant updating.

The digital twin would be reduced to a static model and unable to reflect the actual condition of the physical system in the absence of this continuous flow of data from the real world.

According to recent projections, more than 90% of IoT platforms will have Digital Twin capabilities by 2027 (Attaran and Celik, 2023).

4.2. Cloud Computing

The volumes of data generated by IoT sensors are considerable, and their local storage and processing are often impractical. Cloud computing provides the necessary infrastructure: scalable storage capacity, access to data from any location, and sufficient computing power to run complex simulation models (Shu et al., 2016). In addition, cloud platforms allow for reduced computation times for complex systems and solve one of the common practical limitations of Digital Twin implementation - the high cost of dedicated local infrastructure. Not coincidentally, companies such as Google Cloud and Microsoft Azure have launched specialized cloud platforms for Digital Twin in recent years, signaling the maturation of this technological ecosystem (Attaran and Celik, 2023).

4.3. Artificial Intelligence (AI)

If IoT and cloud computing ensure the capture and storage of data, AI is the one that transforms it into usable information. AI can automatically analyse collected data, spot trends, forecast the physical system’s future condition, and recommend remedial actions before issues worsen by using machine learning, deep learning, and neural network techniques (Lv and Xie, 2021). For instance, AI included into a Digital Twin in manufacturing may forecast equipment wear and tear and suggest the best moment to intervene, lowering expenses brought on by unplanned malfunctions.

The predictive capability is among the most significant contributions of Digital Twin technology to the industrial sector.

4.4. Extended Reality (XR)

Extended Reality is an umbrella term that covers Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). These are technologies that merge the physical and digital worlds in different ways (Marr, 2019). Within the Digital Twin, XR adds a layer of interactivity: users can view and manipulate digital representations of physical objects, test simulated scenarios before their real implementation, and intervene on physical systems via the virtual interface. Applications are diverse - from training industrial operators in simulated environments, without real risks, to supporting surgeons in planning interventions based on a digital patient model.

The four technologies do not act independently, but condition each other, forming the integrated infrastructure on which any Digital Twin implementation is built. Figure 2 illustrates how they are articulated around the digital twin.

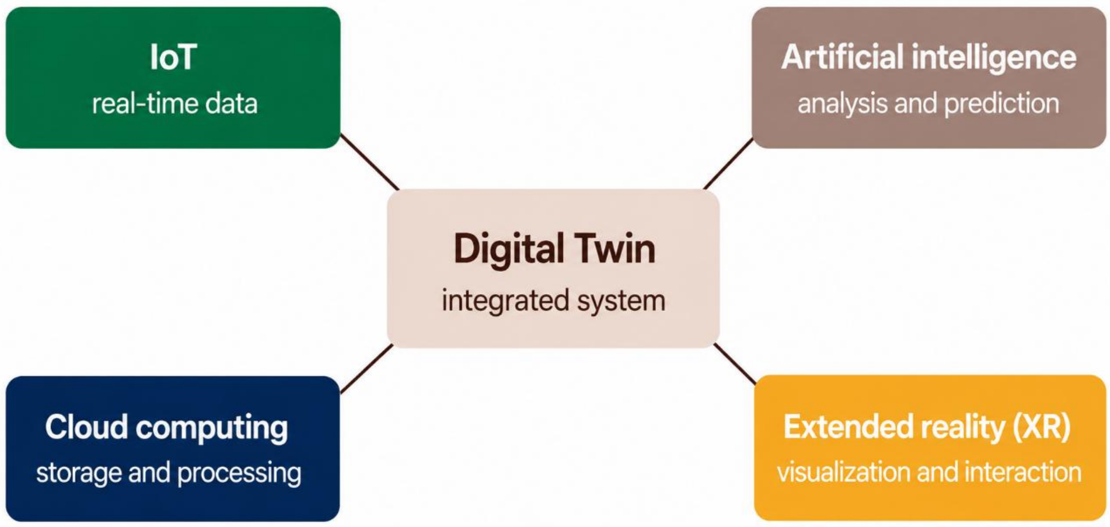

Figure 2. The technologies underlying Digital Twin (adapted from Attaran and Celik, 2023)
Source: Authors' own research

5. Digital Twin Application Areas

The potential of Digital Twin technology manifests itself differently from one industry to another, depending on the complexity of the physical systems involved, the volume of available data, and the maturity of the existing digital infrastructure. The maturity of the literature also varies significantly: manufacturing benefits from the richest empirical base, while agriculture and services represent emerging directions with a corpus of research still in the making.

