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Digital Twin applications toward Industry 4.0: A Review

Mohd Javaid [1,*], Abid Haleem [1], Rajiv Suman [2]

[1] Department of Mechanical Engineering, Jamia Millia Islamia, New Delhi, India
[2] Department of Industrial & Production Engineering, G.B. Pant University of Agriculture & Technology, Pantnagar, Uttarakhand, India

A R T I C L E I N F O

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A B S T R A C T

Digital Twin is a virtual representation of objects, processes, and systems that exist in real-time. While Digital Twin can represent digital objects, they are often used to connect the physical and digital worlds. This technology plays a vital role in fulfilling various requirements of Industry 4.0. It gives a digital image of a factory's operations, a communications network's activities, or the movement of items through a logistics system. This paper studies Digital Twin and its need in Industry 4.0. Then the process and supportive features of Digital Twin for Industry 4.0 are diagrammatically discussed, and finally, the major applications of Digital Twin for Industry 4.0 are identified. Digital Twin sophistication depends on the process or product represented and the data available. Manufacturers can learn how assets will behave in real-time, in the physical world, by putting sensors on particular assets, gathering data, creating digital duplicates, and employing machine intelligence. They can confidently make wise judgments, which helps improve company performance. Digital Twin assesses material usage to save costs, discover inefficiencies, replicate tool tracking systems, and do other things. Manufacturers construct a digital clone for specific equipment and tools, exclusive products or systems, entire procedures, or anything else they want to improve on the factory floor. Sensors and other equipment that collect real-time data on the state of the process or product collect this information, which on the other hand, must be handled and processed appropriately. It is made feasible by IoT sensors, which collect data from the physical environment and transmit it to be virtually recreated. This information comprises design and engineering details that explain the asset's shape, materials, components, and behaviour or performance.

1. Introduction

A Digital Twin is a software model of a physical thing. At the very least, this technology comprises the unique identity of the actual item. It gives a digital representation of a tangible item, such as an automotive engine, a structure, a solar farm, or even an entire city. The digital twin may mimic various processes that material things might go through and forecast their performance under those settings. Digital Twin is a simple algorithm that forecasts how a product or process will perform based on real-world data [1–3]. These applications incorporate the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics to improve output results. The digital twin frequently includes auxiliary data such as the device's firmware version, configuration, calibration, and setpoint data. With adequate information, Digital Twin can recommend solutions that are more likely to work for each individual, considering their unique medical history and statistics [4,5].

As digitised duplicates of equipment/machines or physical places outfitted with sensors, Digital Twin, or virtual counterparts of physical assets are created, smart components are connected with physical objects that employ sensors to collect data about working

* Corresponding Author
E-mail addresses: mjavaid@jmi.ac.in (M. Javaid), ahaleem@jmi.ac.in (A. Haleem), dr.r.suman@gbpuat-tech.ac.in (R. Suman).

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conditions, real-time status, or position [6,7]. These components constitute a cloud-connected system that collects and analyses all sensor data. This data is compared to industry and other contextual data. Digital Twin also necessitates a robust digital culture. This operates best when companies already use sensors and other data collection techniques to learn as much as possible. The Digital Twin lives on up-to-date and correct data, and modifications can be applied gradually. Introducing this technology in incremental increments, as an introduction or as an experiment, can assist in introducing this new method to personnel at all levels, from engineers to business analysts [8,9].

Digital Twin can be used to stress test operations in hospitals and medical institutions, mimicking how to best function amid mass catastrophes. Such organisations frequently contain components, such as accessible personnel, patient beds, and access to various testing facilities, that may be modified to manage increasingly complex scenarios. Similarly, when it comes to using Digital Twin in direct healthcare goods, such technology might help clinicians provide unique, personalised treatment for particular patients. A digital twin's lifespan begins when professionals investigate a physical system's mechanics and operational factors to create a mathematical model replicating the original [10–12]. Developers create Digital Twin or virtual models that may get feedback from sensors linked to the physical system. The sensors collect critical operational data, and the digital model simulates what happens in a real-time physical system. Users can employ a digital twin to investigate options for product lifetime extension, manufacturing and process improvements, product creation, and prototype testing [13,14].

The Digital Twin open up a world of possibilities. The conventional method of creating something and refining it in subsequent versions and releases is no longer viable. The optimum feasible efficiency level of a product, process, or system may be recognised and built using a virtually-based design approach by simply analysing its characteristics, performance abilities, and any concerns that may emerge. Digital Twin functioned as a virtual testbed to examine functional relationships and their impact on electricity generation. In this scenario, the advantages of Digital Twin were a less expensive and more effective method of analysing control process phenomena and reducing downtime. Increasing plant dependability and optimising resource utilisation were also mentioned as advantages. Employees can learn about operations in a virtual environment using Digital Twin of plant systems and processes [15–17]. The main aim of this paper is to study the significant applications of Digital Twin for Industry 4.0

2. Digital twin

A digital twin is a virtual model duplicating an IoT device's physical components and behaviours across all phases of its lifespan. A digital twin is formed by employing sensors to capture real-time data from real-world elements. That data is then utilised to produce a digital replica, which may aid teams in better understanding and analysing real-world objects or systems [18,19]. A digital twin's main advantage is that it gives real-time data that can aid in learning, reasoning, and understanding how objects and systems function. It enables users to analyse, model, and optimise a physical object's performance across its lifespan. Because of the numerous advantages, many enterprises employ digital twin cloud services to model and simulate infrastructure assets. Furthermore, maintaining a digital replica of assets in the cloud allows firms to track changes and make appropriate modifications to enhance performance [20–22].

Digital twin refers to the digital twin itself, an application that integrates to create a near-real-time digital replica of the physical environment and process. A digital twin's goal is to detect unacceptable deviations from ideal circumstances along numerous dimensions. Such a divergence is a case for business optimisation; either the twin has a logical flaw, or an opportunity for cost savings, quality improvement, or increased efficiency has been uncovered. The next opportunity might lead to an action in the physical world. Digital Twin is propelled by data and analytics [23–25]. Digital Twin uses data, Machine Learning (ML), and the IoT to improve the efficiency of systems and enterprises, resulting in improved outcomes [26,27].

A digital twin is defined in various ways by industry and academics. Some define a digital twin as an integrated model of an as-built product intended to represent all manufacturing faults and continuously update to incorporate wear and tear incurred while in use. It is primarily described as a dynamic digital profile of a physical object's past and current behaviour or process that aids in optimising business performance. The digital twin is built on various dimensions of significant, cumulative, real-time, real-world data measurements. These measurements can result in a developing profile of the object or process in the digital world, leading to actions in the physical world, such as a change in product design or manufacturing process [28–30].

3. Industry 4.0

Industry 4.0 refers to the wide range of new technologies and digital advances altering production by integrating the physical and virtual worlds. While development has been gradual, many organisations have hesitated to develop comprehensive digital ecosystems for their manufacturing processes, integrating Industrial Internet of Things (IIoT) platforms with Digital Twin of manufacturing equipment and production lines. A comprehensive digital twin needs a large amount of data from several sources to build a representation that is accurate to the actual thing. The digital twin must simulate the behaviour of specific physical components and their interactions with other components and the Digital Twin. Remotely operated, optimal predictive maintenance is possible using augmented and virtual reality equipment [31–34].

Industry 4.0 refers to the many technologies and solutions needed to create the legendary "lights out" factory, in which human presence is dramatically minimised, and worker safety is optimised. Manufacturers must reaffirm their commitment to invest in IIoT platforms that gather and analyse data and Digital Twin that utilise the data to monitor, manage, and improve industrial operations to remain competitive in future years [35–37]. Implementing Industry 4.0 business models begins with data collection, analysis, obtaining insight or taking specified actions. The Digital Twin for Industry 4.0 product aims to digitally depict genuine equipment and processes related to their physical counterparts by mechanical and geometric aspects and their behaviour [38,39].

The Digital Twin for Industry 4.0 solution is relevant to any business in various fields interested in the industrial digitisation of its assets. More precisely, the solution is intended for manufacturing organisations who want to improve the efficiency of their production system, improve the quality of their goods, and decrease waste and environmental effects. Using the Digital Twin idea to transition to Industry 4.0 presents unique obstacles. The Digital Twin model is not limited to IoT devices. Digital Twin must also have a much broader range of abstraction capabilities. A Digital Twin solution must support the modelling of relationships between IoT devices. Customers should be able to design new Digital Twin models customised for their sector or use case. A platform must provide a provisioning framework for generating Digital Twin and its association with various IoT devices [40–42].

