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Digital Twins in Manufacturing: A Survey of Current Practices and Future Trends

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Abstract

Digital Twin (DT) is the advanced tool of smart manufacturing which provides a proper way to model, analyse, and control the physical systems. A DT is the lifelike rendition of a physical object or phenomenon that uses real-time actual phenomena data to depict its actions, efficiency, and responses within the surrounding context. This technology allows electronic manufacturers to obtain a real-time stream of their systems, in which predictive maintenance, increased operation effectiveness, and improved product quality can be attained. By developing an ever-evolving replica of the physical structures, systems or even operation lines, Digital Twins enable the functionality of exploring various demanding circumstances and schemata, all in order to make effective decisions. When the manufacturing environments are rapidly changing, and there are more interconnections between them, the use of Digital Twins is especially useful. They continue improvement by highlighting problems, forecasting failure, and making choices based on data. The purpose of this article is to examine smart manufacturing via the lens of IoT DT technology. It gives general information about its uses, such as in the processes, time-saving and safety measures. As well, the paper considers the difficulties related to the practical application of DT, including costs, data management, and requirements for the formation of standards. Thus, based on analysing future developments and the role of Digital Twins as an innovation enabler in different industries, this study can benefit scholars, practitioners, and politicians who look forward to unlocking the potential of this innovative solution.

Keywords: Digital Twin; Smart Manufacturing; Real-Time Data; Predictive Maintenance; Process Optimization; Manufacturing Efficiency

1. Introduction

The phrase "digital twin" describes a computer model that may be utilised for analysis, real-time monitoring, and optimisation of a physical system or process. An use of DT in smart manufacturing allows for optimisation and simulation of a production process, the prediction and prevention of equipment breakdowns, and the improvement of production efficiency and component quality [1][2]. An exact and comprehensive model of the real-life item or system, including its features, functions, and interactions with its surroundings, may be created by creating a digital twin [3][4]. DT applies ML, data analytics, and multi-physics simulation to build and analyse how different working conditions and other factors affect a system [5]. Future technology is also very crucial since it can be used in the development of the DT and influence numerous industries across the globe [6]. Real time data analysis by the DT enables it to observe the performance of the physical device, offer recommendations and even predict a problem [7].

In essence, by replicating the relevant characteristics of a physically existent system and singling out aspects that require enhancement, a digital twin may be employed to enhance the system's functionality [8]. Furthermore, before direct commitment of resources to the fabrication of real prototypes and assets, DT may be used to visualize, estimate, and optimize artifacts and production lines across industries including automotive, green energy, and aviation [9]. As a

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result, digital twin may help some companies and industrial processes and even make some decisions concerning the improvement of performance, cutting of costs in different fields and applications.

This reduces the time and expense for testing and prototyping because engineers and designers can simulate these procedures and modify the environment using digital twins [10][11]. Product makers must use DT technology to increase production process efficiency and reduce time-to-market [12]. Smart manufacturing allows for the construction of DT by merging CAD models with data acquired in real time by physical sensors using various numerical simulation tools. This enables producers to track and analyse processes and equipment in real time, anticipate problems, and optimise production using data-driven choices [13][14].

To maximise efficiency and effectiveness in production, "smart manufacturing" uses cutting-edge technology like AI, robots, the IoT, and big data analytics [15][16]. As a result of increased customisation in manufacturing activities, the production environment is becoming more complicated. Therefore, the ability to analyse and modify the manufacturing process necessitates a high level of cognitive and learning abilities inside the production system. Besides real-time SCM, smart manufacturing provides opportunities to individualize and improve each product. It allows the production of goods in conformity to the client's specifications and to adapt rapidly to changes in needs, market forces, and trends [17].

The purpose of this paper is to evaluate how an adoption of DT technology can affect the smart manufacturing system. Among the research goals it is necessary to identify how DT can be used to enhance production, the application of DT and its advantages and disadvantages, and the further evolution of the concept into manufacturing decisions. It also searches for challenges and limitations that limit the broad adoption of digital twin technology and how to overcome them in the study. This research aims at presenting recommendations about the importance of DT and its practical applications in modern manufacturing environments to scholars, practitioners, and policymakers.

