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Digital Twins and Industrial Internet of Things: Uncovering operational intelligence in industry 4.0☆

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ABSTRACT

The Industrial Internet of Things (IIoT) and Digital Twins (DTs) are changing how digital models and physical products interact. IIoT connects to intelligence in the physical world, and DTs virtually represent their physical counterparts. As a result, DTs will be invaluable for testing and simulating new parameters and design variants. However, Despite the undeniable potential of DTs, they still cannot differentiate themselves from simulation technologies, and their application and adoption remain limited. This study defines the concept, highlights the evolution and development of DTs, reviews its key enabling technologies, identifies IIoT's role as the backbone of DTs, examines DTs trends, highlights the key challenges, and explores its applications in the manufacturing process and Industry 4.0.

1. Introduction

The industrial sector has experienced a significant transformation due to several factors, the most notable being the shift in how products are sold, from the factory floor to the point of sale [1]. Over the past 15 years, there has been a growing trend among consumers to embrace e-commerce and digital channels for their purchasing needs [2,3] Buyers' habits changed to home ordering–a shift that industry experts forecast to be permanent. This consumer shift brought changes to supply chain disruptions — a dramatic need for increased agility and resilience in the consumer product manufacturing industries. As a result, manufacturers incorporated robust digital platforms in a post-pandemic marketplace to maintain competitiveness, optimize their manufacturing value chain, and provide end-to-end supply chain visibility [4,5]. According to a new survey, manufacturing companies leveraging digital technologies to transform their operations have reduced costs by 5–30 percent, increased productivity by 5–40 percent, and achieved substantial agility and sustainability improvements [6].

The second factor having a correlating impact on industrial companies' business models is COVID-19. The pandemic has led to significant disruptions affecting nearly every aspect of global industry [4]. While supply chain disruptions have uncovered operational vulnerabilities, they have also presented transformative opportunities for manufacturing companies [7]. Manufacturers quickly adapted during disruptions by implementing new advanced technologies at the core of true fourth industrial revolution innovation [6]. The swift advancement of digital technology and designed intelligence has driven the 4th industrial revolution [8]. Similarly, Industry 4.0 helped advance the usage of technologies like the Industrial Internet of Things (IIoT) and DT and enabled progress and betterment in the industries that utilize DT [9–11].

The third factor impacting the industrial sector is that we live in an age of digitization. Technological advances such as big data, service-oriented architectures, and networking have triggered a digital revolution [12]. Manufacturers use information technology to become more productive, improve quality, and reduce business costs [13]. Digital data provides a bridge between software applications and automated information processing and is becoming the link that binds the manufacturing processes that design, produce, and maintain all modern industrial equipment, automobiles, airplanes, and power systems [14].

DT is attracting the attention of practitioners and scholars alike. Manufacturers are already bringing DT intelligence to the factory floor [11,15,16]. The application of DT goes beyond the industrial sector. It is used across many industries, including retail, health care, agriculture, aviation, construction, smart city, and more, to provide accurate virtual representations of objects and simulations of operational processes [17]. A Gartner survey predicted that 75 percent of IoT organizations also use DT technology or plan to use it by 2020 [18].

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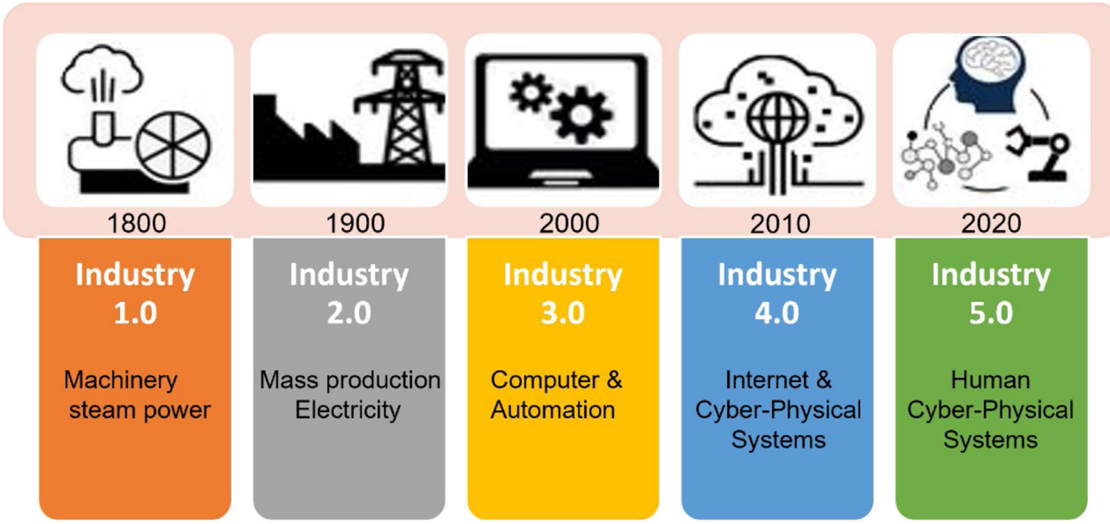

Fig. 1. Industrial evolution.

Gartner also estimates that by 2027, over 40 percent of large companies worldwide will use DT in their projects to increase revenue [19].

While manufacturing often takes center stage in discussions about DTs and the Industrial Internet of Things (IIoT), their impact extends far beyond factory floors. In our earlier work published in the Decision Analytics Journal, we delved into the transformative effects of DT technology on intelligent automation across various sectors [20]. We examined its utility in streamlining operations and enhancing efficiency through multiple applications, including healthcare, transportation, agriculture, energy, etc. This list is not exhaustive, and the potential applications of DTs and IIoT are constantly evolving. As technology advances and data becomes more accessible, we can expect these transformative tools to shape diverse industries in even more innovative ways. Building on that foundation, the current paper extends the discourse by focusing on the synergistic roles that DTs and the IIoT play in unlocking advanced operational intelligence. Specifically, we investigate how these technologies converge to revolutionize manufacturing processes within the framework of Industry 4.0, offering new avenues for data-driven decision-making and process optimization.

This paper is structured in the following way: Section 2 presents the primary viewpoints and definitions of DT from existing literature. Section 3 underscores the vital role of IIoT as a foundational prerequisite for harnessing DT's full capacity, shedding light on other key technologies that enable DT. Section 4 delves into DT's applications and use cases across Industry 4.0, including supply chains and logistics management. Section 5 provides a concise overview of DTs' economic and environmental benefits in industrial settings, Section 6 discusses the drivers and opportunities this technology poses, and Section 7 discusses the economic and environmental challenges linked to DTs. Section 8 reviews DT's Challenges, Threats, and Obstacles. Section 9 concludes the paper with a summary, and the final section (Section 10) provides suggestions for future research.

2. Background and definition

2.1. Industrial evolution

The first industrial revolution originated used water and steam power to mechanize production. The second industrial revolution was marked by using electricity to create an assembly line and mass production. The third industrial revolution transformed factories using embedded hardware and computing technologies to automate production. The fourth industrial revolution is broadly described as a digital manufacturing environment combining advanced manufacturing technologies to create an interconnected manufacturing that analyzes, communicates, and uses data to take intelligent actions in the physical world. Industry 4.0 utilizes analytics, artificial intelligence, and the IoT to enable superior decision-making and operations [21]. Finally, experts anticipate the beginning of the 5th Industrial Revolution, which integrates various techniques into a single infrastructure. It is radically different since it is more than only a technological shift. It brings the human back to the operation center through a human-cyber–physical system for value creation [22].

