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Review

Impact of Digital Twins on Real Practices in Manufacturing Industries

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Abstract

In the era of Industry 5.0, the digital revolution stands as the paramount tool for achieving efficiency and elevating the standards of quality and quantity. This study delves deeply into the invaluable applications of digital twins within real production settings, highlighting their transformative potential across a multitude of industries. Focusing particularly on textiles, machinery, and electronics manufacturing, the authors illustrate how digital twins enhance productivity, anticipate challenges, bolster the food supply chain, refine healthcare services, and propel sustainability initiatives within each sector. Through concrete examples, we demonstrate how digital twins can markedly decrease waste, energy consumption, and production downtime, all while elevating product quality and enabling virtualization. By virtually simulating physical systems, numerous operational issues can be mitigated, underscoring the pivotal role of digital twins in fostering hyper-personalization, sustainability, and resilience the foundational tenets of Industry 5.0. Nevertheless, this evaluation acknowledges the inherent challenges associated with the widespread adoption of digital twins, including concerns regarding data infrastructure, cybersecurity, and workforce adaptation. By presenting a balanced assessment of both the advantages and disadvantages, this review aims to guide future research and development endeavors, paving the way for the successful integration of this revolutionary technology as we journey toward Industry 5.0.

Keywords: digital twins; industry revolution 5.0; spatio-temporal; manufacturing industry; automation; AI

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1. Introduction

Researchers from a variety of fields convened at the workshop to define concepts, specify research priorities, and lay out a research agenda about "thinking machines", where Artificial Intelligence (AI) was, for the first time in 1956, formally recognized as a research subject titled "Dartmouth Summer Research Project on Artificial Intelligence" by John McCarthy. Since the field's interests are broad and do not only pertain to subjects like cybernetics, automata theory, and sophisticated information processing, they adopted the term "Artificial Intelligence" to reflect this [1–3]. More precisely, one of the newest and most significant technological advances is digital twins (DT), which is driven by the combination of AI models of physical objects with Big Data Analytics for processing IoT data. Due to their potential and significant influence in industries including manufacturing, aircraft, healthcare, and medicine, DT models are becoming more popular. Leading the

charge in the industrial 4.0 revolution is the Digital Twin, made possible by powerful data analytics and Internet of Things (IoT) connectivity. IoT has increased the amount of data that can be used from manufacturing, healthcare, and smart city contexts. When coupled with data analytics, IoT's rich environment provides an invaluable resource for predictive maintenance and fault detection, to name just two, as well as the long-term health of manufacturing processes and smart city developments [4,5]. It also supports anomaly detection in patient care, fault detection, and traffic management in a smart city. The challenge of smoothly integrating IoT and data analytics can be addressed by the Digital Twin by creating a linked physical and virtual twin [6–9].

Accurate analytics enables quick analysis and in-the-moment decision-making in a digital twin environment. How can the price of creating a prototype and running testing on it be lowered? How is it possible to subject a prototype to rigorous testing that is not possible in a lab setting? In what way can a prototype include all the data and results of these experiments to yield a precise forecast of future actions? How can someone keep an eye on a physical item in real-time and receive alerts before something seriously goes wrong? How can people obtain real-time information about all the parts that make up a physical asset and information about the asset itself, conduct insightful real-time analysis on this data, and use that data to make timely, reliable, and effective decisions about operations in the future? Digital Twin is the response (Figure 1) (DT) [9–11]. Virtual replicas of goods, procedures, or services that meet all the criteria are known as Digital Twins. Grieves and Vickers define a Digital Twin (DT) as "a set of computer-generated representations that accurately represent a potential or real physical manufactured product through the micro atomic level until the macro geometrical level." At best, a product's DTs can provide all the information that could be discovered by physically evaluating the thing. By combining twinning, simulation, real-time monitoring, analytics, and optimization, the DT seeks to achieve the best of all worlds. In the context of Industry 4.0, where several sectors are undergoing a digital metamorphosis, Digital Twin (DT) technology is regarded as indispensable for attaining a competitive and financial edge over rivals. With its roots in the field of aerospace, DT has the potential to revolutionize several other sectors. DT finds use in several important industries, including designing and arranging, optimization, maintenance, safety, taking decisions, remote access, and training [12–16].

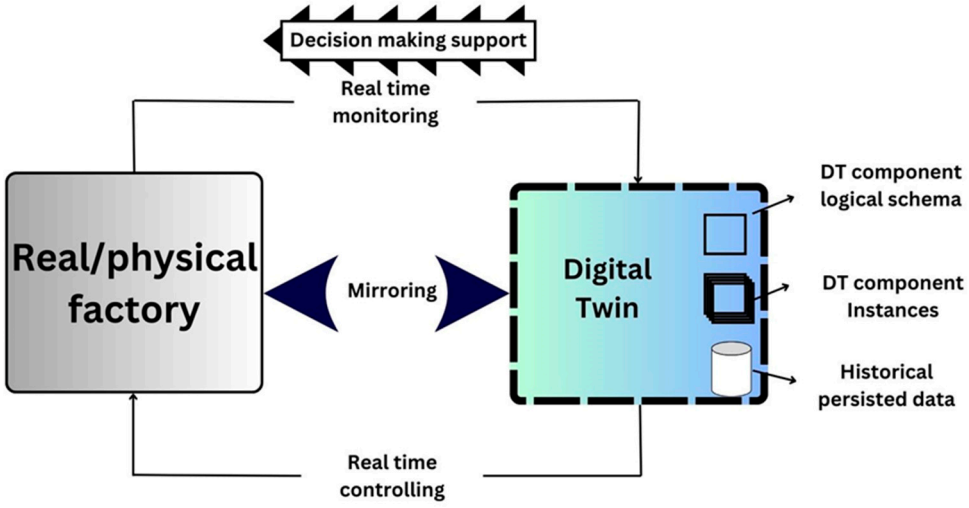


Figure 1. Real-time monitoring and controlling.

It may serve as a very helpful tool for companies trying to increase production, growth, and efficiency [16]. Real-time linking of the physical and virtual realms is possible with DT, allowing for a more comprehensive and realistic assessment of unplanned and un-

predictable events. DT's ability to reduce time to market, streamline operations, save maintenance costs, increase user engagement, and integrate information technologies makes it an indisputable asset to any industry. The global DT market was expected to be worth USD 3.1 billion in 2020, and it is expected to grow significantly in the ensuing years [12,16,17]. The COVID-19 epidemic has altered the way that maintenance and manufacturing are perceived, which has sped up the use of Digital Twins. As a result, depending on the type of industry where DT is implemented, it becomes crucial to comprehend what the repercussions could or should be. By definition, a Digital Twin is an exact duplicate of an actual procedure that is expressed alongside the real-time process and usually runs in perfect synchronization with it. The phrase was first used in the early 2000s by whose experience in product design first gave the concept a foundation in production engineering. Nevertheless, the concept has grown in scope and adaptability since then, and it is currently employed or rather, used to describe a variety of digital simulators that work in combination with real-time operations associated with social and physical systems. Determining the distinctions between a real system and any computer model of that system is therefore an urgent subject. In this regard, it is important to note the difficulties this presents for the debates over what defines a Digital Twin of a city [18–23]. The following are some advantages of Digital Twins:

Real-time remote monitoring and control: Physically obtaining a complete real-time image of a large system is exceedingly challenging. The Digital Twin may be accessible from anywhere by definition. By using feedback systems, the system's performance can be remotely controlled in addition to being observed [24].

Increased effectiveness and security: Digital twinning is expected to allow for increased autonomy while keeping humans informed as needed. This will guarantee that robots are assigned hazardous, boring, and filthy tasks, with humans operating them from a distance. People will be able to concentrate on more imaginative and creative work in this way [25].

Predictive maintenance and scheduling: Real-time big data generation from numerous sensors monitoring physical assets is guaranteed by thorough Digital Twinning. Smart data analysis makes it possible to identify system flaws well in advance. Better maintenance scheduling will be possible as a result.