Offers an all-inclusive consideration of how DT technology can enhance the manufacturing execution capability with uses in manufacturing emulation, manufacturing status detection, and manufacturing failure diagnosis.

Points out that primary challenges of applying Digital Twins in manufacturing are newness of the technology, its expensive, lack of standardisation, problems with data, and life cycle incompatibility.

Future application and potential of DT technology in various disciplines; automobile, medicine, farming, smart cities and emergence of its significance.

Provides manufacturers with useful information on how to use Digital Twins for real-time process optimisation and continuous improvement in order to increase productivity, reduce expenses, and improve product quality.

Provides strategies for addressing the challenges of integrating Digital Twins into manufacturing, including recommendations for technology adoption, standardisation, and data management.

1.1. Organized of this paper

The paper starts with an Introduction outlining the research scope. Section II defines Digital Twin technology and its use in smart manufacturing. Section III covers its applications, such as improving processes and reducing downtime. Section IV addresses challenges like cost and data issues. Section V explores future trends and applications across various sectors. In Section VI, the report wraps up with a summary and recommendations for further research.

2. Definition and Concept

The phrase "digital twin" refers to an online model of a physical product, process, or system that may receive data in Realtime from several sources. In manufacturing, Digital Twins replicate machinery, production lines, or entire plants, allowing for simulation, analysis, and optimisation of operations in a virtual environment.

Three stages may be distinguished in the use of DT in a production system. DT may be used for validation and testing throughout the system design phase to find inefficiencies rapidly and assess if physical manufacturing solutions are feasible to implement. Performance of a production system may be tracked and evaluated in real-time throughout this phase by using a digital twin. This may be used to anticipate failures, find problems before they become serious, and improve system performance [18].

A DT's main advantage is that it may serve as a miniature version of a real-life system, enabling testing and analysis to take place in a controlled environment. Utilising a DT in smart manufacturing might result in significant increases in efficiency, cost savings, and quality. The increasing complexity and interconnectedness of production means that DT will likely play a pivotal role in helping companies maintain their edge in the global market [19]. The drawback is that maintaining and developing a DT may be costly, time-consuming, and need certain knowledge and skills. However, there are major challenges in developing a DT in the contemporary industrial processes. A DT's capacity to alter a manufacturing process may be limited by poor-quality data gathered during component fabrication. Below is a schematic showing the DT for manufacturing:

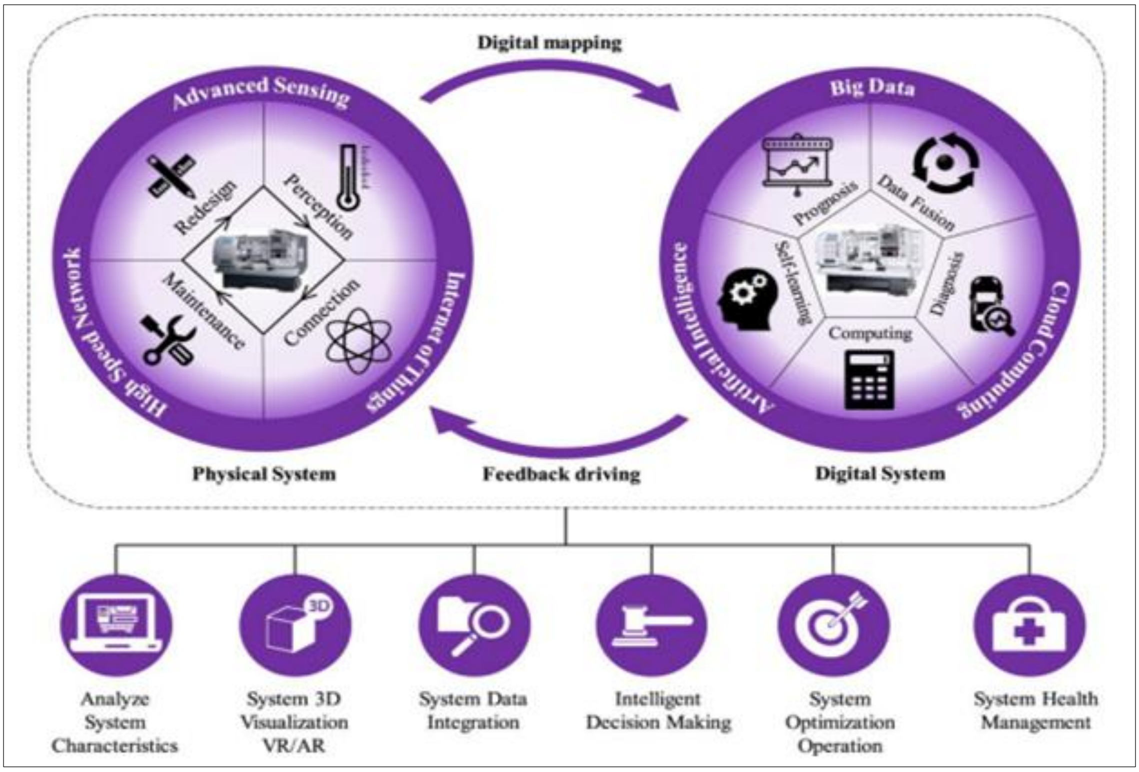

Figure 1 The design of the digital twin for manufacturing

Figure 1 illustrates a concept of "DT" in the manufacturing industry, highlighting the continuous contact among a digital and physical system. Real-time data is transferred onto a digital system driven by Big Data, AI, and Cloud Computing from the physical system via high-speed networks and sophisticated sensors. In order to provide useful insights that are fed back into the physical system for optimisation and decision-making, this digital system mimics processes and analyses the data[20]. The efficiency and efficacy of industrial processes are eventually improved by this interaction's key applications, which include system analysis, 3D visualisation, data integration, intelligent decision-making, system optimisation, and health management.

3. Applications of Digital Twin in Smart Manufacturing

DT applications in part production enable performance analysis and modification of a product. From raw materials to completed goods, the whole production process may be modelled employing a DT. It may be used to predict the likely behavior of the system in the occurrence of different events and to model different events. It also allows the producers to identify issues and improve the system’s effectiveness as a whole [21]. Smart manufacturing makes it possible to adopt DT with real sensors and other devices where production process information can be refreshed in real-time. This helps producers better observe and control the process or make its enhancement by alterations more efficient.

3.1. Digital twin for continuous improvement of manufacturing systems

When planning production systems, enterprises can considerably benefit from digital twins as the technology has a strong potential for improving efficiency, quality, and cost of production. Utilising a digital twin, industrial systems may be continuously improved by simulating and optimising the real system's performance [22][23]. Manufacturers may now track and compare real-time machine performance against expectations due to DT technology. The information can then be used to increase the reliability and lifespan of the equipment. Matters are on a positive side with the help of Hitachi, a market leader. This way producers look at problems that are likely to crop up and address them before they occur, which in turn does not waste time and increases efficiency [24].

3.2. Part production monitoring and modification using digital twin

Facets of whole value chains or products, such as the entire production process, might rise in quality through the concept of the DT idea. Manufacturing components are used to create a DT that mimics a machine or an assembly line for the real-time monitoring of production. This comprises tracking aspects that could possibly impact the quality of the final product, including flow rate, pressure, and temperature [25][26]. Manufacturers might be able to increase the overall output and quality by studying data from the DT and find out where improvements can be made. For instance, if the DT indicates that a particular type of machine is producing more components that have higher failure rates than others, then the quality control of the manufacturing process may be improved [27].