The emergence of Industry 5.0 stems from the observation or belief that Industry 4.0, while focusing heavily on digitalization and AI-based technologies for boosting production efficiency and adaptability, somewhat neglects the core principles of social equity and sustainability. Consequently, the notion of Industry 5.0 presents an alternative focus and perspective, underscoring the significance of research and innovation in aiding the industry to serve humanity sustainably within the planet's boundaries [23].

It is noticeable that rapid technological development considerably shortened the transition time from one industrial revolution to the next [24] (Fig. 1).

2.2. Pivotal cutting-edge notions in industry 4.0

The two critical state-of-the-art concepts in Industry 4.0 are IIoT and DT. IIoT facilitates real-time data acquisition, processing, and analytics produced by sensors installed within an intelligent factory. On the other hand, with exceptional precision, DT technology enables Industry 4.0 to replicate or represent physical machines, processes, or people in cyber space. Hence, IIoT is an essential strategic element and a foundational necessity to unlock the complete potential of DT [10]. Deloitte predicted the DT market to be $16 billion by 2023 and that IoT will be a cornerstone of this growth. Furthermore, IoT deployments are predicted to be doubled by 2020 [17].

IIoT captures the physical experiences of products, processes, and people as fundamental requirements of true DT to optimize operations in the factory and field. As a result, DT enables manufacturing companies to build better products, detect physical issues sooner, and predict outcomes more accurately. Until recently, limitations in digital technology capabilities, such as computing, storage, and bandwidth costs, hampered the broad applications of DT technology. However, significantly lower costs and more powerful computing capabilities have led to the exponential creation and use of a DT in the manufacturing industry [25].

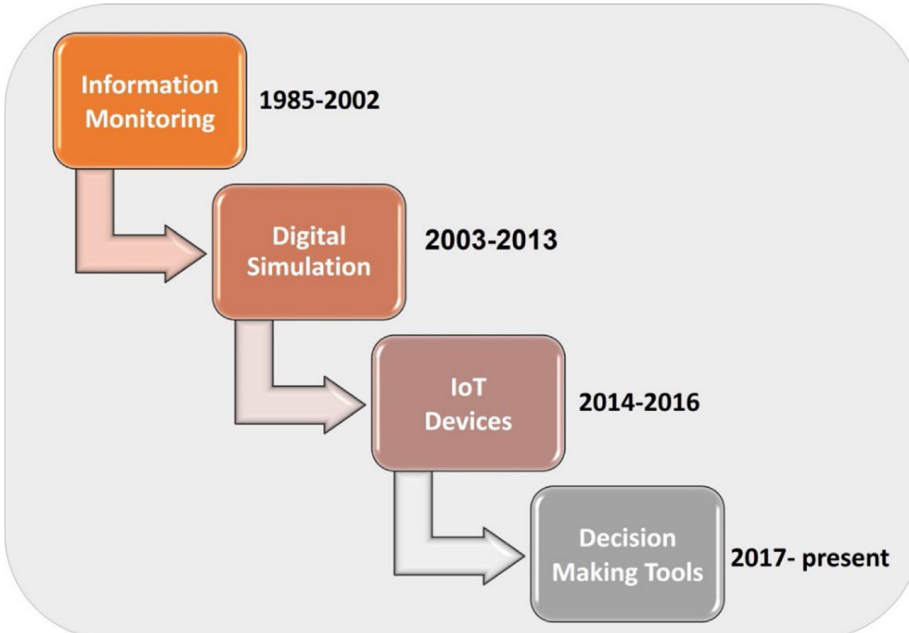

Fig. 2. Evolution of DTs in manufacturing.

2.3. Origins of DT

Professor Grieves of the University of Michigan introduced the concept of DT in a total product lifecycle management course in 2003. The concept is also known as a digital mirror and digital mapping. Since then, many scholars have provided varied definitions of this technology and discussed various stages of DT development https://www.sciencedirect.com/science/article/pii/S2772375522000594#bib0006 [26–31]. Encyclopedia of Production Engineering states: "*The Digital Twin is a representation of an active unique" product "which can be a real device, object, machine, service, intangible asset, or a system consisting of a product and its related services"* [29]. In general, the DT is defined as "virtual representations of physical objects across life cycle that can be understood, learned and reasoned with real-time data, or "a simulation model that acquires data from the field and triggers the operation of physical devices [32,33].

DT consists of three parts, the physical entity, the virtual model, and the two directional data flow between them. Any change in the state of the physical object results in a change in the state of the virtual model and vice-versa [34].

A pioneering application of DT technology occurred when NASA engineers utilized a simulator mirroring the command module and a counterpart of the module's electrical system to rescue and salvage Apollo 13 in 1970. NASA engineers completed the process in under two hours and saved the lives of the three astronauts on board [35]. Today, NASA uses DT to develop next-generation vehicles and aircraft.

2.4. DT vs. Digital shadow, digital model, and simulation

DT differs from Digital Shadow (DS) and Digital Model (DM). The digital model is a fundamental replica of the physical object, lacking any automatic data transfer between the real world and the model. DS is based on scanned laser data, a virtual model representing the physical model only, with one-way data flow and no automated data exchange between the physical world and the model [36]. DS is mostly used after the design is completed in Industry 4.0, and it may not be a 'complete' representation of the entire system [37,38], (Riesener et al., 2019). On the other hand, in a DT, both the virtual and physical entities communicate [39].

While simulations and DTs rely on digital models to mimic objects and processes, they diverge in crucial ways. At the heart of this difference lies the dynamic nature of DTs. Unlike traditional simulations operating on static datasets and predefined scenarios, DTs establish a living, breathing virtual environment fueled by real-time data streaming from the physical counterpart. This constant dialogue between the DT and its "digital shadow" creates a feedback loop that elevates the entire system to a new level of sophistication. Imagine a DT as a vibrant, ever-evolving replica of its physical twin [40].

Sensors embedded throughout the real-world object relay information about its state, performance, and environment. This dynamic data stream constantly updates the DT, allowing it to perform multiple simulations in real time, reflecting the actual conditions and factoring in external influences. This enhanced fidelity paves the way for groundbreaking applications. DT-powered predictive analytics models learn and adapt at an unprecedented pace, providing accurate forecasts of potential issues and opportunities. This empowers proactive decision-making, enabling smarter supervision and management of products, policies, and processes. From optimizing manufacturing lines to preventing equipment failures, DTs have the potential to revolutionize entire industries [41].

In essence, DTs move beyond the limitations of static simulations, embracing the inherent dynamism of the real world. This fusion of data and digital representation creates a powerful tool for understanding, predicting, and ultimately optimizing the things we care about most.

2.5. Evolution of DT in manufacturing

Industry 4.0 has enabled technological advancements in AI, IoT, and cloud computing. The relative strength of these technologies created the groundwork for DT solutions to evolve quickly and find applications in manufacturing and supply chains. In addition, these advancements helped the precise implementation of DT for the real-time monitoring and optimization of the process [16,42]. Fig. 2 highlights the significant technological evolution of DTs over the past four decades (Waker et al., 2021).