What all application areas have in common is the same fundamental mechanism: the possibility of testing, monitoring, and optimizing in the virtual space what in the physical world would entail high costs, risks, or time constraints. The following sections review five areas in which the technology has recorded significant progress.

5.1. Manufacturing and Industry

The manufacturing industry remains the area in which Digital Twin technology has reached the highest degree of maturity. Interest has increased with the shift to the Industry 4.0 paradigm, which has brought extensive sensing, monitoring and real-time decision-making capabilities

(Wagner et al., 2019). Javaid et al. (2023) emphasize that one of the essential characteristics of the smart factory is precisely the ability to maintain rigorous control over interactions on the production line, anticipating and preventing failures before they affect the activity. In this framework, the digital twin is no longer a simple simulation tool, but becomes an active component of the manufacturing process. At the level of product design, a virtual prototype built before the physical one allows testing multiple design variants and identifying weak points without additional material or time costs (Attaran and Celik, 2023). Saeedi (2024) highlights that the Digital Twin can be exploited in all three main phases of a manufacturing system (design, configuration and operation) ensuring continuous optimization based on real-time data. Predictive maintenance remains one of the most cited applications: instead of intervening after a failure occurs or according to a fixed schedule, the system identifies early signs of wear and recommends intervention at the optimal time. General Electric reports reductions in production waste of up to 75% and increases in equipment efficiency of 10% following implementations of this type (Saporiti et al., 2023).

5.2. Health and Life Sciences

In the medical field, Digital Twin operates on a different scale than industry - not machines or production lines, but organs, patients, or hospital facilities. The COVID-19 pandemic has significantly accelerated the digital transformation in this sector, putting pressure on systems to become more efficient and adaptable (Attaran and Celik, 2023). Sun et al. (2023) note that Digital Twin technology in medicine works on the principle of a virtual counterpart of the real patient, capable of integrating data from multiple sources (medical history, imaging, physiological parameters in real time) to support personalized clinical decisions.

The Living Heart project by Dassault Systèmes exemplifies a remarkable application, having developed a fully operational digital model of the human heart that simulates blood flow, mechanics, and electrical activity. According to Meijer et al. (2023), these digital twins of organs are among the most promising developments in personalised medicine, demonstrating that they can help anticipate medication effects prior to actual clinical testing as well as identify new therapeutic targets. Digital twins can optimise patient flows, hospitalisation capacity, and resource planning at the hospital level, giving medical institution management a tool for making decisions based on real data and simulated scenarios (Sun et al., 2023; Attaran and Celik, 2023).

5.3. Construction and Real Estate

Building Information Modelling (BIM), a technique for simulating the functional and physical aspects of a construction project, has long been used in the construction industry.

According to Baghalzadeh Shishehgarkhaneh et al. (2022), the Digital Twin concept in the built environment was made possible by integrating BIM and IoT, which adds a layer of real-time data to the static BIM model and turns the project document into an active management tool.

On the construction site, this capability translates into the ability to track the progress of the works against the initial plan, detect costly deviations from time and manage resources more efficiently (Attaran and Celik, 2023). According to Nguyen and Adhikari (2023), the Digital Twin can greatly improve construction safety by integrating data from mobile devices, sensors, and video cameras to instantly identify dangerous circumstances. The digital twin does not become obsolete after building is finished. Recent research documents extensive applications in assessing the energy efficiency of buildings and monitoring indoor environmental quality, areas where optimization through real-time data has shown consistent practical benefits.

5.4. Agriculture

The application of Digital Twin in agriculture is more recent, but its potential is considerable in a sector where decisions depend on natural factors that are difficult to control. Purcell and Neubauer (2023) emphasize that Digital Twin is in a unique position to eliminate the boundaries between the perception of the system state, understanding the physical entity and the automation of intervention, through high-fidelity modeling and bidirectional data flows. A digital twin of a farm can integrate data from soil sensors, weather stations, drones and irrigation systems, generating simulations of crop evolution according to different intervention scenarios.

Nasirahmadi and Hensel (2022) identify the digitalization of agriculture through the Digital Twin paradigm as a major direction for addressing the challenges related to food security, climate protection and resource management. Peladarinos et al. (2023) extend the perspective by showing that smart agriculture combined with Digital Twin can bring direct benefits in crop modeling, precision agriculture and farm management, with an impact on water, fertilizer and pesticide consumption. In animal husbandry, recent research explores the use of digital twins to optimize housing conditions (air quality, temperature, energy consumption) with the aim of maximizing animal welfare and economic efficiency (Attaran and Celik, 2023).