3.3. Downtime reduction in process of part production using digital twin

Another potential of the DT can be the minimisation of the time for component manufacturing since the various conditioning can be tried and tested for the emergence of any problems. For instance, one may simulate effects of changing the machine speed or the temperature in the environment by adjusting the parameters of the digital twin. These scenarios may have to be staged in a bid to identify possible future issues and adjust the process in a bid to minimize on downtime [28]. Real-time monitoring of production process is another strategy by which a digital twin might help to reduce down time. In a bid to reduce chances of comprehensive or part production stops resulting from mistakes, it is possible to check the production process online [29].

3.4. Safety enhancement by identifying hazards and risks of manufacturing process

The first way to enhance manufacturing process safety is to improve the knowledge of possible hazards and threats. The general safety of the industrial production applying digital twins can be improved, using preventative maintenance to identify dangers and threats [30][31]. It is also used to measure operating conditions and health of the machines in a facility or industry. The adoption of a DT has a potential to enhance production safety by making it easier to identify potential dangers. By simulating the system's behaviour in different scenarios, a digital twin may aid in the detection of manufacturing process hazards. It is possible to assess the dangers associated with discovered hazards by using a DT. The likelihood and impact of a danger's consequences may be assessed by simulating its impacts in different contexts [32].

4. Challenges to Implement Digital Twin in Manufacturing

A demands and dynamics of an industry decide an unique challenges of employing DT technology in manufacturing. Although DT has the ability to revolutionise industrial processes, it is often not used due to many common problems.

4.1. Novelty of Technology

DT in manufacturing is quite a young concept; therefore, it stirs doubts concerning its applicability. Due to such a scenario, manufacturers may lack technical as well as practical knowledge to understand how DT can be utilised to increase productivity, maximise efficiency or even enhance a quality of a product. This could delay integration of DT into 'Factory 4.0' because some companies are reluctant to invest in tools they still do not fully understand and cannot trust [33][34].

4.2. Time and Cost

The manufacturing sector, where cost reduction and production time reduction have the most emphasis, suffers a lot in DT technology because of high initial investment and operating costs. It may take time and many resources to create semantically exact and highly accurate mirrors of complex manufacturing systems. The necessity to use high-performance computers to reproduce processes and phenomena accurately makes the costs higher. The cost of DT implementation & the time that may be required to implement the same may form a major challenge for some enterprises particularly the small enterprise that may not be in a position to fund such advanced technology [35].

4.3. Lack of Standards and Regulations

The manufacturing industry, which often relies on standardised processes and regulations, faces complications due to the absence of a unified framework for DT. With a huge range of DT models and architectures in existence, the lack of standardisation can lead to compatibility issues, making it difficult for different systems and components to communicate and function together seamlessly. This fragmentation can hinder the efficient design and integration of DTs in manufacturing, slowing down the adoption process. Moreover, without industry-wide standards, ensuring the security and accessibility of data across different platforms becomes a challenge, potentially leading to operational inefficiencies and increased risks [36].

4.4. Data Related Issues

Manufacturing processes generate vast amounts of data, which are critical for an operation of DT. However, factors such as data privacy, ownership and data transparency raises major concern [12]. Manufacturers have to also understand data governance policies that are specific to industries and regions. There is a fear of sharing the DTs' necessary data due to the security concerns of the proprietary information and the security of the sensitive data. This unwillingness or lack of willingness to share or use data because of privacy consciousness or compliance with regulations can hinder the formation of integrated and efficient DT in manufacturing [37].

4.5. Life-Cycle Mismatching

The primary fabrication facility equipment, including machinery, structures, and vehicles, can endure significantly longer than the software used to build and manage their DTs. Thus, the DT may become irrelevant or incompatible with newer technologies at some point in time which causes disconnection between a physical asset and digital twin. This life-cycle mismatching of requirements can culminate in difficulties in continually updating the DT so that it remains accurate and pertinent, which in turn raises questions as to the preparedness of the DT for contemporary usage in operative ongoing manufacturing processes[38].