4. Need for Digital Twin

Engineers may accelerate the design process and remove many laborious stages generally needed in designing a new product by employing 3D simulations enhanced by augmented and virtual reality. Product specs, materials to be utilised, and how the design compares to key rules, standards, and laws may all be decided virtually before any materials are invested. Digital twin allows engineers to discover any possible concerns with quality and viability before designs are completed, resulting in significant cost savings [43–45]. Data collected for Digital Twin can indicate when equipment maintenance is required and when failures will occur. Timely reporting these needs to human monitors may save businesses time and money and reduce downtime for essential repairs. The benefits of Digital Twin extend beyond the design process and into the product's lifespan. The twin can also answer critical issues regarding an asset's behaviour under stressors and varied environments. The data may then be analysed to see its effect on the copy [46,47].

IT workers collect and synthesise data from many sources to build a digital twin of any physical asset. Shortly, IoT simulation models and cloud-based apps will fuel the digital twin. Users can employ Digital Twin to benefit from the convergence of the physical and digital worlds. The increased usage of a digital twin to improve resource management and the customer experience in numerous business verticals has considerably contributed to market revenue development [48–50]. Because of their capacity to portray things online fully, Digital Twin can substantially ease this procedure. Instead of wasting time and money while repeatedly replacing physical prototypes, we may make changes and conduct testing instantaneously, avoiding the possibility of future difficulties. With as many systems as the production line is likely to juggle, making significant adjustments without potentially jeopardising the entire structure can be challenging. A digital twin may duplicate a specific process or an entire system in a virtual environment, enabling to change of various features using data from the actual setup [51,52].

5. Research objectives of the paper

Digital Twin for reservoir simulations can save millions of dollars while avoiding environmental issues. These organisations can predict how water and hydrocarbons travel beneath the earth between wells using specialised software programmes. This enables them to use supercomputers to examine potentially troublesome circumstances and virtual manufacturing plans. These exploration corporations can limit losses when committing to new projects by assessing the risks in advance using Digital Twin [53,54]. Businesses may evaluate how well a manufacturing process works in different circumstances by using a virtual model of how it could operate. This is the most basic strategy for developing an effective manufacturing system. This technique may be fine-tuned using a digital twin for each piece of equipment. For businesses, this entails the capacity to implement preventative maintenance programmes. This reduces the likelihood of costly downtime while also speeding up industrial activities safely and effectively [55–57]. The primary research objectives of this paper are as under:

RO1: - to study Digital Twin and its need in Industry 4.0;
RO2: - to discuss the process used in Digital Twin for Industry 4.0;
RO3: - to study the supportive features of Digital Twin for Industry 4.0;
RO4: - to identify and discuss applications of Digital Twin for Industry 4.0.

6. The process used in Digital Twin for Industry 4.0

The digital twin is a highly scalable, industry-ready technology that introduces Industry 4.0 capabilities to traditional industrial manufacturing. It uses a cloud-based IIoT platform, including information monitoring tools, specific operator training, and remote help. Developing Digital Twin necessitates the creation of high-fidelity virtual representations of the physical world that adapt in real-time when the physical environment changes [58–60]. Digital Twin has attracted much attention as the IoT has become increasingly prevalent. A digital twin is a virtual replica that mimics the behaviour of an actual object or process throughout its existence. This technology allows remote monitoring and operating equipment and systems, providing a near real-time bridge between the physical and digital worlds. It can run simulation models to evaluate and forecast assets and process changes under various situations. Companies that use Digital Twin may reap significant benefits such as enhanced operations, faster time-to-market, and product and service innovation [61–63]. The process used by Digital Twin in Industry 4.0 is shown in Figure 1.

Some sensors record the operational behaviours of assets and processes and their operating surroundings. A digital platform that acts as a contemporary data repository, gathering and storing shop floor sensor data with high-level business data. Digital Twin, first achieved in the aerospace sector, is increasingly gaining popularity across industrial verticals. The amount of detail of digital twin models is determined by the availability and maturity of IT infrastructure [64,65]. A manufacturing line's digital footprint integrating sensor and ERP data can thoroughly monitor production rates and scrap counts. TA comprehensive, integrated historical

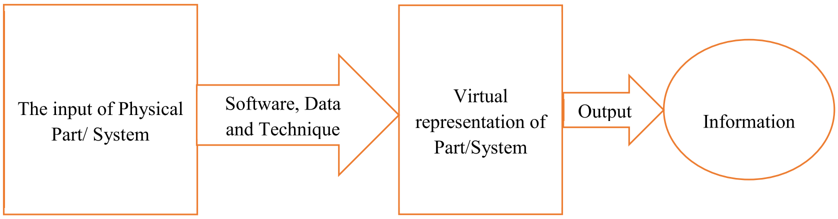

Figure 1. Process used in Digital Twin for Industry 4.0

data on equipment, processes, and environments may be used to optimise production scheduling through downtime predictions [66–68].

Digital Twin aims to create a digital version of an organisation's or a manufacturing plant's physical assets. The Digital Twin idea delivers tangible and intangible to a digital platform, whether a facility, a building, heavy machinery, high-value equipment, or a system or structure. The focus on the types of information that will be required throughout the asset's life cycle under evaluation is critical to the digital twin. Organising information in a reusable manner [69,70]. The development of a canonical data model can help in this regard. A canonical data model is a data structure that is common and enterprise-standard. A canonical framework enables multiple systems that interface with the digital twin to communicate in a single agreed-upon format. The novelty of Digital Twin is that it is a method of offering a complete solution to corporate organisations all over the world. It brings together significant technological disruptors such as Big Data, ML, Cloud Computing, AI, and, most critically, IoT [71–73].

Digital Twin provides complete knowledge of the performance of varied corporate assets. Aside from that, the digital sensors Digital Twin uses to play an essential role in immediately detecting and reducing performance bottlenecks. As a result, having a clear perspective of assets and resources aids in maximum usage. Digital twin technology, paired with cutting-edge ML and AI capabilities, assists businesses in various sectors lower operational costs, increasing efficiency, improving performance, and changing how predictive maintenance is performed. Digital twin technology, in particular, is critical for product manufacturers in order to achieve more efficient production lines and shorter time-to-market [74–76].

It is challenging to keep track of all equipment and locate it quickly in complex organisations with many offices, such as hospitals, industries, and ports. In an emergency, a digital twin of a hospital can assist hospital workers in quickly locating the required instrument or equipment. The IoT sensors integrate all equipment and continually communicate data to the Digital Twin system, indicating the present location of assets. Many advantages are promised by Industry 4.0 and Digital Twin, including an efficient batch size and many optimisations [77–79]. However, applying these notions necessitates a complex IT infrastructure. A scalable architecture can respond fast to changes in quantitative requirements. Changes in the number of users or data points that must be processed are supported. The solution's architecture was designed with scalability in mind; each Industry 4.0 component is offered as a container image with explicit background storage that can be shared between containers [80,81].

A digital twin is a virtual version of an object or system that spans its lifespan, is updated from real-time data, and aids decision-making through simulation, ML, and reasoning. By analysing evolving client preferences, modifications, and experiences, Digital Twin is already assisting firms in staying ahead of digital disruption. Because of this expertise, organisations can offer goods more quickly and with superior quality, from the components to the code. IoT enables linked equipment and gadgets to exchange data with their digital counterparts and vice versa [82–84]. This is because Digital Twin always-on and up-to-date computer-simulated representations of the real-world IoT-connected physical items or processes they represent. Digital Twin can capture the physics of buildings and changing circumstances both within and outside, as sensed by a network of linked sensors powered by edge computing. They may also use the virtualisations to perform simulations to test for faults and seek improvements through service upgrades [85,86].

The manufacturing industry is experiencing an exciting period due to the appearance of creative, technical breakthroughs. The rise of technical improvements creates opportunities for organisations to become more efficient, flexible, and sustainable. Digital Manufacturing in Industry 4.0 will also enable new ways for robots and humans to communicate, allowing businesses to acquire more knowledge, minimise the risk of mistakes, and make better decisions. Smart City Digital Twin can help with better development planning and continuous improvement [87–89]. Smart cities are constructing 3D representations of themselves in order to perform simulations. These Digital Twin aid in optimising traffic flow, parking, street lighting, and a variety of other areas to enhance city life, and these changes may be applied in the real world. Networks have gotten increasingly complex over time. The size of networks, the number of nodes, and the components' interoperability all contribute to their complexity, affecting preproduction and staging processes [90,91].