Scenarios and risk assessment: What-if analyses that produce a more accurate risk assessment are made possible by a Digital Twin, or more accurately, a digital sister of the system [26]. The system can be perturbed to create unexpected scenarios and observe how the system responds, along with the related mitigation techniques. A Digital Twin is the sole tool that allows for this kind of study without endangering the original item.

Improved collaboration and synergy both within and between teams: Teams that have more autonomy and instant access to information can make better use of their time, which results in increased production.

An enhanced and well-informed decision assistance system: Making decisions more quickly and intelligently will be aided by the real-time availability of quantitative data and sophisticated analytics.

Customization of goods and offerings: The need for personalized goods and services will only grow because of intricate past requirements, diverse stakeholder preferences, and changing market trends and rivalry [27]. In the context of future factories, a Digital Twin will allow for quicker and more seamless gear shifts to accommodate shifting demands.

Improved communication and documentation: Transparency will increase with readily available real-time information and automatic reporting that keeps stakeholders informed.

1.1. Digital Model

The absence of automated data flow between the physical and digital models is necessary for the correct definition of a digital model. A digital replica of a planned or real physical object is called a digital model. Digital models include designs and designs for products, as well as blueprints for buildings. The main feature that distinguishes this is that there is no automated transfer of information between the physical system and the digital model. This suggests that changes made to the original object after the creation of the digital model have no effect on the digital model at all [28].

1.2. Digital Shadow

An item that has a one-way flow between its physical and digital forms is called a digital shadow. It is a digital item that changes when the physical object changes, not the other way around. Figure 2 shows an example of a digital shadow [29].

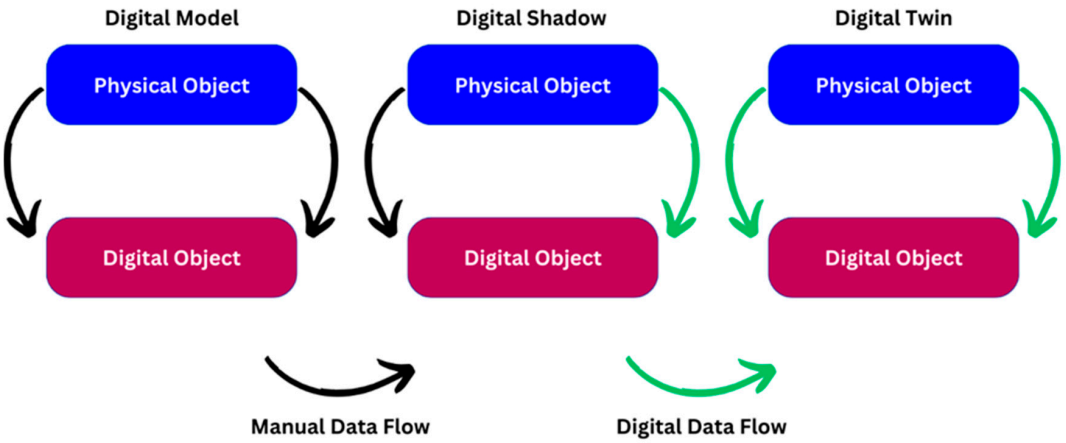


Figure 2. Digital model, shadow, and twin.

1.3. Digital Twin

A "Digital Twin" is a reference where information travels between a digital object and an actual physical object in both directions, fully integrated. Changes made to the physical object automatically change the digital object as well, and vice versa [30]. The term Digital Twin was defined by different authors/researchers/experts in different eras as mentioned in Table 1.

Table 1. The definitions of Digital Twins by experts.

Sr	Author	Definition	Reference	Key Limitations
1	Nasa 2012	A Digital Twin is a comprehensive Multiphysics, multiscale, statistical simulation of an auto or system as built that utilizes the best physical models currently on the market, sensor updates, fleet history, etc., to mimic the life of its corresponding flying twin.	[10]	Highly domain-specific (aerospace focus); limited generalization to other industries at the time.
2	Chen 2017	A computerized representation of a physical system or equipment that interfaces with the operational components and reflects all functional attributes is called a "Digital Twin."	[27]	Emphasizes data representation but lacks clarity on lifecycle integration and scalability.

Table 1. *Cont.*

Sr	Author	Definition	Reference	Key Limitations
3	Liu et al., 2018	The Digital Twin is essentially a living, breathing copy of the corresponding physical asset or system. It is able to anticipate events in real time and adapts to changes in operations on a constant basis by using data collected from the internet.	[28]	Conceptually broad; lacks specification on data standards, model structure, and implementation frameworks.
4	Zheng et al., 2019	A Digital Twin is a collection of virtual data that, from the micro-atomic to the macro geometrical levels, completely characterizes a possible or real physical output.	[29]	Focused on data characterization; omits feedback mechanisms and real-time synchronization aspects.
5	Vrabič et al., 2018	A Digital Twin is an integrated simulation and service data-based digital model of a real object or assembly. Throughout the product life cycle, data from many sources is stored in the digital representation. This data, which forecasts future conditions in the design and operating contexts, is updated often and presented in multiple ways to enhance decision-making.	[30]	Requires extensive and continuous data input; implementation complexity and cost are high.
6	Madni 2019	A Digital Twin is a virtual image of its physical counterpart that is updated with details on overall health, performance, and maintenance throughout the physical system's life cycle.	[31]	Focuses on monitoring; offers limited discussion of predictive or adaptive capabilities.

These definitions aid in pointing out the typical misunderstandings found in the literature. Nonetheless, several myths are seen, and they are not exclusive to these instances.

Meta-Analysis and Proposed Unified Taxonomy

The analysis in above Table 2 reveals that the two non-negotiable components of a Digital Twin definition are:

Table 2. Meta-Analysis and Proposed Unified Taxonomy for Digital Twin by experts.

Sr	Author (Year)	Core Definition Focus	Physical Link (P) (Required)	Simulation/Modeling (S) (Variable)	Real-Time Data (R) (Required)	Lifecycle Scope (L) (Variable)
1	NASA [10]	Comprehensive multiphysics, multiscale statistical simulation to mimic the life of its corresponding flying twin.	✓	✓	✓	✓
2	Chen [27]	Computerized representation that interfaces with operational components and reflects all functional attributes.	✓	×	✓	×

Table 2. *Cont.*

Sr	Author (Year)	Core Definition Focus	Physical Link (P) (Required)	Simulation/Modeling (S) (Variable)	Real-Time Data (R) (Required)	Lifecycle Scope (L) (Variable)
3	Liu et al. [28]	Living, breathing copy able to anticipate events in real time and adapt to changes using data collected from the internet.	✓	✓	✓	✓
4	Zheng et al. [29]	Collection of virtual data that completely characterizes a possible or real physical output.	✓	×	×	×
5	Vrabič et al. [30]	Integrated simulation and service data-based digital model that forecasts future conditions throughout the product life cycle.	✓	✓	✓	✓
6	Madni [31]	Virtual image updated with details on overall health, performance, and maintenance throughout the physical system's life cycle.	✓	×	✓	✓

Physical Link (P): A clear connection to a physical counterpart (present in 6/6 definitions).

Real-Time Data (R): The concept of synchronization or continuous updating (present in 5/6 definitions).

The elements of Simulation (S) and Lifecycle Scope (L) are highly valuable but variable. While simulation allows for prediction and advanced use cases, some definitions focus solely on mirroring state (Madni, Chen). Similarly, while many DTs cover the entire lifecycle, some definitions are focused purely on the 'as-built' state (Zheng).

Proposal for Unified Taxonomy: A Digital Twin is fundamentally a live, functional, and computationally rich representation of a unique physical asset or system that is synchronized with its physical counterpart via continuous or near-continuous data exchange.