DTs have moved from idea to reality much faster in recent years. As a result, Gartner includes DT on its list of top 10 technology trends for 2017 [43]. Gartner also predicted that half of the large industrial firms to use DT in crucial business applications by 2021

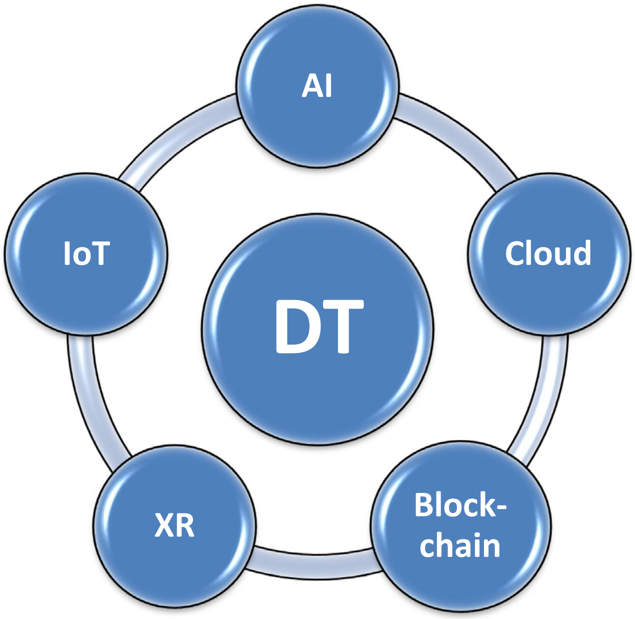

Fig. 3. Technologies of DT.

[43]. The forecast also suggests that DT will experience swift growth in the upcoming years, integrating further with technologies like voice recognition, augmented reality, IoT, and AI. IoT will be a cornerstone of this growth. Analysts agree that 30 percent of Global 2000 companies will use data from DT created by IoT-connected products and assets. Furthermore, DT applications within Industry 4.0 enhance product innovation success and boost organizational efficiency, realizing up to 25 percent improvements [44].

3. Key enabling technologies

A DT differs from computer-aided design (CAD) and Internet of Things (IoT) solutions; it is much more than either [45]. CAD has demonstrated moderate success in modeling complex environments (West and Pyster). IoT technology measures position and diagnostics for a component but not interactions between components [45]. As a result, manufacturers can use IIoT to gather additional insights to improve processes that were not previously available. In addition, manufacturers use IIoT to monitor industrial facilities remotely and vastly enhance operational efficiency and product quality [46]. DT technology, on the other hand, provides a comprehensive linkage between the physical and digital worlds. As a result, DT solutions can promise richer models with more realistic and holistic measurements of unpredictability.

DT uses five major technologies to collect and store real-time data, obtain information to provide valuable insights, and create a digital representation of a physical object (Fig. 3). IoT has become mission-critical technology, AI optimizes every process in real-time, AR and VR make DTs come to life, and cloud computing offers hosted services. In addition, DT uses a particular technology, such as Blockchain, to a greater or lesser extent, depending on the application type [30]. In the following sections, we review the applications of each technology in enhancing DT solutions.

3.1. Internet of things

IoT is the primary technology used to enhance DT [47]. IoT refers to a giant network of connected “things”. The connection is between things–things, people–things, or people–people [48]. IIoT is a powerful technology for Industry 4.0 that uses connected, intelligent sensors and actuators to connect people, products, and processes to power digital transformation. Using IIoT platforms, companies connect, monitor equipment, and analyze industrial data to improve efficiency, maximize revenue growth, maximize uptime, optimize operations in factories and fields, reduce costs, and more (Maninder et al. 2020). IIoT is the primary technology enhancing DT in different ways. By 2027, more than 90 percent of all IoT platforms will have Digital Twinning capability [49]. IoT uses sensors to constantly collect, process, update, and orchestrate data from real-world objects. The data transmitted by IoT is used to create a digital duplication of a physical object. The digital version can then be analyzed, manipulated, and optimized [47]. Many companies are incorporating DT technology into their IoT solutions to generate real-time feedback between physical objects and digital models. As a result, these companies have derived immense value from DT solutions. Implementation of IoT with DT technology in Industry 4.0 provides [50]:

- Better visibility of the operations of the machines and the status of their interconnected systems.
- Accurate prediction by retrieving the future state of the machines from the DT model.
- Perform what-if analysis by interacting with the model to simulate unique machine conditions.
- Comprehend, record, and elucidate the behavior of a particular machine or an assembly of machines.

3.2. Cloud computing

A vital benefit of the Industry 4.0 is real-time data collection by IoT and IIoT sensors on all factory assets. This data, collected continuously and transmitted, can provide critical insights into factory performance. They can also be utilized in making production, inventory control, or forecasting decisions. Nevertheless, the advanced technologies of Industry 4.0, such as AI, IoT, and DT, demand substantial computational capabilities and storage. Establishing an internal solution is not cost-efficient. Cloud computing provides hosted services, enabling manufacturers to store and retrieve data effectively via the Internet [48]. Cloud technologies are the foundation stone of today’s smart manufacturing. Cloud technology can speed up the process and help companies with increased flexibility, security, collaboration, and cost savings. Cloud computing provides DT with data computing technology and cloud data storage technology. Cloud computing allows DT, with large volumes of data, to store data in the virtual Cloud, reduce the computation time, and easily access the required information from any location [51].

Additionally, analytics techniques are used to analyze the data generated by IoT from all systems into helpful information used by the DT to produce insights. The optimal goals of DT are to work on physical and virtual models simultaneously and significantly accelerate product development and manufacturing processes. This is made possible by using cloud-based workstations’ powerful, agile computing capabilities, cloud rendering, simulation and analysis, and AI to facilitate global mobility and simultaneous collaboration in the virtual and physical world. Cloud solutions can provide advanced and immersive visualizations that bring processes or entire production lines into the real world. Cloud technology further enhances DT, enabling interaction with models in virtual and physical space simultaneously. Engineers can simulate potential changes before they are executed or train new equipment. Cloud technologies empower DT to go beyond simply creating a digital model of the physical entity and instead provide entirely new functionality that eliminates technology constraints to facilitate real-time collaboration across the manufacturing space. Companies like Microsoft offer cloud capabilities in their end-to-end solutions, such as Microsoft Azure Big Compute portfolio, Microsoft HoloLens, Microsoft Azure IoT, and Azure Cortana Intelligence. These cloud-based solutions offer complete capabilities, enabling manufacturers to quickly deploy DTs and realize the powerful results DTs can deliver [52].

3.3. Artificial Intelligence (AI)

As a discipline of computer science, AI seeks to mimic the basis of intelligence to create a new intelligent machine capable of responding like human-to-human intelligence. Areas of AI study include Robotics, image recognition, language recognition, Neural Networks, Machine Learning, Deep Learning, and expert systems. AI can assist DT by providing an advanced analytical tool capable of automatically analyzing obtained data, providing valuable insights, making predictions about outcomes, and suggesting how to avoid potential problems [53]. Both DT and AI technologies are considered to be critical enablers for Industry 4.0. AI enables DT to simulate a complex real-world system. It taps into data gathered by IoT devices, learns, runs alongside real-world manufacturing systems, identifies improvement areas, and supports tactical decision support.

Recent research suggests that integrating AI can boost the ability of DTs to adapt to dynamic changes in factories and workshops. This enhanced adaptability opens valuable applications, particularly in production planning, control, and quality assurance [54]. The findings are based on a survey of 300 manuscripts on AI-driven DTs in Industry 4.0 over five years. In addition, the study summarized the state of AI integration, advantages, challenges, and development prospects in smart manufacturing and advanced robotics [54].

3.4. Extended Reality (XR)

XR is a general term used to describe immersive technologies like Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). These technologies can merge the physical and virtual worlds and extend the reality we experience [55]. They are adding layer upon layer of digitized overlaid information to the world around us, making it rich, meaningful, and interactive. These revolutionary technologies offer innovative approaches that can effectively visualize and interact with DTs [56]. XR technologies usher in a new era of immersive and interactive experiences that have the potential to enhance our relationship with digital information drastically. With the ability to overlay or entirely simulate 3D environments, XR can deliver rich, dynamic, and interactive visualizations of DTs. By enabling users to view, manipulate, and interact with these DTs more intuitively and naturally, XR can lead to deeper understanding and better decision-making processes [57].