Creating Digital Twin in Omniverse for architects, engineers, and construction teams to evaluate designs together can help accelerate development and keep contracts on track. Because of the usage of Digital Twin, much of this may be done in a virtual environment, and simulations can be undertaken to reduce bottlenecks and other issues. Thus, to allow edge computing and AI solutions like real-time product detection, factual information, data, and operational technologies must support a network of intelligent shops and fulfilment centres [92–94]. This results in more rapid, agile product inspections and order fulfilment. Digital Twin in the healthcare industry can detect flaws or problems with the equipment used in many medical professions. For example, MRI scanners

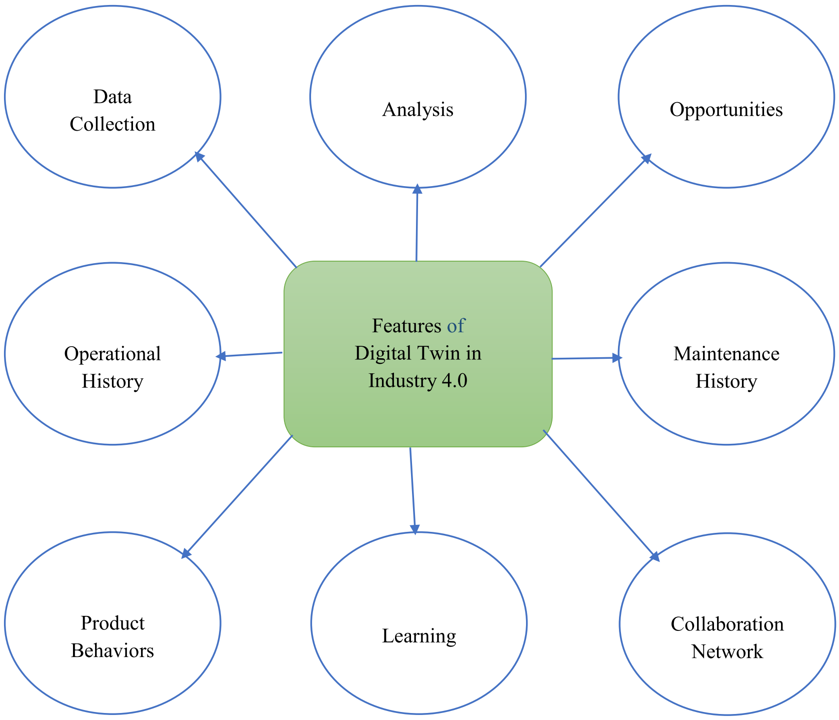

Figure 2. Features of Digital Twin in Industry 4.0

create massive quantities of daily data and messages, which may be fed into the Digital Twin to analyse its present state and project emerging concerns [95,96].

Most industrial automation systems support the Functional Mock-up Interface (FMI) to integrate a real-time version of the Digital Twin to operate in parallel with the real machine. This enables speedy job planning and testing in the virtual environment before making any system modifications to the computer. Beyond the creative process, the Digital Twin provides limitless potential in the industry [97,98]. An in-line Digital Twin allows an operator to learn on a virtual machine until they have the abilities and confidence to run the actual machine without the expenditure of a specialised training simulator. Predictive maintenance is the ability of Digital Twin to foresee issues and propose remedies in advance. All remote copies continually watch their physical counterparts and collect data via sensors. This data is evaluated in real-time, allowing for the prediction and resolution of any outages or malfunctions. Human operators use this data to flag and fix problems immediately [99–101].

At the product level, organisations may employ Digital Twin models to track a product from conception through in-store placement. Companies may use this platform to analyse production processes, supply chains, and logistics and test innovative, simplified solutions to minimise costs. On a broader commercial level, retail shops may utilise Digital Twin technology to reproduce their store and observe consumer behaviour using sensors. This data may be saved on the Digital Twin to help researchers determine the ideal locations for essential items [102–104]. Changes and layout modifications can then be recommended and digitally evaluated. Digital Twin technology, on a far grander scale, can reproduce whole cities down to individually simulated components and use this to enable real-time two-way communication. Analysing traffic as it builds with each automobile, intersection, and traffic signal simulated individually makes it possible to forecast where traffic will build up ahead of time. When combined with ML, the model can swiftly evaluate potential solutions. Once a working answer to an imminent issue is found, it can transfer these control signals back into physical equivalents [105–107].

7. Features of Digital Twin in Industry 4.0

Digital Twin can be used with a prototype to provide feedback on the product while it is produced, or it can function as a prototype on its own to mimic what would happen with a physical version when it is built. A digital twin requires data linked to a product's lifespan, such as design requirements, manufacturing methods, equipment, materials, etc., to replicate its behaviour in a real-world application [108,109]. It may also gather operational data, including real-time feedback, historical analysis, and maintenance records. Any changes to systems on a vehicle, probe, or rover are frequently tested on a system simulation to ensure that any change delivers the desired result. Engineers can resolve unintended consequences before implementing the system's modifications [110,111]. The significant features of Digital Twin in Industry 4.0 are shown in Figure 2

This technology recently gained traction, particularly in the healthcare, automotive, and manufacturing industries. Because of the competitive advantage that Digital Twin may provide, an increasing number of firms are implementing Digital Twin to boost efficiency, optimise operations, and decrease risks. Furthermore, the IoT has made Digital Twin more accessible to many enterprises, allowing companies from several industries to reap the benefits of this technology. One of the essential characteristics of a smart factory is its capacity to maintain a firm grasp on current factory floor interactions while forecasting and avoiding asset failures/downtimes and poor output. Digital Twin enhances machine monitoring and inventory management through internet-enabled connections, sensors that gather real-time data, and calculations that offer analytics [112–114].

Unplanned downtime risks may be considerably decreased by using Digital Twin as a lead towards attaining a smart factory. As machine monitoring in the factory onsite is continual with Digital Twin of the necessary IIoT technology, automated digital asset checks reinforce the planned utilisation and maintenance downtime schedule. Aside from reducing unexpected downtime, Digital Twin assists in using assets to their most excellent potential capability. This is the product of a digital twin, the foundation for machine performance monitoring and assessment [115–117]. The digital twin enhances productivity with machine production analytics by facilitating scheduled maintenance and root cause analysis of machines and assets, generating constructive models for running machines. Logistics and supply chain management are critical in the industrial industry; the digital twin provides precise supply chain management with operational transparency by tracking logistics [118,119].

AI and ML can provide business and operational operations with insights, predictability, visibility, and automation. Using data from these assets may help firms execute predictive maintenance based on ML algorithms, resulting in optimal uptime and greater efficiency. Manufacturers may now construct Digital Twin, virtual clones of processes, factories, supply networks, and manufacturing lines, thanks to the digital revolution enabled by Industry 4.0 [120–122]. Automation allows producers to work more quickly; predictive maintenance reduces machine downtime, and data analytics helps executives to make data-driven choices and boost productivity. Monitoring systems provide real-time yield optimisation across the whole operation. Manufacturers will understand the value of the connected factory when they can get the most out of their production with sensor-monitored machinery, all while providing customised attention and speedy support to consumers via AI and field service [123,124].

When paired with analytics, digital twin data may reveal hidden value for an organisation and give insights on enhancing operations, increasing efficiency, or detecting and fixing issues before the real-world asset is impacted. The next generation of digital twin technologies and standards will give apps a comprehensive picture of the value chain and life cycle. These technologies will help streamline development and business operations across system or company borders by standardising access, configuration, and representation of physical assets, processes, and other assets [125,126]. These virtual models using this technology have become a standard in modern engineering to drive innovation and enhance performance as ML and other elements, such as big data, have advanced. Developing one can advance critical technological trends, prevent expensive failures in physical objects, and test processes and services via enhanced analytical, monitoring, and predictive capabilities [127,128].

Digital twin in manufacturing provides intelligence to networked machines on the shop floor, allowing them to organise and execute production efficiently. Even though increasing connectivity, computing power, advanced multi-physics simulation tools, IoT, and new levels of automation allow for the realisation of a holistic digital twin in manufacturing, companies continue to struggle due to the intricate nature of complex systems, a lack of a consistent framework and a precise level of integration between physical and digital domains, data exchange, and, to some extent, technology maturity [129,130]. This technology can assist businesses in monitoring operations, doing predictive maintenance, and providing information for capital purchase choices. They also help firms establish long-term business goals, find new ideas, and enhance procedures by simulating situations that are too time-consuming or expensive to test with tangible assets. Companies may use Digital Twin to test and certify their products before they are released into the real world. Engineers can utilise them to detect process faults [131,132].