These challenges obviate the fact that impose the implementation of the Digital Twin in manufacturing technology a challenge. Bypassing them appears to be a question not only of technology but a question of cultural change within the industry that centers on sharing, repeatable processes, and skills acquisition. As the industry moves toward embracing Industry 4.0, addressing these barriers will be critical to unlocking the full potential of Digital Twins in transforming manufacturing processes.

5. Future Trends of Digital Twin in Manufacturing

The industrial and aerospace industries have made use of DT technology, but DT is still in its infancy in a number of other industries, including a construction, healthcare, automotive, and agricultural sectors. The COVID-19 pandemic in 2020 is one among the causes propelling the need for DT across several industries. This viral pandemic has led to an upsurge in demand for DT in the industrial, healthcare, and pharmaceutical sectors.

DT is anticipated to play a pivotal role in MBSE in the industrial sector in the not-too-distant future, due to the practicality of applying DT MBSE throughout the whole system life cycle. If MBSE wants to expand into other industries like manufacturing, construction, or real estate, DT is a great partner. With the ability to make decisions and integrate into the production process via online monitoring, DT is anticipated to enhance future non-destructive testing.

General Electric is of the opinion that the automobile industry as a whole, from manufacturers to individual consumers, will embrace DT technology as predictive maintenance and analytics continue to progress. Auto owners will no longer have to worry about unexpected breakdowns and the car may even arrange maintenance appointments autonomously, making auto maintenance a breeze. Prior to the appointment, the technicians and the service department will have access to all the vehicle's information, which will enable them to provide faster and more effective solutions. With DT's assistance, garages may better manage their inventory and supply chain in addition to their customers. When it comes to auto dealerships, DT can handle all the fleet health and performance monitoring on its own, and it can also assist with important financial and commercial choices based on asset performance management and depreciation[39].

DT has been able to expand its healthcare business as a result of the worldwide COVID-19 outbreak. The 'Cardio Twin' team is hopeful that its platform may one day be able to stop strokes and ischaemic heart disease (IHD) [40]. Every single person on our globe will soon have access to highly individualised, cost-effective healthcare because of the advancements in DT technology in the medical industry.

DT's growth in the agricultural business is still in its early phases. (1) DT can be used to store and collect data, (2) it can organise actions in complex workflows, (3) it can automate data analysis, (4) it can learn and measure the soil's content and capacity, (5) it can simulate crop outcomes, (6) it can predict the weather, and (7) it recognises when resources are being strained by things like pollution, invading species, low soil quality, and so on [41].

The interest in establishing DTs in their own cities is growing among national and regional administrations. Planned and governed more effectively are these cities with its own DT. Better service to stakeholders and quicker issue-solving will be possible for the administration. Natural catastrophes like earthquakes, cyclones, and tsunamis, among others, provide these cities' disaster tracts an extra edge.

DT technology has the potential to be used with other technologies in the future to provide improved results. For instance, combining mixed reality and DT technology can improve DT visualisation and enable remotely supervised inspections. Besides that[42], DT is beginning to be used in the field of education. Demonstrated how DT combined with AR/VR can be utilised to create digital pedagogy for students studying construction, engineering, and architecture. This can be helpful for teachers who are delivering remote classes, either as part of regular online learning or in emergency situations like pandemics.

6. Literature Review

Previous research in this field has mostly focused on using data analysis methods to address the difficulties involved with integrating Digital Twins in manufacturing.

This paper, Lin and Low, (2020) reviewed a blueprint for an industrial cyber-physical digital twin system's infrastructure. A high-level description of the system's architecture was followed by an exhaustive breakdown of its many constituent modules. Sub-modules of this kind may be found in software like wireless modular tracking, E-scheduler, simulation, and DT dashboards. An extensive prototype is being built to showcase the features and capabilities of the industrial cyber-physical DT system [43].