2. Digital Twins and Cyber-Physical Systems

According to Alessandra Spagnoli et al., smart manufacturing is powered by cutting-edge technologies that rely on cyber-physical integration, such as IoT, cloud computing, big data analytics, and AI [32]. Digital twins (DTs) and cyber-physical systems (CPS) are essential for this integration because they provide robustness and efficiency through real-time interaction. CPS and DTs differ in their development, origin, engineering processes, mapping, and fundamental elements, yet they share many essential concepts. This study examines and contrasts CPS and DTs, highlighting the distinctions and relationships between them [33,34]. Smart manufacturing depends on achieving cyber-physical interaction, which makes CPS and DT the ideal instruments. The comparison facilitates comprehension of these technologies by drawing attention to conceptual parallels and opening new avenues for investigation [35–37].

3. Digital Twins: Practice, Challenges, and Open Research

When Angira Sharma et al. first presented Digital Twin (DT) more than ten years ago, it offered the promise of accurate forecasting, modeling, optimization, and real-time monitoring [38,39]. Widespread implementation, however, is hampered by the lack of public information on successful cases, which makes thorough evaluation and comparison difficult. This assessment discusses challenges such as developing concepts, lack of universal standards, problem-dependence, security problems, and evolving technologies

and focuses on important DT features, techniques, and successful implementations [39]. Although advancements in big data, IoT, and machine learning improve DT characteristics, gaps still exist, preventing mainstream implementation. The book presents real-world case studies, defines a DT conceptualization, and validates its uniqueness. Despite progress, problems still exist, which help us comprehend DT better [40].

3.1. Improving Design-Led Sustainable and Hybrid Retail Experiences via Digital Twins

According to Alessandra Spagnoli et al., the fashion industry has undergone significant changes in terms of design, manufacturing, presentation, distribution, and consumption because of digitization [41,42]. A dematerialized economy arises in the age of connection, redefining purchasing habits for environmentally friendly behaviors. The fashion business is embracing dematerialization and experimenting with different strategies to improve customer connections and advance sustainability [43]. Following COVID-19, high-end labels make investments in apparel digitization and establish profitable alliances with the gaming sector [44,45]. Using computer graphics and 3D design streamlines processes, increasing output and lessening environmental effects. The merging of the digital and physical worlds brings up novel user experiences. Fashion's traditional retail and communication channels are being disrupted by Digital Twin technology, which is widely used in other industries. This article investigates novel approaches in the fashion retail industry, with implications for sustainability, customer experiences, and the merging of physical and digital domains [46,47].

3.2. Cloud-Based Framework for the Elderly Healthcare Services

According to YING LIU et al., Applications of Digital Twins in precise simulation across industries have been made possible by developments in big data, cloud computing, and IoT technologies. Medical pathway planning, resource allocation, and activity prediction in healthcare all depend on simulation [48]. Healthcare can be revolutionized by integrating Digital Twins; yet there are still obstacles to overcome to achieve lifelong personal health management and the convergence of the physical and virtual worlds [48]. This research suggests a Cloud DTH framework that makes use of cloud-based Digital Twin healthcare (DTH) to track, diagnose, and forecast an individual's health, particularly that of the elderly. The goal of Cloud DTH is to bring virtual medical and actual places together and encourage engagement. In addition to introducing the DTH concept and outlining a reference framework for Cloud DTH, the article also examines important supporting technologies and uses a case study to illustrate real-time supervision [49,50]. The use of Digital Twin technology to meet real-time supervision difficulties in senior healthcare is the contribution. In the Cloud DTH platform, future work will concentrate on device integration, accuracy verification, collaboration, model management, and data integration.

Recent implementations of Digital Twin (DT) technology in both healthcare and the food supply chain have demonstrated measurable operational improvements.

In the healthcare sector, DT-driven predictive models have reduced equipment downtime by approximately 20–30%, while improving process efficiency by 10–15% through real-time monitoring of medical assets and patient flow optimization. Additionally, hospitals integrating DT-based maintenance frameworks reported an average ROI of 15–25% over a three-year period, primarily due to reduced machine failure and improved resource allocation.

3.3. Digital Twin Framework: Specification and Opportunities

James Moore et al. describe that one of the main components of Industry 4.0 or Smart Manufacturing (SM) is the Digital Twin (DT), a disruptive technology in engineering and design. Although DTs have been used in fields such as maintenance and process con-

trol, a framework is necessary for their broad incorporation in the development of SM or I4.0 [51,52]. Reusability, interoperability, interchangeability, maintainability, extensibility, and autonomy throughout the DT lifespan are among the requirements for a DT framework that are derived from DT definitions, present applications, anticipated future usage, and long-term trends. Numerous criteria have been addressed by developing a baseline framework that includes object-oriented architecture and DT definition. The benefits of the framework in assisting DT solutions and SM trends are illustrated through case studies.

3.4. A Survey on Digital Twin: Applications, and Design

Cristina Barbara Barricelli et al. explains how artificial Intelligence (AI) has become an increasingly important part of daily life since it was first recognized as a subject of study in 1956. Over the last ten years, there has been a confluence of big data, cloud computing, broadband, sensors, and networking, which has resulted in the creation of Digital Twin (DT) technology. Healthcare is still in the early stages of DT's implementation, even though it streamlines manufacturing and aviation operations. This research examines existing application areas, evaluates DT definitions, and pinpoints important traits. The design implications center on the DT lifespan and socio-technical elements. Three concerns are addressed in the study: application fields, essential properties, and definitions of DT. Novel DT application trends and lifecycles will be investigated in future studies, providing insights into the smooth interactions between digital and physical twins. Over the last ten years, conversations on social automation have been dominated by terminology like artificial intelligence, big data, cloud computing, smart cities, and machine learning [53]. The term "Digital Twin," which was first used about 20 years ago as mentioned in Figure 3, but it is now widely used as digital infrastructure becomes more and more essential to communities and businesses, is a more recent addition to this vocabulary.

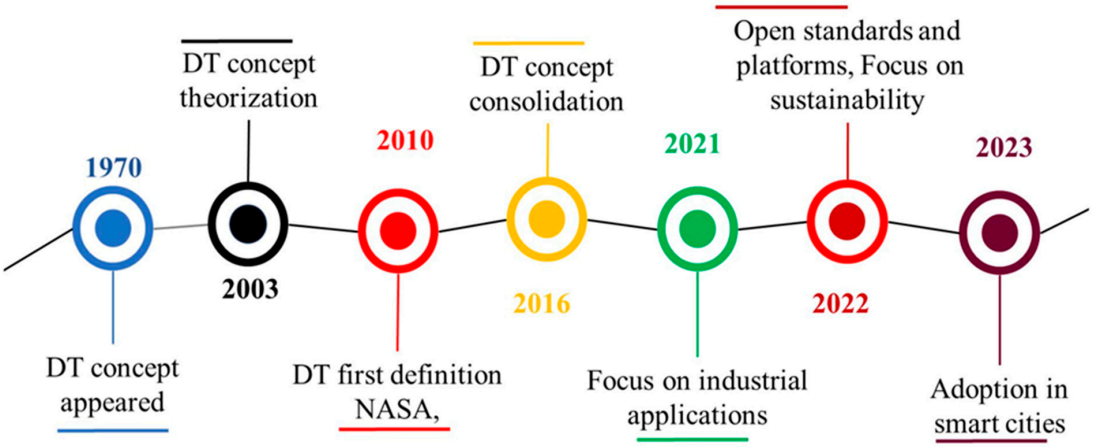


Figure 3. History of Digital twin.

The conceptual origins of DT can be traced back to the 1970s, when initial ideas of mirroring physical systems in digital form began emerging. The first formal definition was introduced by NASA in 2012 as part of its model-based systems engineering framework for spacecraft lifecycle simulation. Between 2003 and 2016, the concept underwent theorization and consolidation, with researchers like refining its structure and emphasizing real-time adaptability [54]. Subsequent phases (2021–2023) highlight the expansion of DT applications toward industrial systems, open standards, and adoption in smart cities, marking DT as a cornerstone technology for Industry 4.0 and sustainable innovation, see Figure 3.