The energy and infrastructure industries are two of the most potential digital-twin application areas. Utility companies constantly look for methods to save operating costs, improve efficiency, and identify issues. Digital platforms and linked solutions can enable energy companies to control physical assets remotely, reducing human labour hours and costs. Sensor technologies, IoT, and smart platforms combine into Digital Twin. Operators can accurately map physical assets into digital versions [133–135]. Virtual reality is also a rapidly expanding market, encouraging innovation in utility management. The virtual depiction of the elements and dynamics of a process, equipment, or service in digital twain brings the real world to the virtual world. It might be a smart automobile, building, manufacturing floor operation, or anything else. It depicts how the design, construction, and operations are built, with real-time monitoring of its workflow. This is continually optimised based on analytics, feedback, and updates tailored to a consumer's demands [136,137].

Data collection and analysis technologies, such as edge computing hardware and IoT solutions, are regularly implemented within facilities to execute a wide range of data-driven policies. The digital twin combines the data acquired by various technologies into a single virtual environment to reflect an industrial facility's precise and present operational condition. A digital twin provides a real-time virtual mirror of a company's production processes [138,139]. Data-capture technologies supply the digital twin with real-time information on shop-floor activities. The digital twin may improve present manufacturing performance and accelerate Industry 4.0 growth. It improves virtual testing and validation processes. Virtual testing for process validation is a crucial Industry 4.0 idea since it lowers waste, minimises downtime, and educates factory-floor operators on new initiatives. Because of its capacity to map out industrial activities in real-time, the digital twin is positioned as the ultimate validation tool [140,141].

Industrial organisations can use the digital twin to assess strategies, educate new operators, and address difficulties linked to decreasing throughput. Because the digital twin offers a virtualised environment and duplicates fundamental processes with great precision, it is a best-in-class validation tool because the impacts of limits can be visualised and correctly studied without just numbers' limitations. Digital Twin is virtual or digital representations of actual objects or processes. These digital representations are supplied with actual data collected by sensors embedded in the objective process and analysed using AI algorithms. This virtual representation

Table 1
Applications of Digital Twin in Industry 4.0

S. No	Applications	Description	References
1	Simulate complex processes	Digital Twin is intended to simulate complex processes that interact with their environments in various ways, making it challenging to anticipate results over a product's life cycle. This technology is frequently used to model complicated deployed assets, such as jet engines and big mining vehicles, to monitor and analyse wear and tear and specific types of stress as the asset is operated in the field. Such Digital Twin might provide valuable information that could influence future asset design. The Digital Twin of individual deployed assets might be the digital twin of the manufacturing process looks to be an exceptionally potent and attractive use. The digital twin programme examines incoming data streams in real-time. The evaluations may reveal undesirable tendencies in the actual performance of the manufacturing process in a specific dimension over time when compared to an ideal range of tolerated performance. This is the most complicated level of Digital Twin, comprising all the equipment in the factory's production lines.	[153–156]
2	Development of innovative products	Digital twin technology provides insight into assets and production, allowing for the identification of bottlenecks, the streamlining of processes, and the development of innovative products. Companies can spot abnormalities and deviations in their operations more quickly if they have a comprehensive picture of the health and performance of their equipment. Maintenance and spare component replenishment can be scheduled ahead of time to reduce time-to-service and avoid costly asset breakdowns. Predictive maintenance utilising Digital Twin can give a new service-based income stream while improving product durability. Virtual models of in-use goods give detailed insights into usage patterns, degradation points, workload capacity, flaws, etc. Designers and developers can appropriately evaluate product usability and enhance future component design by better understanding a product's features and failure mechanisms. This can provide customised products for various client groups based on individual usage habits and product installation scenarios. Digital twin technology assists in developing virtual prototypes and executing robust simulations for feature testing based on empirical data.	[157–159]
3	Encompasses automation	The Digital Twin is at the heart of Industry 4.0 development, encompassing automation, data interchange, and manufacturing processes, creating limitless chances for companies to thrive. With its technical advancements, Digital Twin provides a more virtual system-based design approach, resulting in a much more active role for any equipment or system. This technology assists operators in understanding unique characteristics, performance, and possible faults in the virtual simulation model by offering an accurate digital reproduction of the machine. It is a hybridisation of the natural and virtual worlds and a notion in which each industry receives a dynamic digital representation. Digital Twin combines information and technology such as AI, ML, and software analytics to create live digital simulation models that update and alter in response to changes in their physical counterparts. As a result, the organisation gains the advantage of creating a comprehensive digitised footprint of its whole product development cycle, from design to deployment. This digital replicating of physical assets, activities, and frameworks constantly generates data.	[160–164]
4	Provide better knowledge	Digital Twin can acquire a better knowledge of product performance, improve customer service, and make better decisions based on data. Digital Twin have a significant impact on how objects are described. It increased manufacturing efficiency and superiority while decreasing throughput times. This technology can be used in the automotive industry to create a virtual replica of a related vehicle. It captures the vehicle's operational data and assists in breaking down the overall vehicle execution and the associated highlights. By creating virtual twins for clients and showing styles for them, digital twin execution may play a critical role in enhancing the retail consumer experience. In conjunction with information from IoT, Digital Twin may play an essential role in healthcare, from cost reserve funds to consistent checking, deterrent support, and personalised social insurance. As industrial processes get computerised, the digital twin is becoming a reality. This helps organisations discover physical defects sooner, anticipate outcomes more precisely, and design better goods by providing a comprehensive digital footprint of their products.	[165–168]
5	Mimic the physical asset and operation	The digital twin application is often created in the enterprise's principal system language, employing the abovementioned techniques to mimic the physical asset and operations. Furthermore, standards and security measures may be used throughout the process for data management and interoperable networking. The computational power of big data, the adaptability of analytics technologies, the aggregation area's vast and flexible storage capabilities, and integration with canonical data enable the digital twin to simulate a far more prosperous and less isolated world than ever. Digital models of complete plants or manufacturing systems are also created. Many operational data may be acquired from various devices and products in an existing system. This aids in developing fresh and better business prospects that optimise all related processes. Some expect Digital Twin to replace human labour in identifying broken equipment eventually. With a digital twin, a company may receive better and more accurate insights about product performance and improve customer service. Organisations can make better operational and strategic decisions based on the insights collected.	[169–172]

(*continued on next page*)

Table 1 (*continued*)