DT technology utilizes significant data to create a digital model of the physical objects and provide actionable insights within the product or process. It is equally important and helpful to visualize the data. Combined with DT solutions, VR technology allows manufacturers to immerse themselves and fully understand data, providing necessary solutions. As an essential tool of Industry 4.0, IoT continuously collects data from these devices. DT solutions digitize and analyze these data. VR and AR provide connected workers with opportunities to visualize, spot areas of concern, reduce errors, and save time. VR and AR complement the benefits provided by DT and give a sense of reality to digital data DTs [56].

Moreover, XR technologies can significantly enrich human-to-human interactions, particularly in training and remote assistance areas. For instance, in an industrial setting, a trainer could demonstrate procedures or processes in a virtual environment, allowing trainees from across the globe to experience and learn in an immersive and interactive context. Similarly, remote assistance can be transformed by providing real-time, AR-enhanced guidance to technicians, reducing the need for physical presence, increasing efficiency, and reducing costs [57].

3.5. Blockchain technology (BT)

Blockchain technology is a decentralized and continually growing series of records, known as 'blocks,' maintained across numerous computers connected in a peer-to-peer network. Every transaction added to a blockchain is validated by multiple computers on the internet. Once the blockchain processes the information, every computer in the network simultaneously locks it in, thus creating permanent, difficult-to-alter digital records [58]. This technology enhances DT solutions with improved data security, privacy, and trust [21].

Currently, the function of IoT sensors as secure and trustworthy data sources is still a challenge that requires addressing in the DT domain [59]. Most cloud-based IoT platforms currently provide device virtualization with various levels of detail and complexity. However, this approach carries the disadvantages and risks inherent in cloud computing, such as the centralization and isolation of information. Therefore, a blockchain-based DT could present unique properties to tackle these challenges, ensuring data availability, integrity, and confidentiality [60].

Moreover, the integration of DTs and Ethereum-based blockchains could offer multiple benefits. These include greater transparency regarding handling Intellectual Property Rights during the manufacturing process. It also allows for the development of smart contracts, facilitating the optimization and automation of material flow throughout the manufacturing system on an individual product basis [61].

Other benefits of using Blockchain with DTs are information sharing, end-to-end connection, trusted traceability, scalability, anonymity, audibility, and resistance to modification or changes to the data [62].

4. DTs use cases and applications in manufacturing

Today, engineering and manufacturing predominantly use DT to provide accurate virtual representations of objects and simulations of operational processes [63]. The concept of DT is instrumental in modeling, simulating, and optimizing cyber–physical systems. It offers a profound understanding of intricate physical processes through services related to diagnosis, simulation, monitoring, optimization, prognostics, and health management [64]. Consequently, DTs empower companies to make more precise forecasts, reasoned decisions, and strategic plans [31].

DTs are applied in engineering to predict the future behavior and performance of physical systems. They help to accumulate relevant industrial big data, enabling the self-adaptive behavior of machinery and supporting decision-making processes [65]. Literature shows that approximately 18% of DT's engineering applications focus on design, 35% on production areas, 38% on prognostics and health management, and 9% on other areas [31]. However, the applications can vary based on the engineering product lifecycle stage, including design, manufacturing, distribution, usage, and even end-of-life.

DT applications in positions and supply chain management, especially DT's role in operations traceability, transport maintenance, remote assistance, asset visualization, and design customization, are reviewed in several publications [11,15,16,30,42,66–70]). DT applications in positions and supply chain management, especially DT' role in operations traceability, transport maintenance, remote assistance, asset visualization, and design customization, are reviewed in several publications [11,15,16,30,42,66–70]).

Other applications of digital twinning in manufacturing include monitoring and controlling physical assets with virtual objects [70,71]. Moreover, Industry 4.0 has enabled technological advancements in sensing, monitoring, and decision-making tools. These advancements, especially in IIoT, helped the precise implementation of DT technology for the real-time monitoring and optimization of the process [16,42].

Several technology companies, such as IBM, Oracle, and SAP, have launched DT offerings in the past few years. Similarly, IoT providers such as GE and Siemens have built or advanced DT capabilities [17]. In addition, advancements in Industry 4.0 and the availability of technical resources have enabled manufacturers to utilize the benefits offered by DT in multiple domains. As a result, DT is now being used to represent more complex entities such as assembly line processes, warehouses, and transportation networks [17]. Finally, industries in asset-heavy sectors,

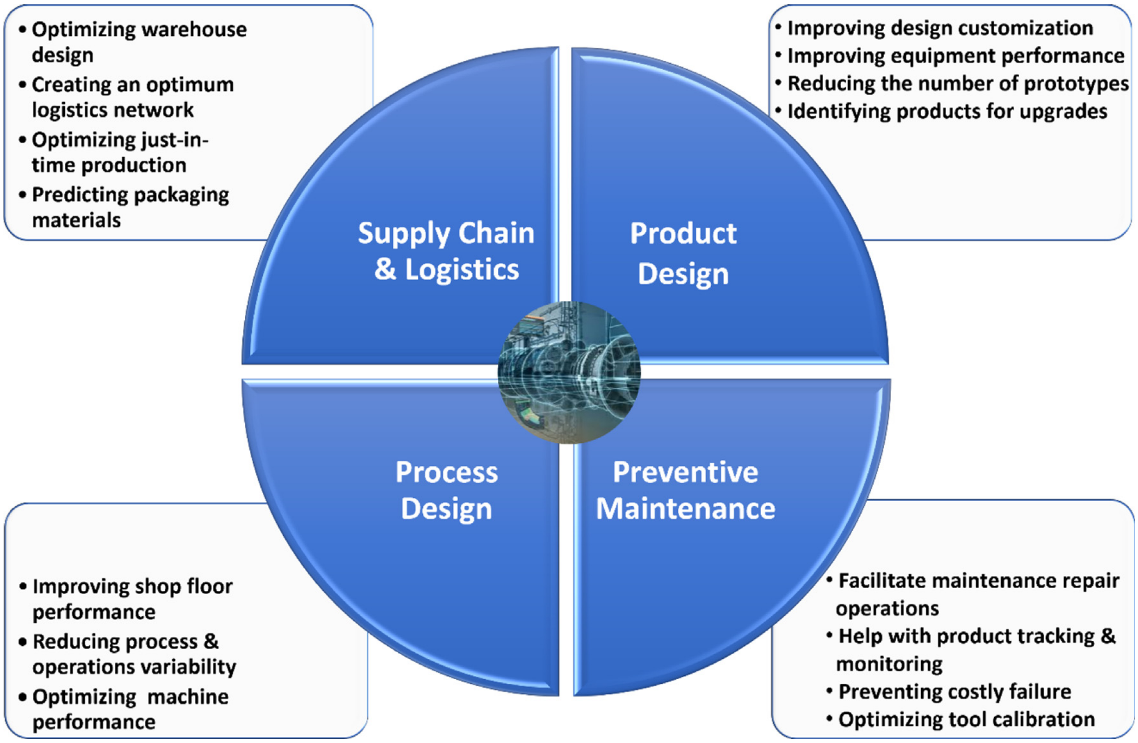

Fig. 4. DTs applications in manufacturing.

such as aerospace, oil and gas, industrial products, and automotive, are using DT to transform production. [17].