The idea, which had its origins in industrial engineering, has expanded to include computer simulation models used in social, economic, and physical systems. There are

concerns about defining the distinctions between an actual system and its computer model, especially in the context of city modeling, which attempts to combine social, economic, and built environment processes [55]. The pursuit of increasingly realistic models, as demonstrated by initiatives such as Virtual London (ViLo), entails integrating real-time data with high-frequency city-data. This investigation is made possible by the Internet of Things and pervasive sensing, which helps us comprehend the intricate interactions that occur between the social and physical domains. Though the concept of Digital Twins is still in its infancy, it is part of a larger scientific endeavor to understand how physical, natural, social, and economic factors are integrated into our pursuit of the science of cities [55–58].

The lifecycle of a Digital Twin (DT) represents the continuous and dynamic interaction between physical and virtual systems throughout the entire product or process lifespan. The DT lifecycle can be divided into five interdependent phases, each contributing to its intelligence and functional maturity.

Phase 1: Design and Modeling

This initial phase focuses on defining the physical system and creating its virtual representation. Using CAD, simulation models, and physics-based parameters, engineers design a digital replica that mirrors the physical asset's geometry, behavior, and performance characteristics. The accuracy of this modeling phase determines DT's future predictive capabilities.

Phase 2: Data Integration and Connectivity

In this phase, real-time data streams are established through IoT sensors, industrial networks, and cloud infrastructures. Data acquisition frameworks ensure synchronization between physical and digital entities. Connectivity protocols, data fusion techniques, and secure communication channels enable continuous monitoring and feedback loops.

Phase 3: Simulation and Analysis

Once integrated, the DT performs predictive simulations to forecast performance, identify anomalies, and optimize operations. Advanced analytics, machine learning algorithms, and what-if scenario modeling are used to assess different operational strategies and preempt potential failures. This stage is where DTs transition from passive digital replicas to active decision-support systems.

Phase 4: Optimization and Control

Here, insights generated from simulations are implemented back into the physical environment. Control signals are sent from the DT to the physical system to adjust operational parameters, resource allocations, or process schedules. The twin thereby supports closed-loop optimization, reducing downtime, energy use, and maintenance costs.

Phase 5: Evolution and Decommissioning

The lifecycle concludes with the continuous evolution of DT. As systems age, upgrades, recalibrations, and design modifications are reflected in both domains. When the physical asset is retired, the DT's accumulated knowledge can be repurposed for future product generations, ensuring sustainability and knowledge retention.

3.5. An Optimization Tool for Production Planning

Ferro Rodrigo et al. address growth issues faced by the Brazilian textile industry, which ranks fifth internationally, using Discrete Event Simulation (DES) and genetic algorithm optimization [59]. The emphasis is on weaving techniques, batch sizing, scheduling optimization, and production planning [60]. This research investigates the relationships between emerging technologies and how they affect the textile sector. One noteworthy

feature is the thorough use of actual production data in the simulation and optimization process using Tecnomatix Plant Simulation 13®. By using genetic algorithms to optimize the production sequence and efficiently shorten production times, the study saves a substantial amount of money during months when demand is high. Decisions about production sequencing are supported by the simulation model [61].

4. Digital Twin: Origin to Future

According to Singh Maulshree et al., a Digital Twin (DT) is an online representation of a physical object that is linked in real-time and can be used for remote access, maintenance, design, optimization, and monitoring [62]. The use of DT in intricate, self-governing systems has increased with the emergence of Industry 4.0. The article clarifies DT terminology misunderstanding and compiles definitions and types of DT. It tracks the development of DT and analysis of the possible effects on many industries as mentioned in Figure 4. Though DT is an idea that has been around for decades, its true influence has only recently become apparent. It promises reduced costs, more production, remote access, and enhanced safety [63]. When DT is combined with other technologies, new opportunities and applications arise. Among the difficulties mentioned in the study are a lack of agreement, standards, laws, knowledge, and worries about data security. Unlocking DT's full potential across a variety of businesses requires addressing these issues [64–69].

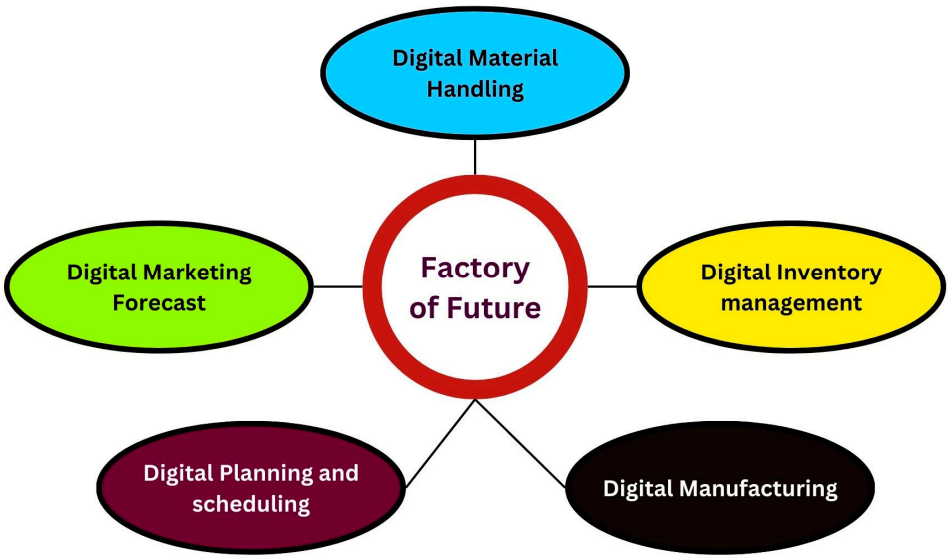


Figure 4. Future of factories and industries.

Author introduce key performance indicators (KPIs) derived from recent Digital Twin (DT) implementations in the industrial sector (Table 3). These metrics provide empirical evidence of the value generated by DT technologies, which complements the descriptive framework shown in Figure 4.

Table 3. Key performance indicators (KPIs) derived from recent Digital Twin (DT) implementations in the industrial sector.

DT Application Type	Average ROI (3-Year Period)	Reduction in Equipment Downtime (%)	Process Efficiency Gain (%)
Predictive Maintenance	15–25%	18–30%	5–8%
Production Line Optimization	10–15%	5–10%	12–22%
Product Lifecycle Management	8–12%	N/A (Focus on Design)	15–25%

Comparative Analysis of DT Implementation Types

Building upon the elements outlined in Figure 5, the following analysis offers a comparative perspective on common DT deployment strategies, differentiating them based on implementation challenges and expected outcomes. The comparison focuses on three key deployment factors: Technical Complexity, Required Data Velocity, and Primary Business Value. This structure assists readers in evaluating the most suitable DT approach for specific industrial needs.

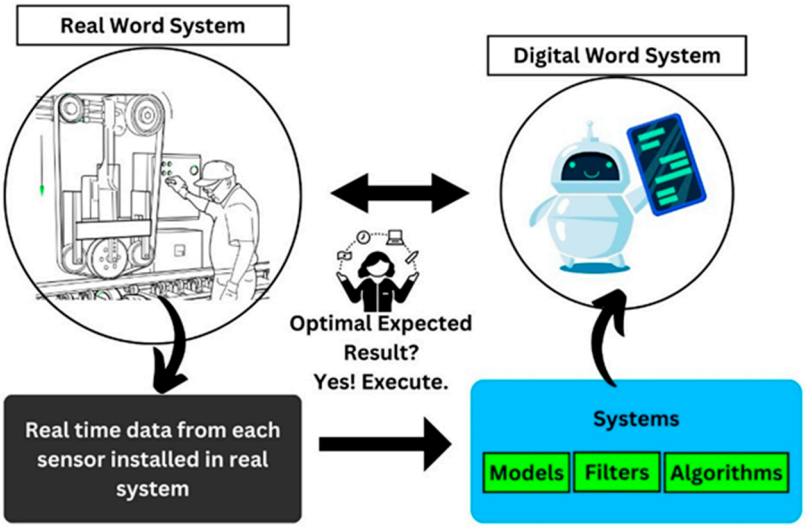


Figure 5. Digital twin elements and how it works.