S. No	Applications	Description	References
6	Provide visibility in manufacturing	One of the essential Industry 4.0 technologies accessible now is digital twin technology. Digital Twin provides visibility into all parts of the manufacturing line and process. This technology gives engineers virtual tools for inspecting, exploring, and evaluating existing assets, processes, and systems. With this ability, we can see what is happening now and in the future. A digital twin creates a virtual representation of a process, system, service, product, or other physical entity using virtual and augmented reality, 3D visualisation and data modelling. This digital twin is a carbon copy of the actual world. Its identical duplicate status is kept up to current with real-time updates. This technology can be used in various contexts, including product monitoring and throughout the product life cycle. Because the technology offers real-time monitoring of a physical plant through the use of sensors linked to the entire setup, operators can receive a forewarning of potential machine breakdowns and risks of downtime and accidents. With real-time operation updates, industrial personnel may optimise machine performance, monitor device coordination, perform diagnostics on virtual plants, and rectify defects with little productivity loss.	[173–175]
7	Enables real-time monitoring	A digital twin enables real-time monitoring of a manufacturing component, asset, system, or process. Improving monitoring capabilities provides a more in-depth insight into what occurs on production lines and throughout the manufacturing process. With ML and inputs from professional engineers, we can utilise the digital twin to discover issues before they exist and forecast future consequences. These forecasts contain outcomes within present parameters and outcomes if those parameters change. Manufacturing operations are progressively becoming computerised. Indeed, digital solutions may provide tremendous value to a company that could only have been achieved after introducing linked, smart technology. The concept of a digital twin has recently piqued interest: a near-real-time digital picture of a physical product or process that aids in optimising company performance. Companies may address physical difficulties faster by recognising them earlier, forecast outcomes to a far greater degree of accuracy, create and construct better goods, and, ultimately, better serve their consumers using a digital twin. With this form of smart architectural design, companies may gain value and advantages iteratively and more quickly than ever.	[176–179]
8	Improve product quality	Digital twin technology also helps decrease waste, improve batch changeover times, improve product quality, traceability, etc. It enables efficient design and development by connecting three-dimensional models to simulation and equipment control code emulation. Furthermore, having a digital twin allows for virtual troubleshooting and support, reducing the physical constraints of having professional engineers. This technology can also serve as the foundation for customer-interactive dynamic supply chains. Designing the digital twin procedures and information needs across the product life cycle from asset design through field usage and maintenance in the real world. As stated in conceptual architecture, the development of enabling technology combines the physical asset and its digital twin for the real-time flow of sensor data and operational and transactional information from the company's core systems. The process of creating a digital twin begins with process design. The process design is supplemented by qualities that increase cost, time, or asset efficiency. These are often the foundational assumptions around which digital twin upgrades should be built.	[180–184]
9	Provide new ways to save costs	Digital Twin has the potential to alter industrial processes by providing new ways to save costs, monitor assets, optimise maintenance, minimise downtime, and enable the production of linked goods. The digital twin model is rapidly gaining traction in manufacturing and other areas such as construction. A pressing problem for any organisation embarking on the digitisation path might be the capacity to demonstrate benefits and realise value from its investment in developing a digital twin. The emergence of increasingly favourable storage and computing costs has dramatically expanded the use cases and possibilities for enabling a digital twin, driving business value. Determining the correct amount of information in constructing a digital twin model may take time to embark on a digital twin procedure. While an overly simplistic model may not provide the value that a digital twin promises, going too fast and broad risks getting lost in the complexity of millions of sensors, hundreds of millions of signals produced by the sensors, and the massive amount of technology required to make sense of the model.	[185–187]
10	Strong information management solution	Digital Twin employs technologically advanced sensors linked to a manufacturing plant's physical assets to provide a robust information management solution. Using digital and agile approaches primarily assists businesses in effectively monitoring past, current, and future performances of industrial machines and high-value equipment, goods, services, etc. Digital Twin is intended to function constantly and consistently. In other words, it uses emerging technologies like AI and ML to assess tasks, learn, and improve from experience. The procedure generates data that is continually examined and kept in the cloud. This gives the human workforce real-time access to critical business insights and other information. In contrast, a digital twin receives real-time updates from the physical asset, process, or system. As a result, engineers' testing, evaluations, and analytical work are based on real-world settings. As the digital twin's state evolves dynamically as it gets new data from the real world, it develops, delivering increasingly accurate and useful outputs.	[188–191]

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Table 1 (*continued*)

S. No	Applications	Description	References
11	Enables maintenance	The key element distinguishing Digital Twin from other big disruptors is its ability to provide organisations with predictive analyses. The Digital Twin enables the maintenance or operations team to estimate how well an asset will operate long-term and how it will contribute to the overall business performance. In reality, it is more accurate to argue that predictive analysis aids lifecycle analysis. It creates data about assets from the time they are designed until they reach the end of their lifespan. As a result, industrial machine breakdowns and numerous other business risks are reduced. Companies may use a digital twin to test and certify a product before it ever exists in the real world. A digital twin allows engineers to spot potential process faults before the product goes into production by generating a duplicate of the intended manufacturing process. Engineers can interrupt the system to create unforeseen events, assess the system's behaviour, and propose mitigation techniques. It improves risk assessment, speeds up the creation of new goods, and increases the dependability of the manufacturing line. Financial data, such as the cost of materials and labour, can be integrated into a virtual depiction of a real thing.	[192–196]
12	Immersive information management system	Digital Twin is an immersive information management system allowing users to remotely access, detect, evaluate, and remedy physical asset concerns. In other words, it aids in the predictive maintenance of a system or industrial equipment by evaluating data on its lifespan. So, regardless of their geographical location, the concerned team may operate remotely to prevent failures, breakdowns, or other faults in business operations. Digital Twin applications are widely used in the automotive and aerospace sectors. These are utilised in vehicle engineering, design modification, and extensive transport and aviation maintenance. Digital Twin's use in aerospace is the most notable instance in weight monitoring, aircraft tracking, precise weather forecasting, and vehicle flaw identification. The availability of a significant quantity of real-time data and advanced analytics helps organisations to make better and faster judgments about whether or not to make changes to a manufacturing value chain. Data from hundreds of remote sensors communicating across unstable networks power digital twin models.	[197–200]
13	Provides opportunities for innovation	Digital Twin applications are now widely employed in a variety of sectors. Its solutions help diverse enterprises quickly provide opportunities for innovation and enhance business processes and performance by providing precise virtual representations of items and simulations of operational processes. Digital Twin includes Product Digital Twin, Component Digital Twin, and Performance Digital Twin, which are all utilised to visualise things and processes, whether simple or complicated. The digital twin technique predicts maintenance failures using reconstruction models based on data from multiple risk variables, operational circumstances, and software settings. They assist in saving money, increasing equipment efficiency, reducing downtime, and extending the life of machines or other gear. Building a digital twin eliminates the need for businesses to study numerous techniques for enhancing operations. It is so successful that there is no need to halt any current processes; instead, they may perform simulations in laboratories/workshops to understand the risks and advantages of new approaches and then continue experimenting with them to discover which adjustments provide the most significant outcomes.	[201–204]
14	Develops a virtual replica	Before creating a complex physical product, digital twin technology develops a virtual replica to be evaluated and modified virtually. Companies can use Digital Twin to mimic and evaluate each stage of development to discover problems and potential failures before manufacturing the final product. Twin Engineering assists development teams in understanding how a prospective modification in the manufacturing process may affect production outcomes and adjust their manufacturing processes to achieve intended improvements. Consequently, firms may improve operational procedures while lowering total engineering costs. Digital Twin has made their place in the IoT and Industry 4.0 with remarkable features. Many industries now rely on the Digital Twin platform for its futuristic, reliable, efficient, cost-saving, and intelligent applications. Collecting and analysing operational data from a vehicle to determine its condition in real-time and notify product changes is one aspect of how building a digital twin plays its role in the automotive industry.	[205–207]
15	Improved visibility of building utilisation	The use of a digital twin allows for improved visibility of building utilisation. The twinning technology can monitor and optimise heating, ventilation, air conditioning (HVAC), and lighting, lowering operational expenses. Furthermore, Twin Building Maintenance enables the detection of issues at an early stage, the prediction of when something will break, and the recommendation of corrective actions. The virtual model of a building allows for the evaluation of space capacity and the intelligent design of the building, making it more useful and easier for residents. This tool is handy in workspaces where space allocation is critical. The Digital Twin's capacity to simulate numerous scenarios enables easy identification and creation of emergency evacuation routes. IIoT and digitalisation are the most hotly debated subjects in the industry today. Today, core technologies underpin Industry 4.0, as well as real-world applications. These technologies aid in the digital transformation of manufacturing by linking previously incompatible systems and processes by interfacing computer systems across the supply and value chain.	[208–212]

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Table 1 (*continued*)