Production is the most popular field for DT solutions [72]. DT may enable manufacturing companies to solve product issues faster by detecting them sooner, designing and building better products, and predicting outcomes more accurately. Indeed, DT may be used in various cases to serve different objectives. For example, DT simulates jet engines and large mining trucks to monitor and evaluate wear and tear. In another example, a DT of a wind farm can provide insights into operational inefficiencies. Whirlpool Corporation deployed its digital transformation strategy by exploring transformative technologies such as IIoT, DT, augmented reality, and data-driven design to extend product lifecycle management [73].

DT with IoT capabilities can play significant roles in other manufacturing use cases, including [31,74]:

- Streamlining operations through twins of the manufacturing process,
- Extending value-added services to field technicians through predictive insights,
- Providing pivotal real-world insight and feedback loop to designers and engineers,
- Empowering sales & marketing teams with digital product information.

These are just a few examples, but the potential applications of DTs are vast and rapidly expanding across various industries. From optimizing building energy usage to predicting equipment failures in complex machinery, DTs are transforming the way we design, operate, and maintain assets in the real world.

The current body of research on DTs primarily focuses on theoretical possibilities, leaving the full scope of their benefits largely unexplored and lacking in concrete demonstrations. To bridge this gap, the following sections will showcase practical deployments, diverse applications, and real-world examples of how DTs transform various industries. Fig. 4 provides a summary of major DT applications in manufacturing.

4.1. Product design

The introduction of new products or services can have impacts throughout the organization. Furthermore, product and service design has strategic implications for the success of an organization. Consequently, product and service design decisions are among managers' most fundamental choices. DT technology enables entire design and process changes unattainable through current methods. A DT provides a virtual replica of a manufacturing asset that collects data and can create, build, test, and validate predictive analytics and automation [75].

Engineers can use the virtual prototype generated by DT during the design phase to test different designs before investing in a solid prototype [76]. This reduces the number of prototypes, saves time, and reduces production costs. Furthermore, engineers and designers can use data collected over time to improve customer expectations regarding product quality, customization, and ease of use [71].

DT solutions have been used in different industries, including steel, aerospace, and automobile, to improve product design, including the steel industry. Testing of quality is an essential step in Steel manufacturing to ensure the end product fits a wide variety of uses. DT can effectively test the designs and compositions of the end products where a virtual copy of the real-world project is subjected to a wide range of conditions to confirm the durability and sustainability of the output [9]. Similarly, a DT of the product can be simulated to test the rusting problem in different weather conditions with varying alloy compositions to arrive at the most suitable product. Moreover, DT can be used to test the benefits of utilizing certain metals in steel alloys for kitchenware, making it more appealing to customers. DT simulations can provide a perfect solution for experimenting with multiple ratios of carbon in steel to arrive at suitable products. In addition to understanding the strength of the materials, DT can also assist in determining the optimal number of materials to be used [9].

In the digital age, airlines face the imperative to overhaul their operations. Many airlines operate with cumbersome and inflexible systems shaped by the stringent rules and regulations that govern the industry. Consequently, transitioning to a digitally advanced paradigm is a complex endeavor [77]. The airline industry can benefit from DT solutions. DT solutions create a virtual model that emulates the real-time functioning of a spacecraft. The simulation of real-time data can help optimize the design and planning of the spaceship, save up costs in research and development, and play an essential role in the safety of the spacecraft [9]. DT can ingest data from various sources like aircraft sensors, weather patterns, and air traffic control to create a real-time replica of the flight. This allows engineers to continuously optimize flight paths, considering fuel efficiency, turbulence avoidance, and noise reduction, leading to smoother and more comfortable passenger journeys. Moreover, DT technology allows aircraft engineers to schedule preventive maintenance, reducing the risk of in-flight emergencies and ensuring on-time departures and arrivals. Finally, DT's ability to glean insights from each flight offers significant potential for optimizing aircraft weight capacity. However, before fully embracing its determinations, rigorous testing is necessary to ensure the accuracy of its calculations [78]. Additionally, Aljubairy et al. describe a real-time flight information system using the IoT [79]. DT can integrate with such systems to provide passengers with even more detailed and up-to-date information. Northrop Grumman uses DT solutions for the assembly line for the F-35 fighters to improve manufacturing efficiency and reduce cost [72]. Intense competition among auto manufacturers for introducing advanced and innovative cars encourages companies to invest in the R&D of products and automation of processes.

DT concepts have been on the rise within the automotive industry; however, most existing work centers around automotive manufacturing processes and prototype testing. The idea of the DT stands as a pivotal catalyst for data-driven manufacturing [80]. Automotive companies use DT technology to simulate and analyze the production phase and design the ideal automotive product even before production starts. Several automobile manufacturers are adopting DT — using interactive automobile dashboards on websites to improve customer engagement. Customers can customize vehicles at their convenience. Companies use the information to monitor consumer behavior and change existing models [81]. Intelligent vehicles use numerous sensors to collect data regarding the car and its environment. DT technology provides testing of every aspect of the vehicles, including road testing and vehicle maintenance, and helps automakers ensure unexpected damage and injuries will be minimized. DT technology is becoming a global area of research where researchers cover DT implementation on various aspects of intelligent vehicles and explore its potential, opportunities, and challenges to the realization [82]. For example, Maserati is using DT technologies to accelerate product design. DT helps the automaker reduce the number of expensive, real-world prototypes required and the need to launch physical wind tunnel tests and test drives. As a result, the company reduced vehicle development time by 30 percent.

4.2. Process design and optimization

Large manufacturers can struggle to know what is happening on the factory floor. Answering a question like how well machines are performing? Are workloads being evenly distributed? And where are the bottlenecks? are not easy. Creating DTs of manufacturing processes perhaps provides a complete answer.

DT helps manufacturers observe processes under multiple performance conditions and eliminate problems before they occur. The DT of the manufacturing process offers a potent and compelling application. The DT represents a replica of a manufacturing process in the physical world, what is happening on the factory floor, and its companion twin in the digital world. That allows manufacturers to move from being reactive to predictive. In addition, DT helps turn existing assets into tools that optimize processes, save money, and accelerate innovation [76]. The DT solutions enable a continuous analysis of incoming data over some time. The results may uncover unacceptable trends in the actual performance of the manufacturing process compared with an ideal range of tolerable performance. Such comparative insight could trigger an investigation and a potential change to some aspects of the existing manufacturing process.

In General Electric's Gas Turbine Power Plants, real-time sensor data from each turbine feeds the DTs. This allows engineers to optimize performance, predict potential failures, and schedule preventive maintenance, resulting in increased energy efficiency and reduced downtime [83]. In Siemens' Virtual Power Plant, a network of DTs representing distributed energy resources, such as solar panels and wind turbines, optimizes energy production and distribution within a smart grid, improving energy security and reducing reliance on fossil fuels [84]

4.3. Supply chain and logistics management

The eternal cycle of rising supply chain costs impacts all players' bottom lines. As a result, manufacturers, retailers, and distributors have identified supply chain cost reduction as critical. The recent pandemic accelerated the trend towards a shipping economy and away from retail-based operations. Additionally, excellent supply chain performance has a strategic value that could lead to rapid financial payback, often within months, and improvements in productivity and profits [85]. DT technology can solve supply chain challenges, including packaging performance, fleet management, and route efficiency [86].