5.5. Services and Product-Service Systems

The vast majority of the review papers on Digital Twins focus on manufacturing and large physical assets. Zhang et al. (2019) point out that this focus leaves a significant potential unexplored: the role of technology in the extended product life cycle, including associated services and product-service models (Industrial Product-Service Systems - IPS2). Bertoni and Bertoni (2022) later deepened this perspective, arguing that integrating the digital twin throughout all stages of the product-service system life cycle is crucial for the intentional design of these systems.

The main idea is that the digital twin should not stop at the product exiting the manufacturing line: throughout the usage phase, the active model provides real-time information about the product's condition and can anticipate service needs, and at the end of the life cycle it contains the entire history of the product (condition, use, interventions) facilitating decisions on reuse, reconditioning or responsible recycling (Zhang et al., 2019). This broadening of the perspective is relevant in the context in which more and more industries are migrating from selling products to offering integrated solutions, and the Digital Twin is becoming the infrastructure that supports these new business models (Bertoni and Bertoni, 2022).

6. Challenges of Digital Twin Implementation

Despite the potential demonstrated in the areas presented above, the widespread adoption of Digital Twin remains hampered by a number of obstacles that are not exclusively technical. Saporiti et al. (2023) conducted one of the few empirical studies dedicated to this topic, using the Delphi method with a panel of 15 experts (academics and industry practitioners) to identify and prioritize the key challenges of implementation in the production environment. Their results, corroborated with the conclusions of other researchers, outline a complex picture in which organizational difficulties tend to be underestimated in relation to technical ones, although in practice they have at least as great an impact.

6.1. System Integration Challenges

One of the common problems encountered in real-world implementations concerns the compatibility between the technologies required for the Digital Twin and the equipment already existing in factories or organizations. Fuller et al. (2020) identify the lack of standardization and interoperability as one of the major structural barriers. Legacy IT systems, machines with proprietary protocols, and the absence of common data exchange formats make it difficult to build a coherent information flow between the physical and virtual worlds. Saporiti et al. (2023) confirm this reality through their Delphi study, showing that practitioners are constantly faced with the need to ensure compatibility between new technologies and existing infrastructure - a challenge that consumes considerable resources before the digital twin itself can be operationalized.

6.2. Security and Data Protection

The operation of a Digital Twin involves a continuous flow of data between the physical system and its virtual representation, which implicitly creates cybersecurity vulnerabilities. Birkel and Müller (2021) point out that the risks related to data protection in the context of Industry 4.0 are significantly amplified by the need to share information between multiple actors (suppliers, customers, technology partners) which makes it difficult to clearly delineate responsibilities and access rights. Saporiti et al. (2023) add that the lack of transparency over the collected data and the absence of clear mechanisms for protecting intellectual property are real concerns for companies implementing this technology, especially in sectors where process data has high competitive value.

6.3. Technical Performance Challenges

Building a functional digital twin imposes high technical requirements, especially in terms of the speed and reliability of communication between the physical system and the virtual model. Fuller et al. (2020) identify the high latency of internet connections and the lack of real-time communication systems with sufficient performance as significant practical limitations, especially in industrial applications where decisions must be made in fractions of a second. Rasheed et al. (2020) complement this perspective by showing that virtualization, updating, and prediction of complex systems behavior remain open computational challenges: digital models must be simultaneously robust, flexible, and fast enough to be useful in real operational conditions - a balance difficult to achieve with current technologies.

6.4. Organizational Challenges

The Delphi study by Saporiti et al. (2023) reveals that the most relevant challenges identified by experts are not technical, but organizational. The lack of necessary skills at the personnel level obtained the highest relevance score of all the challenges assessed, reflecting a worrying reality: the labor market does not produce specialists capable of developing, implementing and maintaining Digital Twin systems in real industrial contexts quickly enough. Alongside this, cultural inertia (resistance to change by operators and managers) was identified as a high-impact obstacle with a high level of consensus among experts.