S. No	Applications	Description	References
16	Enables engineers to identify any fault	A digital twin technology enables engineers to identify any fault before the product goes into production by producing a duplicate of the intended manufacturing process. Engineers can interrupt the system to create unforeseen events, assess the system's behaviour, and propose mitigation techniques. This new capacity improves risk assessment, speeds up the creation of new goods, and increases the dependability of the manufacturing line. Staff may be trained in real-world hazardous settings using digital twin technology. Employees should also be prepared to deal with equipment that is not nearby or too expensive for hands-on experience. A digital twin platform may be accessed from anywhere, allowing users to monitor and manage system performance remotely. Accepting Industry 4.0 digital manufacturing, digital manufacturing, and the interconnectedness that comes with it may provide a multitude of benefits to enterprises, including increased flexibility, agility, and operational efficiency. The IoT digitally connected physical items allowing data transfer and communication through the Internet. These gadgets include smartphones, home appliances, vehicles, and even buildings.	[213–216]
17	Efficient manufacturing	Manufacturing may be made more efficient and simpler using digital twin solutions while reducing production time frames. Industry 4.0 is poised to pervade the whole of Digital Manufacturing. However, industrial organisations will only remain at the vanguard of the new digital era if they understand and embrace the technologies driving Industry 4.0. Data scientists, researchers, and engineers can use this technology to simulate devices or build assets before being physically constructed or manufactured.	[217–220]
18	Digital representations of real-world product	Digital Twin is a digital representation of a real-world product, equipment, process, or system that allows organisations to understand, analyse, and optimise their processes through real-time simulation. While Digital Twin is sometimes mistaken for engineering simulations, there is much more to this concept. In contrast to engineering simulations, Digital Twin uses data from sensors linked to a device or gadget to run an online simulation. Digital Twin is a valuable tool in heavy aerospace machinery, automotive, and aerospace applications. Technological advances such as ML, sensors, and sensors have expanded the concept of digital twinning to other domains. To fulfil society's ever-changing demands, companies generate massive amounts of data about the physical world, linked to IT systems that describe their operations, people, and goods, to improve the digital thread. As a result of technological improvements, Digital Twin is garnering much attention as a way to understand better and anticipate physical product success before constructing the product physically.	[221–223]
19	Data collections	This system enables us to collect all data associated with diverse assets, including physical, operational, manufacturing, and analytical data. AI algorithms are developed and used in digital models to analyse and optimise performance, including self-diagnosis and coordination with other machines, decreasing the need for manual involvement. It is similar to a live virtual model that lives on regular data stream updates, allowing engineers to simulate, evaluate, forecast, and prevent problems/upgrades ahead of time. Digital twin technology would be precious since we only have a vast network of trains, highways, defence, and industrial output. In Industry 4.0, the Digital Twin idea brings limitless possibilities by fusing AI, the IoT, and data analytics. Digital Twin generates considerable corporate value and is being widely implemented in various industries, including telecommunications, engineering, and service. Through the use of digital twin technology, we may visually represent items in order to maximise manufacturing while minimising risk. This has significantly deeper visibility into the manufacturing process than ever before.	[224–227]
20	Update virtual representation	A digital twin is a constantly updated virtual representation, a true-to-reality simulation of the physics and materials of a real-world physical asset or system. Digital Twin is not limited to inanimate items and humans. They may be used as a sandbox for cyberattack simulations as a virtual depiction of computer networking architecture. They can simulate a fulfilment centre process to evaluate human-robot interactions before activating certain robot functionalities in real-world settings. Robotics research and self-driving vehicles are only two of the many examples employed in Digital Twin to imitate actual equipment and settings. Implementing AI from Digital Twin in the real world requires a deployment platform to distribute updates to thousands of edge computers and devices. A manufacturer of electric vehicles may employ a digital twin of a car to execute software update simulations. Moreover, if the simulations reveal that software upgrades may improve the car's performance or address a problem, those updates can be delivered to the actual vehicle over the air.	[228–231]
21	Determine plant performance level	The Digital Twin concept allows power plants to monitor sensors and other data that determine the plant's performance levels. When used with AI and ML, the Digital Twin provides insight into the optimal time to plan maintenance tasks without disturbing production. The development of digital twin technology has resulted in an environment that promotes predictive maintenance across a wide range of systems. Digital Twin is an effective method of locating defective components and a maintenance culture that decreases downtime. The self-contained facility could also conduct self-diagnostics and replace jammed valves that hampered electricity generation. Smart facilities may employ the Digital Twin to foster a predictive maintenance culture, reducing resource waste and downtime due to defective equipment. Digital Twin accelerates early installations by simulating routing, security, automation, and monitoring. They also improve existing operations, such as evaluating network change requests in simulation, which shortens maintenance timelines. With automation, networking operations have also grown to more advanced capabilities.	[232–236]

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S. No	Applications	Description	References
22	Design cost reduction	The combination of Digital Twin technology and cloud computing has reduced the cost of the design, emulation, scheduling, analytics, and simulation services it provides to end users. Small and medium-sized organisations now have access to Digital Twin solutions for complicated issue-solving. This implies that Digital Twin as a Service is gradually becoming a viable business alternative. The role of the Digital Twin in production is self-explanatory. It helps businesses to swiftly and efficiently test new ideas, whether they are little goods or massive, complicated machinery. Testing a new supply chain in a virtual environment is simple; however, testing the physical counterpart requires shutting down production and sacrificing income, which should only be done when required and when the most optimum plan has been decided. The applications of Digital Twin are as diverse as the manufacturers who create them. As AI, image recognition, and other technologies evolve, Digital Twin will adapt and provide fascinating new uses for industrial manufacturing. Many advantages are promised by Industry 4.0 and Digital Twin, such as an efficient batch size or numerous optimisations.	[237–239]
23	Detect possible problems	A Digital Twin can also detect possible problems with its physical counterpart. Consider a scenario in which a high-fidelity physics model runs in parallel with the real machine and immediately detects a malfunction in the actual machine. Any excessive wear in a component would be revealed by a deviation between the machine's performance and the model's behaviour, which may be easily detected. Industry 4.0 provides a variety of application cases and solutions for a wide range of problems. It is primarily driven by advancements in plant software systems and the transfer and translation of knowledge from the IT industry to manufacturing. Products-to-be-produced, work items and gadgets are examples of assets. Digital Twin collects data created in the physical world, allows experimentation with this data in digital representations of Industry 4.0 assets, and delivers insights that may be deployed back into the real world as updated configurations. As a result, the information produced by the Digital Twin may be utilised to coordinate and optimise the facility.	[240–243]
24	Enhance the machine's self-awareness	An embedded Digital Twin would be the foundation for enhancing the machine's self-awareness, allowing it to maximise its performance for specific duty cycles, diagnose and adjust for non-catastrophic problems, and coordinate operation with other machines with little user input. With the capacity for systems to connect remotely with the operator via IIoT technologies, we will soon see increased autonomy applied in machines, similar to what we see in the car sector. The machines communicate with the operator, one another, and themselves. Digital Twin is a revolutionary technology for examining systems or industrial processes like heat control. It may be applied in any industrial process for various goals, such as optimising a component's performance in a specific process, reducing raw material consumption, or making quick operational choices based on external variables. The use of digital transformation technology to prevent downtime and reduce unexpected shutdowns are just a few examples of what Digital Twin technologies may do. Indeed, the capacity to virtualise workplaces and complex systems is critical to accomplishing the smart factory and Industry 4.0 revolution that most sectors envision.	[244–246]
25	Enable system for prediction	Digital Twin play an essential role because they enable the system to operate as a function of the weather prediction, historical demand data, and so on, in such a manner that nominal operation conditions are assured in each scenario. Digital counterparts are linked with network technology. Their capacity to solve problems and deliver more fantastic operational performance has elevated this digital matching component to the status of important technology for any firm. By providing enterprises with a complete digital counterpart of their goods, digital twin technology enables the industry to detect any physical flaws in their equipment well in advance, allowing them to take necessary steps to eliminate such difficulties before they materialise. Data is used to automating business activities in the Industry 4.0 business model. As a result, the Digital Twin presents the ideal setting for gathering data from all aspects of the manufacturing process for analytics and simulation. System integrators, data analysts, and other stakeholders can utilise a Digital Twin to drive corporate policies and enhance decision-making processes when data is appropriately gathered and designed.	[247–249]
26	Simulate reality	The Digital Twin is utilised to simulate reality, which physical representations implement in the real world. Simulations are not a new concept: for decades, engineers have used them in flight simulations, to model dynamic flows when constructing turbines, and for city planners when modelling crowd flow. The Digital Twin's uniqueness is the flexibility of implementation scenarios with various applications that take advantage of the most recent breakthroughs in the IoT sector. Digital twin platforms combine the most cutting-edge technology to create compelling and engaging solutions with enormous potential across several industries. Digital Twin is increasingly used in healthcare, manufacturing, and retail industries. A digital twin symbolises a product, process, or service through IoT devices. This confluence of the natural and virtual worlds allows data analysis and monitoring systems to detect problems before they occur, reduce downtime, and plan for the future using simulations.	[250–253]
27	Provide opportunities for new and superior goods	Due to the simulations in real-world applications, this approach also offers opportunities to build new and superior goods at a lower cost. As a consequence, customers will have a better experience. Big data, AI, ML, and the IoT are all used in digital twin processes, which are the future of engineering and manufacturing. Manufacturers construct virtual models in order to test the product under various scenarios. Before creating manufacturing, line and producing a physical product, any essential adjustments to the product may be made at the single product level. It leads to more efficient design, lowers production costs, and shortens time to market. Accessing and quantifying all information generated by a manufacturing process and the shop floor is critical to automation. Manufacturers can collect data from sensors and embedded devices incorporated into a work floor using Digital Twin technology. The Digital Twin goes a step further by recreating physical production processes and establishing a digital environment to evaluate these processes.	[254–256]