The comparative analysis (Table 4) highlights crucial trade-offs in DT implementation. For instance, while Process Optimization Digital Twins offer the highest potential for efficiency gain, they necessitate high technical complexity and depend heavily on near real-time data streaming. Conversely, Design Simulation Digital Twins often present a lower barrier to entry due to reliance on static data, focusing their primary business value on accelerating product development and reducing physical prototyping costs. This structured comparison grounds the descriptive 'Elements' in Figure 5 within practical deployment realities.

Table 4. Comparative Analysis of DT Implementation Types.

Implementation Type	Technical Complexity	Required Data Velocity	Primary Business Value
Predictive Maintenance DT	Medium–High	Real-Time Streaming	Cost Savings (reduced failures)
Process Optimization DT	High	Near Real-Time/Streaming	Output Maximization (increased yield)
Design Simulation DT	Low–Medium	Static/Batch Uploads	Reduced R&D Costs and Time-to-Market

4.1. Implementation of Digital Twins in the Food Supply Chain

Digital twins (DTs), according to Ying Huang et al., provide answers to problems with the food supply chain (FSC) [70]. Themes such as FSC issues (complexity, safety, waste, information asymmetry, traceability), DT characteristics (monitoring, real-time simulation, scenario analysis, integration, visibility), and applications were discovered through a comprehensive assessment of literature. The paper offers a novel conceptual framework for DT implementation in FSCs by utilizing the Technology-Organization-Environment framework and Innovation Adoption Theory. Pre-adoption, adoption, and post-adoption

are the three phases of the process [71]. The innovative steps are performance evaluation and technology assessment. Organizations use barriers and both internal and external drivers to steer the implementation of DTs. Technology integration, DT performance measures, and interlevel supply chain applications are potential areas for future research. Researchers and professionals in the food sector can benefit greatly from the study's insightful conclusions.

In the food supply chain, DT applications have enhanced traceability and production consistency, resulting in 5–10% reduction in operational delays and 12–20% gains in overall process efficiency. Real-time data integration between logistics, storage, and production nodes has also contributed to cost savings of 10–18%, particularly by minimizing spoilage and optimizing transportation routes.

4.2. Digital Twin: Challenges and Open Research

According to Aidan Fuller et al. Industry 4.0′s essential component, Digital Twin technology, has become more well-known in business and academics, especially in the manufacturing sector. It includes the smooth integration of data between virtual and physical counterparts. This study examines current works on Digital Twins and groups them into three categories: smart cities, manufacturing, and healthcare. An examination of problems, opportunities, and unexplored research fields reveals a focus on manufacturing research. The article clarifies common misconceptions and highlights the necessity of standardizing terminology for Digital Twins. Despite manufacturing's dominance, healthcare and smart cities are gaining popularity as they present both opportunities and difficulties. The evaluation points out gaps, opening the door for additional study and serving as a fundamental source for academics just starting in the area.

4.3. Digital Twin: Enablers from a Modeling Perspective

According to Adil Rasheed et al., a Digital Twin is an electronic replica of a physical asset that is combined with data and simulators to enable real-time monitoring, control, prediction, optimization, and decision-making. Digital twins are a revolutionary trend thanks to recent developments in cybernetics, big data, artificial intelligence, and computational tools. Digital twins have an impact on the development and functioning of intelligent systems. They are sometimes referred to as a computational mega model, device shadow, or synchronized virtual prototype. The methods for creating Digital Twins are the main topic of this paper, which also highlights the difficulties and enabling technology. A thorough understanding is offered by the division into three pillars: Virtual Twin, Predictive Twin, and Twin Projection. Industry, academia, and research institutions are advised to take advantage of Digital Twins' potential across a range of fields [72].

4.4. Digital Twin: Vision, Benefits and Boundaries

Khajavi, Siavash H. et al. investigated the extension of the Digital Twin idea to building life cycle management in addition to equipment. The goal of the project is to create a Digital Twin, or real-time digital model, of a facade element for an office building as mentioned in Figure 5. The study entails setting up a sensor network to gather and examine environmental data, including humidity, temperature, and light. The study offers a methodical framework for developing a restricted Digital Twin, but it also identifies technical challenges and suggests ways around them. The study makes recommendations for possible uses of building Digital Twins, such as enhancing tenant comfort, cutting down on general administration and operating costs, and lowering maintenance costs. Future studies might investigate the cost–benefit analysis of such systems, incorporate more sensors for a variety of uses, and expand the Digital Twin concept to building interiors.

4.5. Digital Twins-Based Smart Manufacturing System

Jiewu Leng et al. investigated the use of Digital Twin technologies in smart manufacturing system (SMS) design [73]. The Function–Structure–Behavior–Control–Intelligence Performance (FSBCIP) paradigm is presented in recognition of the difficulty of concurrent SMS design and the promise of Digital Twins for semi-physical simulations. Definitions, frameworks, blueprint models, design steps, supporting technologies, design scenarios, and future research topics for Digital Twins-based SMS design are covered in the survey. The study emphasizes how Digital Twins can help uncover errors early and save time and money during physical commissioning and reconfiguration. In the framework of DT-SMSD, important enabling technologies such as IIoT, modeling, virtual reality, data analytics, AI, blockchains, and cloud computing are examined. The purpose of the paper is to offer guidance on creating SMSs in the context of Industry 4.0 [74].

4.6. Industrial Applications of Digital Twins

Jiang Yuchen et al. investigated the status of Digital Twins (DTs) in Industry 4.0 smart production and plantwide optimization. A Digital Twin (DT) is an entity that exists only in the virtual world and is updated with data from its physical counterpart regularly. The primary functionalities of DTs, such as mirroring, shadowing, and threading, are covered in the paper. It highlights the difficulties in industrial practice and shows how DT methods might help with them. The paper ends with a look ahead, projecting that DT technology will be a key component of industrial upgrading and restructuring in the next ten years, providing opportunities for new high-value services [75].

4.7. Construction with Digital Twin Information Systems

According to Rafael Sacks et al. To establish closed-loop control systems, Digital Twin information systems are applied in this work to provide the concept of Digital Twin Construction (DTC), a comprehensive style of construction management. It suggests a DTC information system workflow by expanding on current ideas like artificial intelligence, lean project production systems, and building information modeling (BIM). The workflow establishes the parameters of the conceptual space for the data utilized in DTC workflows by incorporating information repositories, processing operations, and monitoring systems. The study separates DTC from a simple BIM extension or monitoring technology integration, highlighting DTC as a proactive mode that prioritizes closing control loops through accurate and timely information [76].

5. Opportunities for Supply Chains, and Business Models

Karol Daria et al. gives a comprehensive summary of the fashion industry's digital transition with a particular emphasis on the use of three-dimensional virtual and digital (3DVD) technology. The impact of technologies on the fashion supply chain, business models, and sustainability-oriented innovations is examined as shown in Figure 6. Examples of these technologies include 3D modeling, virtual and augmented reality, 2D/3D scanning, and Digital Twinning. Opportunities for dematerialization of conventional supply chain models, changes in goods, services, and processes, as well as their impact on cultural sustainability, are all revealed by the investigation as mentioned in Figure 6. The implementation of digital technologies in the fashion sector requires careful consideration of sustainability from a variety of angles, as the essay highlights [77].