This paper, Wang, Zhe and Sun, (2023) analyses the inner workings of digital twins in industrial companies, beginning with the intrinsic causes for digital twin value creation. Companies in the industrial sector may investigate the 4.0 value chain design by collaborating on digital twins and connecting processes. In this study, they examine the supply networks and industrial chains of manufacturing organisations in order to determine the driving mechanism behind the 4.0 value chain. Manufacturing big data is used to investigate this mechanism. In addition, the corporate digital endogenous integration tower 3D process is shown as a paradigm for industrial businesses. The 4.0 value chain is the engine that drives the investigation into the type and origin mechanism of supply chains in manufacturing businesses. The objective is to provide a standardised method for creating and framing the DT[44].

This paper, Yu-Ming, Bing and San-Peng, (2020) offers a solution for intelligent manufacturing that is adaptable in production line design and built on digital twins. First, we improve the autonomous production mode of control and simulation before building the DT of the intelligent manufacturing flexible production line. Utilising the enhanced R-CNN model as the main training network, the next phase involves building the approach and mechanism for real-time interaction with heterogeneous data from several sources, such as equipment and the environment. The research concludes with an investigation of digital twin technology as it pertains to intelligent manufacturing flexible production lines and industrial robots, which offers a solid and efficient solution for the intelligent manufacturing industry as a whole[45].

This study, Sun et al., (2023) The flexible Manufacturing cell comprises mainly chuck class components. The application framework as well as the digital twin model of the flexible production cell was developed through digital twin. If used together with the physical unit, the DT enables observation of equipment operations from a distance[46].

This paper, Xia, Lu and Zhang, (2020) provides an analysis of the DT workshop with the components described as “digital twin engine,” “virtual workshop,” and “physical workshop. ” This paper also defines the DT engine and lays out a plan for how to create the physical DT workshop based on the structure of the virtual workshop. Last but not the least is the DT engine used to verify the effectiveness and working of the digital twin work shop based on the installment of a DT workshop in an intelligent manufacturing unit[47].

The paper, Kozhay et al., (2022) largely revolves around the data and physical layer aspects of DT technology. Additionally, it suggests using artificial intelligence and the HDF5 format database as part of DT for ALM, which may alter the certification of goods used in the aerospace sector by validating the manufacturing process. It would provide a chance for increased use of ALM in the aerospace sector and safety enhancement[48].

In this paper, Azangoo, Taherkordi and Olaf Blech, (2020) showcase our work on the UML modelling of manufacturing facility digital twins. Behavioural models that function as digital twins and can be updated by real-time data from a manufacturing plant are added to the produced class diagrams, all while using the methodology's fundamental important UML properties. We provide a brief example that uses a demonstration and simulation programs. The example and modelling method that is being provided offer helpful insights into a creation of DT in complex industrial systems using UML[49].

In this paper, Liu, Wang and Fu, (2022) promote an ongoing development of DT technology in manufacturing production lines, this article offers an ideal approach for a DT-driven manufacturing production line. It relies on recent advances in enabling technology, simulation, and digital twin modelling. With an eye on the real-world requirements of "Made in China 2025," this study examines the features and benefits of DT technology as it pertains to industry transitions and its potential future applications[50]."