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S. No	Applications	Description	References
28	Reduce errors during manufacture	A company can use Digital Twin to decrease present or prospective errors during manufacturing by allowing engineers to test and simulate the product in a virtual environment. Companies that use a digital twin shorten the time it takes to bring to market and outperform the competition. The entire product life may be recreated in a digital environment, with all enhancements made swiftly and effectively, decreasing risk significantly for the organisation. The time to create is reduced since the virtual copy validates how a product will operate in reality. Digital Twin have mainly been employed in the industry. However, this is rapidly changing, and there is an opportunity for many enterprises, particularly those implementing IoT in operational procedures. Several sectors will see the benefits of Digital Twin shortly. The Digital Twin model assisted in comprehending the various welding concepts and needs. One advantage of creating a Digital Twin of a manufacturing shop floor or plant is the ability to include predictive maintenance in business models. Predictive maintenance is predicting a component or machine failure and taking preventive steps to avoid failure.	[257–260]
29	User-friendly and efficient services	Digital twin services have improved and grown more user-friendly and efficient. Current digital twin cloud services enable more sophisticated digital simulations and models that can learn independently. These technologies result in more significant insights, simple data, and user-friendly dashboards that teams can use without the assistance of data professionals. As digital twin capabilities have evolved, more and more industries are using these models to enhance performance, resulting in better outcomes. Digital Twin ecosystems control complex systems and processes like traditional technologies do. Because AI, ML, and simulations can be applied to the digital environment. Digital Twin assumes management of the process, which entails comparing system performance to predefined criteria, identifying discrepancies, and designing remedial steps to achieve greater heights. This makes it an excellent resource for Industry 4.0.	[261–263]
30	Automate procedures and operations	Smart factories are digitally enabled, allowing them to automate procedures and operations using this technology. Smart factories can integrate physical, human, and operational data to improve production performance/productivity, forecast and execute repairs, and track and manage inventories in real time. Data integration in smart factories is often the result of IIoT technology. The smart factory advances the typical factory and its manual processes. A smart factory has automation capabilities and can digitalise production processes and procedures. A digital twin, a virtual clone of a tangible item created before the prospective construction of a device/thing, is extremely useful in learning and evaluating a product based on its performance. The Digital twin takes and analyses data from the actual world and mimics it using powerful algorithms and software programmes to generate meaningful insights about a product in development. It is an excellent tool for engineers and developers to use before committing financially to a project.	[264–266]
31	Monitor equipment and systems	Organisations can utilise Digital Twin to proactively monitor equipment and systems to arrange maintenance before they fail, increasing production efficiency. Simulations allow engineers to test and inspect a physical asset, but the simulation is static. It is up to the engineer to enter new settings. Engineers may do testing, evaluations, and analytical work using real-world circumstances since Digital Twin get real-time updates from the physical asset, process, or system. Thus, to create a Digital Twin, sensors must first be installed in the impacted items to capture real-time data on their status, operational circumstances, physical position, and so on. This is, in reality, the link to the IoT. The 'intelligent' items are then linked to a cloud-based system that collects and processes all data, allowing it to run analyses depending on specific needs or other data, such as historical data. By getting deep insights into client requirements, improving existing goods, processes, and services, and reimagining enterprises, digital twin technology enables organisations to create a more significant customer experience. The world of industrial automation is changing dramatically. Advanced processing and communications technology has matured to the point where machine makers are making substantial changes in how their products are designed.	[267–269]
32	Enhance the processes	Digital Twin offer various advantages since they enhance processes and goods, making them more efficient. Digital Twin enables us to predict potential difficulties in the future. This, among other things, eliminates product faults and shortens manufacturing time. The digital twin is an excellent Industry 4.0 tool for virtually testing new technologies to imitate behaviours and eliminate risks. Furthermore, they enable real-time monitoring activities and optimise the occurrences of actions and states. Digital Twin enables the simulation of whole processes in all of their stages. As a result, the entire process may be optimised. It may be directly applied to goods during the design and production processes. It enables the prediction of product operation and manufacturing processes. By evaluating vast volumes of data, models based on accurate data may be constructed to anticipate behaviours that maximise activities for power generation. The Digital Twin enable the modelling of power plant performance by reflecting their state and operation.	[270–272]
33	Save development time	A digital twin minimises mistakes throughout the manufacturing process. It also enables the discovery of possible bottlenecks and saves development time in half. It is also used to mimic material and personnel flows, which enables the improvement and optimisation of logistical procedures. They enable the capturing of all process states and the simulation of various situations. These simulations give information for decision-making and allow one to choose the best option in each circumstance. These virtual representations can imitate behaviours and prevent potential problems during construction and subsequent vehicle operation. Engineers must acquire and combine data from several sources, such as production statistics, knowledge about how the product works, and analytics software, to create the precise virtual portion of a particular physical product. Aside from that, AI processes that combine into the computer-generated duplicate of specified equipment are required. This level of Digital Twin emphasises the most important single component in the manufacturing process. A single item is required; the production process relies heavily on that component.	[273–275]

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Table 1 (*continued*)

S. No	Applications	Description	References
34	Minimise human decision-making	A digital twin is a virtual mind that minimises human decision-making with super-informed conclusions based on historical data, smart analytics, real-time environmental conditions, etc. It will have a global impact on all sectors of the economy, from manufacturing to medicine. Large numbers of firms will profit from Digital Twin since it lets them analyse how their assets function in real-time. Digital Twin's use profoundly influences how things are created, manufactured, and maintained. It streamlines manufacturing and decreases downtime, resulting in a significant increase in total profit. Digital Twin can generate a virtual replica of a linked car in the automotive industry. It records the vehicle's behavioural and operational data and aids in analysing overall vehicle performance. By developing virtual twins for consumers and modelling outfits for them on it, digital twin implementation plays a critical role in enriching the retail customer experience.	[276–279]
35	Helpful in material handling system	A digital twin of a material handling system collects data on the movement pattern, distance, and activity periods of the system's robots or carts. This data may be used to develop a digital model of the individual cart and facility-wide operations. As a result, businesses can comprehend and analyse the performance of individual agents and the whole material handling system. Smart city design and implementation using Digital Twin and IoT data help to boost economic development, assure efficient resource management, decrease environmental footprint, and improve the overall quality of life. They can accurately forecast future performance and failure by simulating how devices have performed over time. Manufacturers can test the design against the requirements in the early phases of the process by using formal requirements management and producing high-fidelity dynamic models used in system simulations. This procedure produces a high-fidelity model.	[280–282]

enables the simulation of various production and uses scenarios. This allows it to be confirmed and evaluated in every manner before manufacture. The digital process twins are virtual copies of production lines that include all process phases [142–144].

The digital twin gets real-time data from sensors and simulates what happens in reality. As a result, it is precious for improving machine behaviour and efficiency by representing almost all potential issues that may emerge during the creation or operation of a process or machine. As a result, the entire process must be included in the production of these Digital Twin; if the information is acquired from all phases, this virtual duplicate will reflect more of the natural process. Intelligent analytics and automation are essential to digital transformation, but only if the process and people are well comprehended and empowered. While the factory floor is at the centre of manufacturing operations, a genuine, smart factory goes beyond physical items to include human connection. When corporate operations are compartmentalised, communication is restricted and out of the current [145–147].

8. Digital Twin applications in Industry 4.0

Digital twin technology has become necessary for Industry 4.0 journey to digitalise, optimise, and manage their factories more smartly and efficiently. Digital Twin enables producers to understand their operations better by considering different production aspects. These include equipment monitoring, process optimisation, and digital maintenance. Digital prototyping of processes using augmented and virtual reality, AI, and ML boosts implementation success rates. This enables businesses to eliminate process reengineering while continually optimising production processes [148–150]. Digital Twin can help manufacturers increase efficiency, create innovative products, and enhance procedures. Manufacturers can evaluate improvements to boost capacity or minimise downtime by modelling a manufacturing process. The smart factory is the seamless integration of distinct production processes, from planning to actuators. Soon, self-optimisation will be used by equipment and machinery to optimise operations. Systems will adjust to the network environment with a traffic profile. Autonomous Mobile Robots are essential components of the Smart Factory. Their self-aware intelligence links the plant, enabling smooth operations [151,152]. The significant applications of Digital Twin for Industry 4.0 are discussed in Table 1.

A digital twin can be a computer reproduction of a real thing, such as a jet engine or wind farm, or a more important item, such as a structure or even a whole city. In addition to physical assets, digital twin technology may be used to reproduce processes to collect data on how they will operate. A digital twin is computer software that analyses real-world data to construct simulations anticipating a product's performance. These programmes can improve production using IoT, AI, and software analytics. The digital twin also establishes an ideal maintenance scenario in which an on-site technician and a remote professional can view the same data and debate what to do. Digital Twin must meet three requirements: they must look exactly like the original object, including all minor details; they must behave exactly like the original object during testing; and they must be able to analyse information about the original object, predict potential problems, and suggest solutions. The process may be improved by using product twins for each piece of equipment, allowing preventative maintenance and avoiding costly plant downtime [283,284].