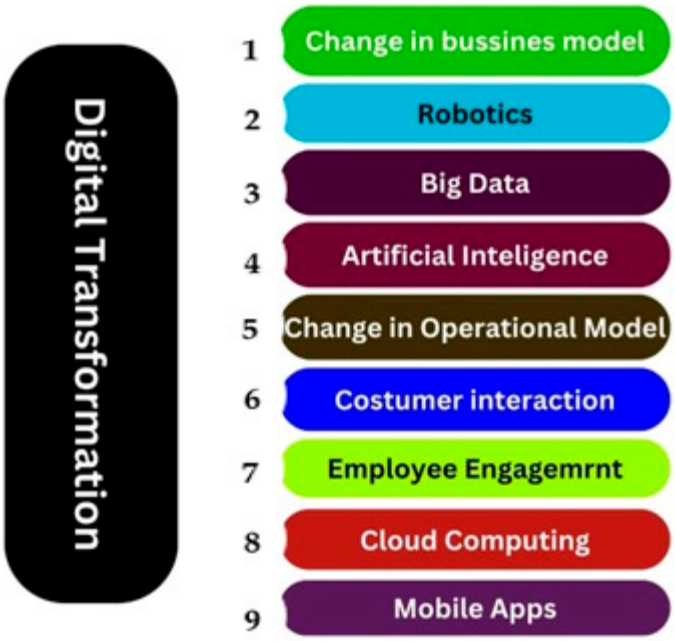


Figure 6. Digital Transformation.

5.1. Industry 4.0 and Digital Twins

Speicher Terrance L. et al. describe in the context of the Industrial Internet of Things (IIoT), Digital Twin analytics has become a useful tool, particularly for small and medium firms (SMEs) [78]. This article focuses on how prognostics and health management techniques used in Digital Twin analytics reduce production downtime and increase productivity for small and medium-sized enterprises (SMEs). It is accepted that small manufacturing organizations encounter difficulties while attempting to integrate Digital Twins; therefore, standard operating procedures, clear definitions, shared nomenclature, and guidelines for implementation are necessary. The essay highlights how Digital Twins can revolutionize manufacturing processes by enhancing their intelligence and intelligence. It is recommended that future research investigate the application of Digital Twins for predictive maintenance in small industrial enterprises. The efficacy of a Digital Twin for a plant is contingent upon its capacity to implement Industry 4.0 technologies at a reasonable cost, incorporating a range of components including modeling, analytics, dashboards, networks, instrumentation, and databases. Businesses must integrate this if they want to remain competitive in the market.

Small and medium-sized enterprises (SMEs) face a range of challenges when adopting Digital Twin (DT) technologies. One of the primary obstacles is the high initial investment cost, which includes expenditures on sensors, data infrastructure, simulation software, and skilled personnel. Many SMEs operate with limited financial and human resources, making it difficult to justify or sustain such technological transitions. Another key challenge is the lack of standardized frameworks and guidelines for DT implementation, leading to inconsistent integration approaches and interoperability issues between systems. Technical complexity also poses a barrier, as SMEs often lack the in-house expertise required for managing advanced modeling, analytics, and data synchronization processes. Additionally, concerns regarding data security, privacy, and ownership discourage firms from fully embracing real-time digital integration [79]. Organizational resistance to change further slows adoption, particularly in firms with traditional operational structures. Finally, the absence of clear performance metrics and demonstrable return on investment (ROI) creates uncertainty, making many SMEs hesitant to commit to long-term DT deployment. Addressing these challenges through government support, standardized methodologies, and cost-effective technological solutions is essential for enabling SMEs to leverage the full potential of Digital Twin innovation.

5.2. Application of Digital Twins in Multiple Fields

According to Guo Jinkang et al., several cutting-edge innovations have emerged as a result of the high-tech industry's rapid expansion, with Digital Twins (DT) being one such innovation [80]. This interactive technology is gaining interest in academic circles worldwide because it successfully crosses the gap between the actual and virtual worlds. Because of its dynamics, integrity, and centrality, DT has developed quickly. It has been used in many different domains, including immersive retail, smart city development, medical digital modeling, smart factories, and aerospace security. In addition to offering insights into key DT-related technologies, the article seeks to provide readers with a sense of the application status of DT. It presents useful applications in industrial production, highlighting the benefits of manufacturing, building models, plant administration, and equipment upkeep. Personalized care, health management, and illness treatment are all aided by DT in the medical industry. While the possibility of DT acting as "private teachers" is taken into consideration, educational applications improve instructional diversity [81]. DT is essential to resource management, citizen management, and urban planning in smart cities. The space industry, from whence the word "twin" originated, gains from DT by accelerating technological improvements and lowering space prices. Online and offline business applications are available, with the main goals being to boost in-store sales and replicate discrete events in logistics. The study highlights the need for digital transformation for the future growth of the global economy and the need for reliable and accurate DT applications to win over users. It is hoped that DT will become a part of everyday life, speeding up global digitization [82–85].

5.3. Digital Twin in Manufacturing

According to Kritzinger Werner et al. Although the term "Digital Twin" (DT) is frequently used to refer to a crucial enabler for digital transformation, different fields have different definitions for it as mentioned also in Table 1. A categorical literature review of DT in the manufacturing industry is performed, which will be categorized according to how much they integrate with Digital Model (DM), Digital Shadow (DS), and Digital Twin [86]. The literature shows that DT is the hot topic for experts for implementing on industrial level for their high efficiency as mentioned in Table 5. The various concentration areas within several disciplines are blamed for the lack of universal definition. Establishing a common definition and creating reference models that are suited to certain domain requirements are crucial to promoting additional contributions. By separating integration levels through a categorical literature analysis, the research suggests a first step toward a common definition. According to the assessment, DT development is still in its early stages and consists mostly of conceptual articles. Applied case studies do exist, though, particularly at lower integration levels [87]. As the primary data sink in production systems, production planning, and control have received significant attention in recent studies. The potential use of DT extends to higher time-frequency domains, like condition-based maintenance and process control. To assess the benefits of DT through industry case studies, more investigation is required [88].

Table 5. Applications of Digital Twin in manufacturing industry.

Sr	Author	Type	Linked to	Specific Area	Tools and Techniques	Reference
1	Mandolla et al. (2019)	Case investigation	Manufacturing	The aircraft	Blockchain, Visualization	[89]
2	Chhetri et al. (2019)	Case investigation	Manufacturing	Assembly Line	AI, Sensors,	[90]
3	Tao et al. (2018)	Review	Manufacturing	Assembly Line	CPS, Industry 4.0, AI	[91]
5	Jain et al. (2019)	Concept	Manufacturing	Fault Diagnosis	Industry 4.0	[92]

Table 5. *Cont.*

Sr	Author	Type	Linked to	Specific Area	Tools and Techniques	Reference
6	Karadeniz et al. (2019)	Case investigation	Manufacturing	Ice Cream Machines	AR, VR, Industry 4.0, AI, CPS	[93]
7	Min et al. (2019)	Case Study	Manufacturing	Petrochemical factory	AI, Optimization	[94]
8	He et al. (2018)	Review	Manufacturing	Power station	Simulation, AI, Analytics	[95]
9	Howard (2019)	Concept	Manufacturing	Product Development	EDA visualization	[96]
10	Kuehn (2019)	Concept	Manufacturing	Smart Industry	Simulation	[97]
11	Lu (2019)	Review	Manufacturing	Smart Industry	Cloud, CPS, Industry 4.0	[98]
12	Shangguan et al. (2019)	Case investigation	Manufacturing	Wind Turbine	CPS	[99]
13	Sivalingam et al. (2018)	Review	Manufacturing	Wind Turbine	CPS, Simulation	[100]

5.4. The Digital Twin in Industry 4.0

According to Ron S. Kenett et al. The adoption of Industry 4.0 for innovation, adaptability, and cost savings is examined in this article, with a particular emphasis on Digital Twins as substitute models. Digital twins record the behavior of physical assets and are updated continuously using sensor data. Automation is improved by the fourth industrial revolution, which combines computation, communication, and control into Cyber-Physical Systems. Industry 4.0 data issues are addressed Via Digital Twin platforms, process analytics, and soft sensors. The study focuses on one particular application: virtual sensors that enhance rotating machinery diagnostics by robustly estimating IAS.

5.5. Digital Twins in Industry 5.0

Zhihan Lv explores the application of Digital Twins (DT) in Industry 5.0, highlighting the technology's ability to upgrade machinery and facilitate machine-to-machine real-time process analysis. It highlights DT's potential to save costs and increase efficiency in industrial manufacturing. The analysis shows how Industry 5.0 uses big data, artificial intelligence, and enhanced digitization to expand upon Industry 4.0's features. The evaluation highlights DT as a critical technology that improves performance, adds value, and offers unmatched insights into the manufacturing sector (Figure 7). The report foresees additional DT applications in Industry 5.0, directing the advancement of intelligence in industrial manufacturing going forward [101].