Table 1 Provides a table of comparisons for digital twins in manufacturing

Ref	Methodology	Area	Limitations & future work
[43]	gives an overview of the sub-modules, including dashboards, E-scheduler, wireless modular tracking, and simulation, that make up a manufacturing cyber-physical DT system architecture. Highlights database module design for switching between production and simulation databases.	Industrial IoT (IIoT) Datasets	Further development of the proof of concept prototype is underway; next tasks will include showcasing all features and functions.
[44]	Examines the internal factors that contribute to the value generation in manufacturing companies' digital twins. Breaks down the 4.0 value chain design and suggests a 3D approach for business digital endogenous integration in a tower.	Public Datasets for Equipment Monitoring	The 4.0 value chain drive's supply chain, including its nature and derivation method, needs further investigation.
[45]	Proposes the use of DT technology to create an intelligent, adaptable production line system. Enhances control production modes and independent simulation. Creates a digital replica of the manufacturing process and implements an enhanced R-CNN model to enable real-time interaction of diverse sources of heterogeneous data. Studies digital twin technology for industrial robots.	Simulated Manufacturing Data	Further research needed to enhance the overall solution of DT flexible systems for intelligent manufacturing.
[46]	Provides a framework for applications and a DT model for flexible production cells for chuck class components. Permits quick implementation, process simulation, online programming, and debugging.	Public Datasets for Equipment Monitoring	Further development of remote monitoring capabilities and validation of the framework's effectiveness in various manufacturing scenarios.
[47]	Separates the DT workshop into 3 parts: the virtual part, the physical part, and the engine that runs the machine. Defining and examining the digital twin engine's functionalities. Proposes architecture based on virtual workshop models. Verifies effectiveness using an example of an intelligent manufacturing unit.	Simulated Manufacturing Data	Further validation and application of a proposed architecture in diverse intelligent manufacturing units.
[48]	The difficulties of DT technology in an aerospace sector are centred on the data and physical layers. Suggests using AI and the HDF5 database format for ALM. Monitors production process by comparing printed parts' characteristics with standards.	Public Datasets for Equipment Monitoring	Future work involves broader application of ALM in aerospace and improving safety standards.
[49]	An employ of UML class diagrams to model digital twins of production factories. Describes static dependencies and keeps an eye on quality and verification factors in real time using diagrams. Enriches diagrams with behavioural models updated by live data.	Simulation programs and a demonstrator	Further work is needed to expand the UML-based design approach and validate its applicability in more complex manufacturing systems.

[50]	Uses digital twin modelling and simulation tools to provide a better approach for manufacturing production lines powered by digital twins. Dedicated to the "Made in China 2025" program. Describes digital twin technology, explains its benefits, and examines its role in the revolution of manufacturing.	Simulated Manufacturing Data	Further research on application trends of DT technology and its impact on a transformation of a manufacturing industry.

6.1. Research gaps

Each article makes a distinct contribution to the conception, design, and practical use of DT, and taken as a whole, they demonstrate the wide range of applications of Digital Twin technology in many industrial settings. Criticising it, nevertheless, shows a number of similar shortcomings. In real-world industrial contexts, scalability and integration difficulties are often not sufficiently addressed by the techniques, which instead place a strong emphasis on system architecture and design. A complete, large-scale validation that may show the long-term viability and advantages of these systems is conspicuously absent from the literature, even if some articles provide interesting case studies or prototyping operations. However, these methods may not be as flexible in many industrial contexts because to their dependence on certain technology frameworks like R-CNN or UML models. Thus, although these studies contribute to our theoretical and conceptual knowledge of Digital Twin systems, they are not as successful in providing solid, globally applicable solutions that the very varied and dynamic industrial sector can readily accept and scale.

7. Conclusion and Future Work

An integration of DT technology into smart manufacturing represents a significant advancement in optimising production processes, enhancing product quality, and reducing costs. By creating a virtual replica of physical systems, DT facilitates real-time monitoring, simulation, and analysis, leading to improved decision-making and efficiency. Despite the advantages, challenges such as high costs, lack of standardisation, and data-related issues hinder widespread adoption. The potential of Digital Twins extends beyond manufacturing to sectors such as automotive, healthcare, and agriculture, where their application could revolutionise practices and outcomes.

Addressing the present difficulties of deploying DT technology, including creating cost-effective solutions and creating industry-wide standards, should be the focus of future research. Exploration of advanced techniques like AI-driven analytics and integration with emerging technologies such as mixed reality could further enhance the capabilities of Digital Twins. Additionally, expanding applications to new sectors and improving interoperability between different systems will be crucial for maximising the benefits of DT. Ongoing studies should aim to refine methodologies, explore novel use cases, and develop strategies for overcoming barriers to widespread adoption.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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