Over the years, the manufacturing, retail, and automotive industries have embraced digital monitoring and control technologies. It should be noted that the Digital Twin of any facility process may be constructed to study the operations of that specific process or system. This data may then be used to create a virtual environment by running a digital twin of a material handling system. The virtual environment will remotely monitor these assets or construct optimal plans to ensure items arrive on time. This data-driven plant performance optimisation business model drives Industry 4.0 growth [285,286].

9. Discussion

A digital twin is a digital representation or abstraction of a physical item, such as a machine or gadget. They are already used in a variety of sectors and applications regularly. However, most of today's digital twin solutions are isolated apps with a limited life cycle or value chain scope. It uses a cloud-based IIoT platform, including information monitoring tools, specific operator training, and remote help. Developing Digital Twin necessitates the creation of high-fidelity virtual representations of the physical world that adapt in real time when the physical environment changes. Thus, the construction industry uses advancements such as AI, ML, sophisticated analytics, and Digital Twin to generate virtual sites. It gives production managers access to process and asset operations, allowing more efficient use of space and resources.

This technology improves project schedules, saves money, and gives actionable data to administrative staff. Continuous railroad development and maintenance are required for adequate movement. Sensors from the Industrial IoT deployed on various railroad assets such as mileposts, derailers, crossing guards, and signals turn the railroad network into a digital twin. Predictive maintenance is enabled by digital twin simulation in factories and manufacturing facilities to reduce downtime. Companies can use such systems to monitor and evaluate individual machines or manufacturing lines. Furthermore, such condition-monitoring technologies anticipate breakdowns and plan maintenance ahead of time to enhance production. To provide personalised solutions, the firm employs AR-enhanced simulation tools and the IIoT. They provide continuous transparency of manufacturing and storage operations and the prediction of bottlenecks by floor managers.

Today, IoT-enabled enterprises have or plan to implement Digital Twin. Today, the Digital Twin is becoming as common as IoT devices themselves. According to famous use cases for Digital Twin in manufacturing, continuous monitoring of product data from IoT devices provides demonstrable advantages for quality control over random inspection. The digital twin can monitor and simulate every manufacturing process step to discover potential quality concerns and assess the product's composition to determine whether better materials and manufacturing procedures should be employed.

Converting a manual production to a smart factory requires careful planning since the shift entails adopting new technology. The Digital twin is essential for understanding the benefits and drawbacks of the Smart factory. Having said that the digital twin plays an integral part in evaluating a technology before adoption, it can be seen and asserted that the digital twin aids in achieving the smart factory. Engineers/developers can use system twinning to operate and maintain whole fleets of opposing or different goods that sync and work together to achieve a system outcome. The advantages of digital twinning extend beyond physical twinning to include process and workflow twinning. A virtual reproduction of a whole process involved in acquiring a finished good / service is called process twinning.

The model, which has the same physical structure as the machine, may detect the cause of deviation within the model and offer signs to the operator where the problem may lie, saving machine life and diagnostic expenses. Assuming the same defect is not catastrophic, the model can propose a method for correcting for a drop in performance without reducing or stopping production. This scenario is conceivable by introducing optimal control, model-predictive control approaches, and superior machine-learning capabilities. Airports can improve consumer experiences by using Digital Twin. Video cameras may watch the Transportation Security Administration (TSA) and use AI to evaluate peak-hour congestion. These might be addressed in digital models before being used in production to prevent missing flights. Baggage handling video may be evaluated in order to develop methods in the digital world to ensure luggage arrives on schedule.

Data is aggregated by Digital Twin, making it simple to find trends in previous occurrences, identify fundamental causes, and optimise line procedures. This ability to aggregate data from and around a physical product or system and operate as a digital stand-in opens the door to many new use cases. The manufacturer optimises production yield by avoiding unscheduled machine downtime, lowering the quantity of 'scrap' generated in each production cycle, and eliminating expensive production quality problems. Engineers may remotely troubleshoot equipment using the digital twin, lowering issue resolution times faster and more precisely. A digital twin provides a more comprehensive perspective of environmental elements, individual machines, and how they interact to impact operational quality and asset performance. The digital twin enables to utilise of data to simulate various scenarios for the new equipment and find areas where new plants can outperform existing production systems. The technology can aid in the optimisation of the supply chain. It can give a much clearer picture of material utilisation and the potential to automate the refill process.

10. Limitations

The advantages of this technology are genuinely fantastic, and they may be game-changers for firms that use them. Businesses will also have a solid foundation for sophisticated analytics monitoring and forecasting capabilities. However, like with any technology, there are several dangers to consider while selecting the technology. One of the major issues with Digital Twin is the security and privacy of data. The system employs intelligent software with natural access to various resources and sensitive information about enterprises, making it a target for cyber-attacks and data theft. Businesses must consider and analyse choices when installing security measures for digital twin technologies. Another disadvantage of Digital Twin is the high investment required to establish them, which only some firms can afford the return on investment when money is scarce. With the amount and speed of progress in ML and the use of big data, these virtual models have a permanent position in contemporary engineering as part of the ongoing drive to accelerate innovation and improve performance. They will be able to avoid costly failures in physical items.

11. Future scope

In future, Digital Technology will enable firms to better examine and forecast potential implementation issues from the beginning of the design process. Problems can be fixed, or early warnings can be provided to avoid downtime. It aids in analysing the state of industrial machines while teaching about the future condition of current machinery. Before deploying IIoT physical assets, the digital twin enables the connection of the complete factory floor activities. This technology will allow for real-time data capture and filtered and will be delivered as analytics for clients. Analytics data may be utilised to create strategic production schedules, arrange downtime, and optimise maintenance. The data accuracy offered by digital twin will optimise operational and production potential, allowing evaluation for future installation of sophisticated technologies for a fully formed smart factory.

Cognitive computing improves the digital twin's talents and scientific disciplines. Natural Language Processing (NLP), ML, object/visual identification, audio analytics, and signal processing are just a few elements that supplement traditional engineering talents. Using cognitively to enhance testing, a digital twin can suggest which product tests should be done more frequently. Cognitive Digital Twin will help us create and enhance future technologies beyond human intuition. Good digital twin software will ingest data from key IT and OT sources and show on a virtual duplicate of the plant line. Process engineers, quality assurance teams, and others may interpret the data in the context of the equipment, raw materials, and overall production line environment. Skilled operators can detect a problem with a machine just by touching its surface.

The digital twin extends that intuition by demonstrating how the problem is represented in data, assisting investigative teams in identifying problems in assets more rapidly and mitigating the same problem in the future. A product's development cycle using Digital Twin will simplify a complex procedure. Organisations will generate a digital footprint of their invention from the design phase through the deployment phase. Each component of these digital creations is networked and can produce real-time data. It enables the simulation of how product modification will influence the manufacturing process and adjust how it operates to accommodate this customisation. The digital twin will transmit precise product data to manufacturing equipment, generating a distinct product variation without requiring costly re-tooling.

12. Conclusion

A digital twin is a virtual representation of a physical system that may also function as an independent entity. This digital replica is a 'twin' of information entrenched in the physical system in the same way as the physical elements are. With the introduction of IoT, a digital twin may continually gather sensor data and send information back and forth with the physical counterpart throughout the system's life cycle. Manufacturing processes, sensor input, and external management software may all be fed into and organised inside the digital twin. Digital Twin enables a complete representation of the manufacturing process, from a single component to the entire facility. Digital twin technology is destined to become a must-have tool for companies embarking on the Industry 4.0 journey that wish to digitalise, optimise, and manage their factories in a smarter, more efficient manner. This technology is transforming the face of the industrial business, lowering costs, controlling assets, and reducing downtime caused by equipment failure. This opens up new opportunities for every firm throughout the world. The digital twin produces a high-complexity virtual model that is the counterpart/twin of a real entity. It uses actual data to estimate the capabilities of a process or a product. Parts twinning assists engineers and developers in better understanding a given part's mechanical, physical, and intellectual features in the context of the entire product. The twinning of working parts or interoperability twinning permits product twinning. It is a step up from individual element twinning. This ensures that all pieces are digitally represented and assembled functionally.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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