Implementation costs represent another significant organizational barrier. The acquisition of sensors, software modules and data storage and processing systems required for a functional Digital Twin involves considerable initial investments, which are difficult to justify in the absence of clear models for quantifying the benefits (Attaran and Celik, 2023). Perno et al. (2022) adds that the implementation process is usually lengthy, which extends the time to return on investment and increases managerial uncertainty.

6.5. Data Quality and Technological Ecosystem Maturity

No matter how powerful the technological infrastructure, a Digital Twin is only as good as the data that feeds it. Fuller et al. (2020) point out that production data is often fragmented, incomplete, or inconsistent, which directly affects the accuracy of simulations and predictions generated by the model. Saporiti et al. (2023) complete the picture by noting that uncertainty about the required technologies and the lack of reference implementations for practitioners to refer to are factors that slow down adoption. Wagner et al. (2019) emphasize, from a product design perspective, that a unified framework for the holistic use of the digital twin throughout the entire product engineering process remains an unfulfilled desire, the achievement of which requires both technical standardization and interdisciplinary collaboration between designers and production engineers.

7. Future Directions and Conclusions

7.1. Future Directions

The evolution of Digital Twin technology in the coming years will be largely determined by the maturation of the technologies that support it and by the progressive resolution of the challenges identified in the previous chapter. A first direction concerns deeper integration with artificial intelligence. If AI is currently used predominantly for data analysis and prediction generation, recent research explores models in which the digital twin and machine learning systems feed each other in a closed loop - the virtual model generates synthetic data to train algorithms, and the improved algorithms in turn refine the virtual model (Lv and Xie, 2021). This synergy could overcome one of the current limitations: the dependence on large volumes of real data to produce reliable simulations.

A second direction aims to expand the use of augmented and virtual reality as interfaces for interaction with the digital twin. Attaran and Celik (2023) predict that the future of the Digital Twin will combine analytical capabilities with immersive experiences, allowing operators to interact with the virtual model intuitively. Standardization is another direction with structural impact. Wagner et al. (2019) argue that a unified framework for the holistic use of the Digital Twin throughout the entire product lifecycle is a necessary condition for the transition from isolated implementations to integrated digital ecosystems on an industrial scale. Last but not least, Saporiti et al. (2023) identify the potential of the Digital Twin as a building block for the industrial metaverse - a persistent virtual environment in which digital twins of equipment, processes, and organizations coexist and interact.

An insufficiently explored direction in the current literature concerns the adoption of Digital Twin technology in organizations with limited digital resources - small and medium-sized enterprises or companies in emerging economies. The challenges identified in the previous chapter, in particular implementation costs and lack of skills, are amplified in this context, and future research should develop scalable models and benefit quantification frameworks adapted to these realities (Attaran and Celik, 2023; Perno et al., 2022).

7.2. Conclusions

Digital Twin technology has come a long way in two decades - from an academic concept introduced in 2003 (Grieves, 2014) to an operational tool used in the most diverse industries, from factories and hospitals to farms and construction sites. This paper aimed to provide a coherent picture of this journey, organized on four levels: conceptual foundations, supporting technologies, application areas and implementation challenges.

From a conceptual perspective, the distinction proposed by Kritzinger et al. (2018) between Digital Model, Digital Shadow and Digital Twin remains the most useful tool for clarifying a term often used with different meanings in the literature and in practice. Only the digital twin in the strict sense (with the automated bidirectional flow of data) offers the predictive and operational capabilities that justify the investments associated with the technology.

The analysis of application areas highlighted that, although manufacturing remains the sector with the richest literature and the most mature implementations (Javaid et al., 2023; Saeedi, 2024), the technology is rapidly expanding into healthcare, construction, agriculture and services. The challenges identified show that successful implementation does not depend exclusively on solving technical difficulties. Saporiti et al. (2023) empirically demonstrate that the human factor (lack of skills, cultural resistance to change and management of managerial expectations) has an impact at least as great as system interoperability or data quality.

Overall, Digital Twin is at a moment of expansion in which enthusiasm for the potential of the technology must be balanced with a lucid understanding of the conditions necessary for this potential to materialize. Future research should focus on standardization and interoperability, on models for quantifying benefits and on building human capital capable of supporting long-term implementations.

The contribution of this paper consists in the simultaneous integration of the technical and organizational perspectives into a unitary analytical framework, consistently applied across five application domains. This approach highlights that the discussion about Digital Twin cannot remain confined to the technological area, the success of adoption depends equally on the human and organizational capacities of the implementing companies, a conclusion with direct implications for both research and managerial practice.

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