Digital Supply Chain (SC) twins are becoming crucial to supply chain management. They empower supply chain control towers to aid in strategic, tactical, and operational decision-making. Digital SC twins provide real-time visibility into crucial logistics data such as Key Financial Performance Indicators (KPIs), inventory levels, stock levels, service levels, capacity, and transportation data. The use of performance-based simulation models aids in the development of effective contingency plans. These plans are designed to prevent or mitigate disruptions by simulating 'what-if' scenarios to forecast future impacts. Ivanov et al. [8] have highlighted the pressing requirement for Supply Chain (SC) network visualization due to the escalating frequency of SC disruptions. Cavalcante et al. [87] note that digital SC twins become invaluable tools for decision-makers in SC planning, monitoring, and oversight. They hold significant potential in facilitating and enhancing end-to-end SC visibility and providing the capacity to evaluate contingency plans. Consequently, DTs can substantially boost SC resilience.

McCarthy and Ivanov (2022) examined the impact of digitalization on contemporary and future supply chains. They note that DT can help optimize just-in-time or just-in-sequence production and analyze distribution routes. The technology is also helpful in other vital phases of supply chain management, including Product inception, Product development, and Product distribution.

The freight and logistics sector is one of the largest industries where DTs are making substantial advancements, which warrants further examination. This is due to the global decision-making aspects requiring shippers and integrators to operate with heightened precision. They must select specific transportation methods that comply with rigorous regulations to prevent bottlenecks [88].

DT solutions enable manufacturers to optimize shipping and see where they could send their products faster, better secured, and more environmentally friendly. DT helps logistics companies virtualize product packaging and test for errors before packaging. DT can also help Logistics companies analyze how different packaging conditions affect product delivery, enhancing shipment protection. More specifically, DT helps to track and analyze packaging performance, fleet management, and route efficiency [89,90].

The technology also helps logistics companies to test warehouse layouts to optimize operational performance. General Electric uses DT at its Nevada facility to improve supply chain and factory processes [17]. At Volvo, onboard DTs in trucks continuously monitor vehicle health, predict maintenance needs, and optimize routes, improving safety, efficiency, and cost-effectiveness for fleet operators. There are other examples of deployed asset-specific DT discussed in the literature. [75].

4.4. Preventive maintenance

Preventive maintenance focuses on predicting when to schedule maintenance for a component or system to reduce cost and increase machine uptime. Predictive maintenance allows the organization to prevent problems without incurring the cost of unnecessary frequent maintenance [91]. As a result, predictive maintenance in manufacturing could extend the life of aging assets, improve uptime, reduce quality risks, and reduce costs.

DT can model individual equipment or manufacturing processes to identify variances that indicate the need for preventive repairs or maintenance. The aim is to estimate, predict, detect, or diagnose the condition of a component or a system for maintenance more effectively. This would prevent costly failure before a serious problem occurs. They can also determine if better materials or processes can be utilized or help optimize cycle times, load levels, and tool calibration [92].

DT solutions are widely embraced in the aerospace industry for aircraft maintenance, tracking, weight monitoring, an accurate stipulation of weather conditions, measurement of flight time, catastrophic malfunction analysis, safety, and security management, and defect detection (Xiong et al. 2022, 72). DT represents the innovation that has spurred evolution and adaptation in the aerospace industry. For instance, employing DT for an aircraft or rocket ship is believed to enhance global tracking accuracy by 147%. In a recent survey, 75% of Air Force executives favored DT solutions for their industry [78]. DT enables engineers to ensure the safety of the aircraft by looking into the potential aircraft's problem before any danger. That would include retesting the airframes, testing its engine, or doing further security checks to enhance the efficiency of dealing with any threat. In addition, DT solutions enable aviation engineers to operate effectively and reduce testing costs by maintaining and repairing aircraft when they are not within physical proximity [78].

For example, Boeing, the world's largest aerospace company, uses DT solutions to improve the safety of the parts and systems used to manufacture commercial and military airplanes. DTs of specific aircraft models enable technicians to use augmented reality (AR) overlaying the DT data on the real plane, facilitating faster and more accurate inspections and improving maintenance efficiency. As a result, Boeing has achieved a 40 percent improvement in the quality of the parts and systems [93]. General Electric's (GE) Digital Twin technology is revolutionizing how the aerospace industry approaches maintenance. Predicting engine wear and tear, like blade spallation in the GE90 engine, saves airlines millions in costs and prevents aircraft from being grounded unexpectedly, especially in regions with sand, a major contributing factor to this issue [94]. NASA built physical twins of rovers, like MAGGIE for Curiosity and OPTIMISM for Perseverance, to test and troubleshoot potential issues. These twins are exact replicas of the originals, allowing engineers to simulate Martian conditions and identify problems before deployment.

Additionally, NASA and Siemens created a DT of Curiosity using Simcenter 3D. This virtual replica and the physical MAGGIE helped analyze and solve heat dissipation issues generated by the rover's MMRTG power source. Moreover, DTs of the Mars rovers allow NASA engineers to monitor their health and performance remotely, plan safe and efficient routes, and troubleshoot problems in real-time, which is crucial for successful space exploration [95]. The European Space Agency (ESA) also adopted the twin approach for their ExoMars mission. They built Amalia, a physical and digital double of the Rosalind Franklin rover. This duo serves a vital purpose: anticipating and solving potential problems before they occur on the Martian surface. Overall, using both physical and DTs significantly increases mission success by minimizing risks and improving rover performance [95].

4.5. Empowerment and cross-functional collaboration

Emerging technologies such as cloud, IoT, and intelligent edge devices are reducing digital transformation costs within the manufacturing realm. Progress in big data, analytics, AR and VR, and mobile applications equips manufacturers with the tools to help operators and decision-makers decipher operational data effectively. DTs are often used to collect operational data over time. This data provides insights into product performance, distribution, and end-user experience and can be shared by engineering, production, sales, and marketing. Employees across disciplines can all use the same data to make more informed decisions [31]. DT transformation makes information more readily accessible to workers by connecting them to plant processes, real-time data, and one another. As a result, the solution incentivizes curiosity and encourages innovation. Finally, the technology provides everyone with the same information simultaneously, allowing multi-disciplinary teams to collaborate on projects seamlessly, thereby improving efficiency and agility in tandem.

4.6. Facility and asset management

In conjunction with virtual reality (VR) glasses, DT can assist facility and operations managers in viewing what is happening on the factory floor at any given time and identify which production adjustments are needed. Using DT technology, operations managers can identify quality and safety problems, monitor machine capacity, and make necessary changes [96].

4.7. Production planning and control

Manufacturers cannot ensure an operational plan is feasible without real-time visibility into plant resources and capacity. Therefore, manufacturers must use digital tools to optimize production scheduling, accommodate real-time operational planning cycles, and improve flexibility when re-planning critical orders [97]. Moreover, scheduling in a job-shop environment is a vital optimization challenge within production systems. The goal is to allocate various jobs to appropriate machines during available periods, all while optimizing specified objectives such as makespan, total delay, energy consumption, and machine utilization rates. This must be accomplished within the framework of various constraints [98]. DT technology blends actual and simulated data to improve machine availability predictions and detect disruptions. Continuously comparing a machine to its DT enables timely rescheduling. Additionally, DT facilitates in-depth performance evaluations for rescheduling using multi-dimensional models that capture various machine attributes [98].

DT solutions may optimize the production schedule to deliver business-critical orders on time and in full at the lowest possible cost. The technology also offers advanced planning and scheduling capabilities, allowing for optimization of the production schedule around business drivers like material, equipment, and labor availability. Finally, DT solutions are vital for aligning people, equipment, and operational processes for efficient and compliant work execution and continuous improvement [99].

4.8. Workforce management

DT collects institutional knowledge, connects workers to instructions, and stores resolutions to previous problems. Manufacturers may use these problems and solutions to train and build a skilled and empowered workforce for the challenges of tomorrow [100].