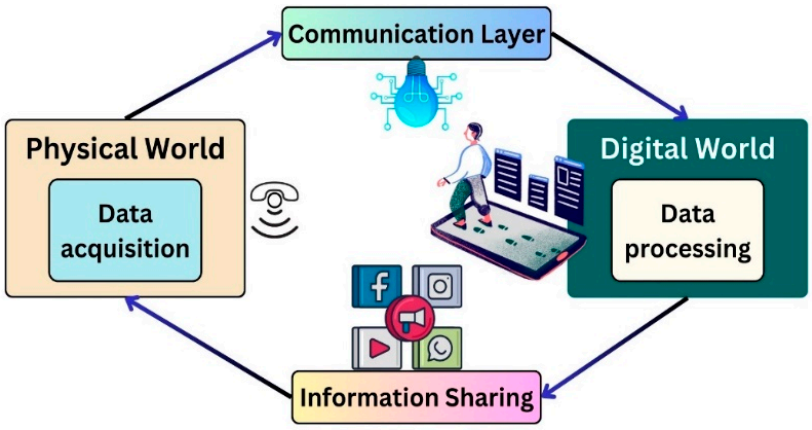


Figure 7. Communication and information sharing through DT.

5.6. Digital Twin-Based Sustainable Intelligent Manufacturing

Bin He et al. state that Digital Twins provide intelligent production that improves sustainability, productivity, and quality. This paper investigates systems, services, and components related to intelligent manufacturing. Analyzed are the sustainable aspects,

which are vital in contemporary production. Predictive maintenance and real-time monitoring are made easier by the incorporation of Digital Twins into intelligent manufacturing. With an emphasis on tools, systems, and services, the framework for sustainable intelligent manufacturing powered by Digital Twins is introduced. The study emphasizes how Digital Twins in manufacturing can increase productivity and intelligence. The focus going forward is on enhancing intelligent manufacturing capabilities and sustaining the integration of Digital Twins for sustainability.

Recent Developments in Intelligent Process Monitoring

Recent studies have focused on integrating multitask learning and adaptive algorithms for more accurate process monitoring under complex, variable conditions. For instance, intelligent process monitoring for tower pumping units under variable operational scenarios has demonstrated how multitasking deep learning frameworks can extract shared representations from multi-source data to handle nonlinear fluctuations and dynamic loads in industrial equipment. This approach provides a powerful reference for DT systems by enabling real-time health monitoring, anomaly detection, and operational optimization through adaptive learning. Such integration strengthens DT systems' ability to replicate and predict physical system behaviors with greater accuracy [102].

Adaptive Remaining Useful Life (RUL) Prediction Models

Another significant advancement involves adaptive RUL prediction for systems operating with limited, unlabeled, or uncertain data samples, such as batteries or rotating machinery. Recent models employ semi-supervised and transfer learning techniques to estimate the degradation state and lifespan of industrial assets even under conditions of data scarcity or uncertainty. This has direct implications for DT applications, as it enhances the capability of twins to forecast maintenance needs and optimize system reliability. For example, intelligent RUL models allow Digital Twins to autonomously update their degradation parameters and self-correct prediction errors, creating a continuous feedback loop between the physical asset and its digital counterpart.

Integration with Digital Twin-Based Intelligent Systems

The inclusion of these recent studies enhances the theoretical and practical depth of the paper by linking system intelligence analysis directly with DT architecture. Advanced intelligent monitoring methods serve as the computational backbone of DTs, enabling them to achieve self-learning, self-optimization, and predictive capabilities across multiple domains—such as energy systems, smart manufacturing, and transportation. The convergence of DTs with these intelligent analytical models marks a transition from reactive digital representations to proactive cognitive systems capable of predictive decision-making.

Implications for Future Research

By integrating these latest works into the review, the paper now offers a more comprehensive and contemporary understanding of how DT technology benefits from intelligent monitoring and adaptive learning research. Future work can build upon these insights by developing hybrid frameworks that combine Digital Twin simulation, multitask learning, and adaptive RUL prediction to achieve autonomous maintenance optimization and real-time system resilience in complex industrial environments.

5.7. The Use of Digital Twin for Predictive Maintenance in Manufacturing

P. Aivaliotis et al. present a method for determining the RUL (Remaining Useful Life) of mechanical equipment by utilizing the Digital Twin idea in conjunction with physics-based simulation models. This method makes use of prognostics and health management (PHM) to enable predictive maintenance. Digital models use sensor and controller data to

imitate real-world machine behavior [103]. The machine's status is evaluated by simulation results, which enable precise RUL prediction without the need for intrusive methods. A case study estimating the RUL of an industrial robot with a malfunctioning gearbox in Axis 1 validates the methodology. Benefits of the technique include real-time updates, continuous condition monitoring, and predictive insights for production planning and decision-making. Subsequent efforts will center on improving component-level modeling and incorporating this methodology into a more comprehensive predictive maintenance framework [104].

5.8. Digital Twins and Various Technologies in Museums/Cultural Heritage

Wolfram Luthe et al. examine several kinds of Digital Twins (DT) and virtual museums (ViM) of real museums (PM). The study examines the intricacies, benefits, and downsides of sensor equipment and enabling technologies at various stages of the DT life cycle. Forty contributions are identified by the research and are categorized as risk-informed, collaboration-centric, communication-centric, and content-centric ViMs. Using standardized metadata formats, expert/curator software, and stakeholder collaboration throughout the life cycle, the concept promotes a template-based, generative approach to DTs. To digitize cultural assets, create virtual exhibitions, and connect projects with museum objectives, collaborative efforts are crucial, as the article argues. It stresses the application in the Heritage 4.0 domain, exposes significant difficulties in DT life cycles, and responds to the needs of stakeholders [105].

6. The Dual Strategy for Textile and Fashion Production Using Clothing Waste

To solve garment waste disposal and material development in the fashion business, Hyewon Lee outlines a dual physical and digital plan. Using garment waste, three creative groups worked together for ten months to create eighteen digital items, three physical products, and one Digital Twin. Material analysis, design, material development, and product production are all integrated into the dual strategy. Over 90% of physical products and Digital Twins match, according to expert evaluations confirming the suitability of each process stage. It is determined that the technique is appropriate for 80% of the education sector and 50% of the industrial sector. An innovative process technique for sustainable fashion practices is provided by study [106].

7. Revolutionizing the Garment Industry 5.0

According to Semih Donmezer et al. With the integration of digital human modeling (DHM), virtual modeling for fit sizing, ergonomic body-size data, as mentioned in Figure 8, and e-library resources, this study suggests a revolutionary strategy to modernize the apparel business. This combination improves the accuracy of clothing design, encourages inclusivity, and expedites manufacturing procedures. DHM enhances the buying experience by offering anthropometric information and virtual depiction. E-library materials promote variation in sizes and styles by enabling data-driven, customer-centric design. By reducing the need for physical prototypes, integration improves sustainability and efficiency. According to the study, people will eventually have their bodies scanned for Digital Twins, which would allow for customized shopping experiences and real-time updates based on changing body types and preferences.