5. The economic and environmental consequences

The preceding sections explored how DTs revolutionize industrial applications, offering significant economic and environmental advantages. Nevertheless, it is essential to recognize the potential drawbacks of this technology. We thoroughly discuss the economic and environmental challenges linked to DTs in Section 7. Below is a concise overview of the economic and environmental benefits of DTs in industrial settings, as elaborated in earlier sections:

5.1. Economic impacts

- Enhanced Efficiency and Productivity: DTs improve production efficiency by optimizing processes, minimizing waste, and forecasting maintenance needs. This leads to higher output and cost reductions.
- Better Product Quality and Innovation: By facilitating virtual testing and simulation, DTs quicken product development, enhance quality control, and spur innovation.
- Improved Decision-Making: The real-time data insights provided by DTs aid in making well-informed decisions regarding resource distribution, scheduling, and maintenance, which in turn improve business results.
- Emergence of New Business Models and Services: DTs pave the way for novel revenue sources, such as data-driven services like predictive maintenance and remote monitoring.
- Job Creation and Skill Advancement: While new technologies like DTs generate jobs in fields such as DT development, data analysis, and cybersecurity, they may also lead to the replacement of some existing roles through automation.

5.2. Environmental impacts

- Reduced Resource Usage: DTs enhance resource efficiency by simulating and refining processes, reducing material wastage, and lowering energy consumption.
- Decreased Emissions and Pollution: Through more efficient operations and reduced energy requirements, DTs contribute to a decrease in greenhouse gas emissions and air pollution.
- Enhanced Environmental Monitoring and Adherence to Regulations: DTs offer real-time tracking of environmental impacts, facilitating improved monitoring and compliance with environmental laws.
- Sustainable Design and Development: DTs are instrumental in designing and creating products and processes that are more environmentally sustainable.

6. DTs drivers

COVID-19 exacerbated the shortage of skilled workers in the manufacturing industry. Manufacturers combat that problem using digital tools to ensure institutional knowledge can be retained. Digitalizing work processes enables manufacturers to connect workers to instructions and efficiently collect data. The surge in the DT market size across diverse applications was propelled by the COVID-19 pandemic [81]. In response to economic upheavals triggered by the pandemic, many organizations are turning to DT technology to enhance their supply chains and streamline operational procedures [101]. For example, a manufacturer may use DT solutions as a part of their digitization strategy to ensure execution follows scheduled product, work process, and quality specifications.

Initially, the significant effort required to implement DT, namely creating or maintaining large-scale machinery, restricted technology use. The current acceleration in the applications of DT is due to the availability and ease of use of technologies that enhance both IoT and DT. Data collection is getting more accessible and less expensive. Progress in machine learning and richer insights from analytics and simulation make it easier to gain insights from large volumes of IoT and data to predict risks and simulate solutions [102]. Augmented Reality (AR) and Virtual Reality (VR) simplify the interaction of workers with DT. The recent uptick in DT adoption can also be attributed to the convergence of digital design and manufacturing systems, encompassing lifecycle management, manufacturing execution systems, and enterprise resource planning (ERP) [14]. DT continues to be used in Industry 4.0, but companies in different sectors, including agriculture, construction, retail, healthcare, and consumer goods, also explore this technology.

Another driver for the acceleration of DT technology is the incredible potential of 5G in terms of speed, latency, and accuracy. This transition facilitates DT technology in providing an emulated replica of the physical asset that allows for continuous testing, prototyping, and optimization of the physical asset. Furthermore, cloud companies like Google Cloud and Microsoft Azure are launching cloud-based DT platforms for easy accessibility and customized solutions. For example, in January 2022, Google Cloud launched a supply chain DT solution to give the manufacturing industry visibility of operations occurring in their supply chains [81]. Finally, the emergence of Industry 4.0 and IoT has also accelerated the adoption of DT.

7. DTs challenges, threats, and obstacles

Several articles investigated the risks and threats that could target the DT's physical and digital components. They are described in the following sections.

7.1. Common challenges and limitations

In this article, we have explored the numerous benefits of DT technology. Despite these advantages, the technology currently grapples with common challenges like those faced by AI and IoT technologies. These issues range from data standardization, data management, and data security to hurdles in implementing and transforming legacy systems Technavio [101].

DT solutions pull data from various sources such as IoT sensors, Computer-Aided Design (CAD) models, historical data archives, and real-time data lodged in other systems, stored in multiple formats. Fusing this data assortment into a cohesive, singular model can pose significant complexities and challenges. Any inaccuracies within this data can diminish the efficacy of the DT solutions, thereby raising the stakes in ensuring the precision and completeness of the data involved [103].

Furthermore, scaling DT technology to manage substantial data and intricate models can be demanding and presents a significant hurdle. For instance, as the data size and the models' complexity increase, so does the computing power and storage capacity required to process and manage them. This calls for efficient algorithms and infrastructure that can scale with the needs of the DT system. All these factors underscore the need for robust data governance frameworks and scalable technical infrastructure to realize the full potential of DT technology, as noted by Technovio in 2022.

Moreover, the materialization of DTs necessitates the assimilation, coordination, and administration of data and models that emerge from various engineering fields, enabling us to harness the advantages of digital (software) technologies. Yet, coordinating the disparate models, sources of data, and their associations to develop DTs can be a formidable task [104]. Finally, significant challenges persist in DTs development, upkeep, and evolution, specifically: (i) handling diverse models sourced from disparate disciplines, (ii) ensuring a two-way sync between DTs and the physical systems they represent, and (iii) facilitating cooperative development through the entire life cycle [105].

Other challenges in the literature include the need to update old IT infrastructure, connectivity, privacy and security of sensitive data, and the lack of a standardized modeling approach [27]. The absence of established standards and recognized interoperability, particularly within the manufacturing sector, is attributed to the limited implementation of DTs [106].

Moreover, the limited implementation of DTs can be attributed to the absence of established standards and recognized interoperability, particularly within the manufacturing sector (Harrison et al. 2021). Furthermore, formidable challenges likely to severely hinder DT technology applications include the high deployment cost and complex architecture. The prohibitive costs associated with implementing DTs, attributable to the increased need for sensors and computational resources, are a significant barrier to the broader adoption of DT technologies [107]. Deploying DT solutions necessitates considerable upfront investment in infrastructure development, maintenance, and security solutions. Maintaining DT infrastructure is cost-intensive and demands substantial operational investment. The high fixed cost and the complex infrastructure of DT are expected to slow down the deployment of DT technology [101].

One final hurdle impeding DT progress lies in communication networks. To overcome this, faster and more robust communication interfaces like 5G are crucial. A recent study [108], underscores the pressing need for 5G in smart cities, citing its potential to:

- Connect a vastly more extensive network of sensors and devices,
- Provide pervasive high-speed connectivity,
- Enhance reliability and redundancy,
- Enable ultra-low power consumption.

The study emphasizes that these benefits are critical for enabling real-time data exchange and maximizing the operational efficiency of DTs [108].

7.2. Implementation challenges

DT technology, being in its nascent stages, necessitates addressing key challenges and limitations for contemporary implementation. These include high costs, complex information handling and maintenance, a lack of established standards and regulations, and cybersecurity and communication concerns. DTs' technological capability and maturity are still in their early stages for most applications. Future research should provide a valuable method to gauge DTs from three perspectives: technical capability, societal preparedness, and maturity [88].