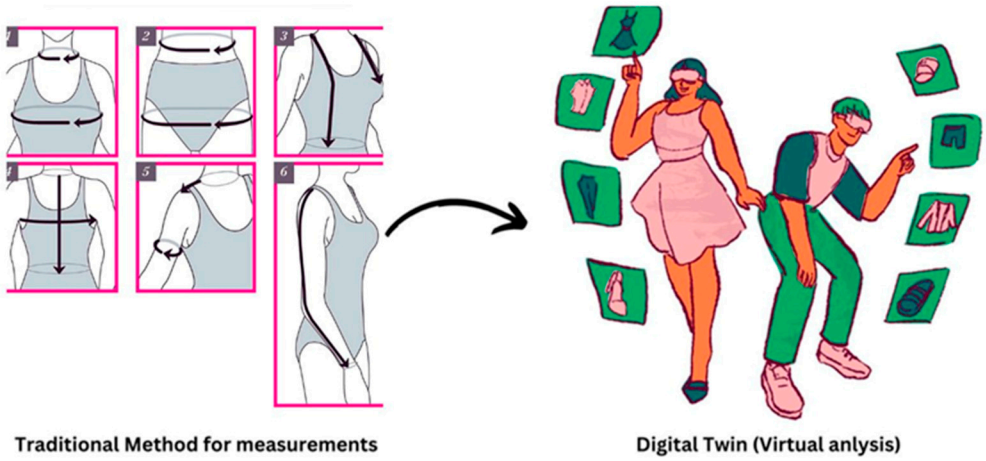


Figure 8. Digital twin in the Garments industry.

To enhance the discussion on the integration of Digital Twin (DT) technology with emerging digital systems, this section expands on the innovative applications that combine DTs with big data, artificial intelligence (AI), the Internet of Things (IoT), blockchain, and extended reality (VR/AR). These integrations significantly expand the functionality, intelligence, and reliability of DTs, enabling more dynamic and predictive industrial ecosystems. The convergence of DTs with big data and AI allows for intelligent analytics, real-time decision-making, and system optimization. Through AI-driven algorithms, DTs can analyze large volumes of operational data gathered from IoT-enabled sensors to simulate behaviors, detect anomalies, and predict failures before they occur. This capability enhances productivity and operational efficiency by 20–30% in several industrial applications, while reducing unplanned downtime and maintenance costs. The incorporation of machine learning models within DT platforms further supports adaptive optimization, where feedback from real-world performance continually refines predictive accuracy. In addition, integrating blockchain technology with DTs strengthens data integrity, traceability, and transparency, especially within complex supply chains. By leveraging blockchain's decentralized ledger system, every event, transaction, or system modification recorded within a DT can be immutably verified. This integration allows for complete product traceability and ensures trust between multiple stakeholders in industries such as food production, pharmaceuticals, and high-value manufacturing. Blockchain-enabled DTs ensure that all data exchanged between systems is tamper-proof, fostering secure collaboration and compliance with quality and safety standards [107].

The integration of DTs with virtual and augmented reality (VR/AR) further enhances the level of interaction and visualization between humans and digital systems. VR/AR-powered DTs enable immersive design simulations, remote maintenance, and collaborative decision-making in real time. Engineers and operators can interact directly with the digital model of a physical asset, test different operational scenarios, and identify optimal solutions before physical implementation. This immersive integration improves design accuracy, enhances worker training, and minimizes the risks and costs associated with physical prototyping. Recent developments also point toward hybrid integration scenarios, where AI-driven DTs operate within blockchain-secured IoT frameworks and are visualized through VR/AR interfaces. These combinations are transforming DTs into intelligent, autonomous cyber-physical systems capable of self-optimization and real-time decision support. Such systems form the foundation of future smart factories and intelligent logistics networks characterized by predictive maintenance, operational transparency, and remote collaboration.

8. Sustainable Value in the Fashion Industry

Ralf Wagner et al. With an emphasis on sustainability, it investigates how Digital Twin (DT) technology is affecting the fashion sector [108–111]. The research emphasizes the advantages and difficulties of generating long-term value using conventional physical processes and digital transformation using DTs. Even if DTs make virtual fashion shows and design processes more efficient, research indicates that stockholders have profited more from technology than stakeholders [112–114]. The study recognizes the drawbacks of focusing just on environmental and economic sustainability while ignoring social sustainability. Prospects for future study are striking a balance between sustainability and technological advancement, as well as tackling more general issues in more established industries like the fashion industry.

9. Digital Twin-Driven Product Design and Manufacturing

According to Fei Tao et al. The current movement in manufacturing toward big data-driven processes highlights the necessity of a more comprehensive approach to product lifecycle management (PLM). However, current research mostly concentrates on physical product data, which leads to information that is dispersed and isolated and impairs sustainability and efficiency [115–120]. To solve these issues, a novel approach powered by Digital Twin technology is put forth in this study. Converged cyber-physical data is created and used in this method to improve service, production, and product design. Three exemplary cases that highlight the potential of Digital Twins in every stage of product development are provided by the study, which also examines application methodologies and frameworks for Digital Twin-driven PLM. By bridging the gap between real and virtual product spaces, this strategy seeks to improve manufacturing processes' intelligence, efficiency, and sustainability [121,122].

By considering all these studies I have noticed that there are some research gaps given below.

- Insufficient studies examining two-way, real-time interactions between Digital Twins and physical assets. Insufficient investigation of spatiotemporal dynamics, security obstacles, and interpretability problems in the context of Digital Twins.
- Lack of all-inclusive solutions for creating synchronized, identical Digital Twins in a variety of businesses. Minimal attention is paid to how physical assets change over time and how Digital Twin models maintain backward compatibility.
- Inadequate consideration of the imperatives of safety and security, which call for more interpretability and transparency in decision-making based on Digital Twins. Insufficient investigation into Digital Twin user interface design impedes smooth integration and user-friendly functioning. All things considered, there is a research vacuum when it comes to tackling the complex issues involved in optimizing the capabilities of Digital Twin technologies in diverse fields.

10. Future Innovations and Development Trends in Digital Twin Technology

- High-performance simulation, quantum computing:

The incorporation of quantum computing to eliminate computational bottlenecks in large-scale simulations is one of the most promising directions of future Dt development. Traditional DT models can be limited to processing nonlinear large-dimensional data of complex industrial systems. Through quantum machine learning (QML) and quantum-enhanced optimization algorithms, quantum computing can significantly accelerate the speed of simulation, allowing scientists to perform real-time predictive modeling of highly

dynamic systems, including smart grids, autonomous transportation networks, and large-scale manufacturing ecosystems. DTs will be able to handle millions of variables in parallel with quantum-scale calculations, leading to more accurate decision-making and lightning-fast scenario analyses.

- Interaction with the Metaverse to Immersive Visualization and Collaboration:

The metaverse will be strongly connected to the future of DT technology, as virtual, augmented, and mixed reality objects enable immersive communication with digital replicas. Engineers, operators, and policymakers can also enter the Digital Twin space in such settings to visualize what is going on in the factory, simulate how to respond to disaster, or design a new product in real-time, without regard to location. Powered by the metaverse, the DTs will be interactive digital ecosystems, offering cross-disciplinary collaboration and making decisions in areas such as urban planning, healthcare, and aerospace.

- Autonomous Digital Twins that run on AI:

The next developmental stage of DT will involve the development of autonomous Digital Twins, which will be minimally human controlled. These systems will combine learning through reinforcement, deep neural networks, and generative AI to keep learning through operational data, automatically adjusting parameters to maximize performance. An example is an AI-based DT of a production line that might automatically rearrange production timetables depending on supply chain changes or energy supply.

11. Conclusions

In the current era, the adoption of digital tools, such as Digital Twins, is imperative to enhance real-time communication protocols. This facilitates smoother interaction between physical assets and their digital counterparts, ultimately increasing industry efficiency. The refinement of spatio-temporal modeling methodologies is essential to address challenges related to latency, data variety, and resolution. As Digital Twins and physical assets evolve concurrently, methodological research is necessary to ensure seamless transitions and backward compatibility. To achieve widespread adoption and provide optimal user experiences, innovative user interface designs tailored to specific industries will be required for Digital Twin technology. This technology holds the potential to revolutionize various sectors, including the fashion, manufacturing, and textile industries, enabling real-time monitoring, integration, and control. However, there are existing research gaps concerning real-time integration, necessitating solutions for latency, data variety, and resolution issues. Future efforts should prioritize enhancing user interfaces for industry-specific adoption, ensuring interpretability in safety-critical systems, and advancing technical methodologies. These advancements are crucial for realizing the full potential of Digital Twins and fostering their broader acceptance.

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