Moreover, substantial work remains to fully integrate autonomous, sustainable, and accepted DTs into real-world scenarios. As technology continues to evolve within the framework of innovation and sustainability, overcoming these and other hurdles will become increasingly feasible. Critical enablers for advancing DTs will be technologies and tools for data processing and analysis [88].

There is a significant gap in understanding how to translate DT concepts into practical applications. Research should prioritize methods to deploy DTs that are both effective and offer a favorable cost-benefit ratio. Given the frequent mentions and near-miraculous potential attributed to DTs, it is crucial to educate decision-makers about realistic and proper implementation [103]. The insights from this paper emphasize the need for a holistic strategy in integrating DTs. This encompasses more than just overcoming technical challenges; it is about recognizing the pivotal role of human elements. Factors like skill enhancement and expertise acquisition are essential for the fruitful adoption of this technology. In the future, the emphasis will be on leveraging the wisdom and skills of specialists adept at navigating the multifaceted world of DTs. The manufacturing sector, in particular, will lean heavily on these experts to address the complexities involved in launching and managing DTs [109].

A recent survey highlighted the importance of focusing on the technical challenges of implementing DTs and addressing the human factors critical to successfully adopting this technology, such as skills development and expertise. An investigative study involving 61 industrial professionals was conducted to gain insights into the most significant obstacles in implementing DTs. These participants were asked to evaluate various categories of issues and specific impediments based on their potential to create complications in DT deployment [110]. The study's findings revealed that while there are persistent technical issues, such as a lack of standardization of data and models, the more prominent barriers were found to be non-technical. The collected data suggested that a scarcity of expertise and specialized knowledge was more likely to give rise to difficulties in DT implementation [110]. The importance of these non-technical factors cannot be overstated. Professionals with specialized knowledge and experience are crucial to overcoming the complexities of setting up and running DTs. They are needed to navigate the nuances of integrating different data sources, managing large volumes of data, and ensuring data security. They also play a critical role in training other team members and fostering a culture that embraces this advanced technology.

7.3. Security threats, privacy, and unintended consequences

DTs must be treated as critical systems where security issues regarding the availability, integrity, and confidentiality of data and resources must be considered. Two types of attacks must be considered to improve DTs security threats: digital and physical. The physical attack includes all those security threats associated with access to endpoints, facilities, IoT nodes, and communication infrastructures. Digital attacks embrace security threats related to the software, such as poor coding and upgrades, default security settings, and components like the network and its information systems. As discussed earlier, the deployment of DT requires technologies such as IoT, AI, virtualization, big data, and cloud computing. Implementing these technologies and the interaction of DT with the physical entity in the real world generate multiple security threats. They are prone to different attacks that have not yet been sufficiently studied [111]. The risks and threats that target the components of DT, from IoT, AI, and data communication, need to be analyzed, and potential countermeasures to be taken to alleviate the security threats.

Another major challenge with DT is associated with data reliability and trust. Therefore, DT solutions must be integrated with a highly secure architecture and constantly improved at every level of development to ensure data quality. Blockchain technology is one of the methods of enhancing data reliability that can overcome problems related to data security, privacy, and trust [21]. Moreover, other obstacles to overcome before DT may be adopted include interoperability, authentication, decentralized decisions, and Feasibility and reliability within the manufacturing unit [112].

Several articles investigated the risks and threats that could target the DT's physical and digital components [111,113–116]. These threats, potential limitations, and unintended consequences are listed below:

- Data integrity and confidentiality
- Gaining unauthorized access to the DT software or source code from poor coding could cause weak software protection.
- Data communications and transmission from or to IoT and the cloud may face serious threats. The commonly known threats are Denial of Service (DoS), distributed denial of service (DDOS), and spoofing and eavesdropping.
- Stored data in the cloud is sensitive and can be exposed to many risks, especially trust concerns and privacy issues related to storing data, especially in the public cloud
- The physical security of the IoT and DT devices is essential as they can be damaged, destroyed, or even stolen by the attacker.

By proactively tackling technical hurdles like data integration, security concerns, and ethical considerations while simultaneously cultivating a spirit of open collaboration between researchers, engineers, and industry leaders, we can truly unleash the transformative power of DTs. This collaborative approach will be crucial in overcoming challenges and pushing the boundaries of what is possible.

8. Summary and conclusions

In the post-pandemic, manufacturers use digital transformation to gain much-needed agility by improving supply-chain visibility, creating feasible production plans, deploying advanced production planning and scheduling, and providing visibility, transparency, and traceability to consumer demand. We analyzed the use of DT and showed that DT technology with IoT capabilities has emerged as a critical concept in the digital transformation of the industry. It is used in Industry 4.0 and connected digital factories. The construction of DTs can be tailored for various objectives, including the conceptualization, production, examination, modeling, and management of non-digital systems. This is done to comprehend, supervise, and potentially enhance the real system. This paper explored the possibilities, challenges, and limitations of DT implementation and its use in different manufacturing domains. Research concerning DT solutions in manufacturing deals with production planning and control, the primary data sync within a production system that ties everything together. Supply chain and logistics management is another area where use cases of DT are reviewed in the literature.

DTs have been effectively utilized across various application fields, positioning them as a crucial component in Industry 4.0. Combining DTs and IIoT can enable new business models, such as predictive or product-as-a-service maintenance. In addition, with the ability to monitor and analyze data from multiple sources in real-time, companies can offer new value-added services to their customers. Overall, implementing DTs and IIoT can unlock significant benefits for industries regarding operational efficiency, cost savings, and new business opportunities.

Incorporating more sophisticated technologies like Artificial Intelligence (AI) and Machine Learning (ML) can enhance DTs' predictive and analytical capabilities. Augmented Reality (AR) and Virtual Reality (VR) integration can also improve the visualization and interaction with DTs, providing more immersive experiences. DT heralds an era where physical systems will be proactively governed using a companion system—a dynamic, real-time, and precise virtual model. These innovations will continue to evolve, influencing the structuring, coordination, and administration of manufacturing and supply chain operations. As the digital revolution progresses, these transformations will fundamentally alter the information and decision-making systems we employ to design, manage, and control manufacturing and supply chains.

We also noted that the deployment of DT may present several open research challenges, such as security, privacy, efficiency, and adaptability. The challenges that might arise depend on the scale and integration complexity of the application. These open research issues provide insights for future researchers to address these problems. Acknowledging and overcoming potential hurdles and promoting their responsible development and utilization, DTs can be crucial in steering the industrial sector towards a more sustainable and thriving future.

9. Future research

The adoption of DT technology is rapidly growing, but its transformative potential for businesses and globally remains untapped. Current literature highlights the vast, yet underexplored, benefits of DT solutions. As the technology evolves, its applications will expand across various industrial sectors, spanning the entire product lifecycle. This expansion underscores the urgent need for in-depth research, especially case studies, to understand DT's full impact.

Despite progress in the DT domain, much remains undiscovered. Integrating advanced technologies can enhance DT's predictive and analytical capabilities. As DT matures, research should explore its adaptability in diverse manufacturing systems and critical data security and privacy issues. Companies need to establish ethical data governance practices to build trust with stakeholders. Effective data management and standardization ensure DT's consistent and integrated application across sectors. Future studies should also address DT's role in sustainability, user interface design, workforce implications, and training. Crucial legal and ethical aspects, like data ownership and consent, need thorough consideration. Moreover, addressing the current lack of standardization will ensure the accurate development and understanding of DTs.

Declaration of competing interest

This is to notify you that there is no financial/personal interest or belief that could affect my objectivity in this paper. I also certify that no funding or research grant was used in writing of this research paper. Also, there is no conflict of interest.

Data availability

No data was used for the research described in the article.

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