Rover Publications
United International Journal of Engineering and Sciences (UIJES)
An International Peer-Reviewed (Refereed)Engineering and Science Journal
Impact Factor:8.075(SJIF) Vol-5, Issue- 2,2025 ISSN:2582-5887 www.uijes.com

# Digital Twins as Enablers of Industry 5.0: An Analytical Review of Manufacturing Applications and Challenges

**Raghav Sharma**

**Abstract**

Digital twins (DTs) have emerged as industrial innovation cornerstones with the international market set to exceed USD 73.5 billion by 2027. Despite growing research, fragmented understanding persists with limited synthesis across diverse manufacturing applications and challenges. This critical review addresses this gap by systematically examining DT development, applications, and deployment issues in manufacturing.

The study scope encompasses five application areas: predictive maintenance (real-time monitoring and remaining useful life prediction), design management (lifecycle optimization), real-time monitoring (continuous operational observation), fault diagnosis (failure prediction), and process control (adaptive responsiveness).

Key findings reveal measurable DT benefits including minimized downtime, improved design flexibility, real-time optimization, and enhanced diagnostic accuracy, yet significant barriers persist: data quality issues, non-standardization, limited model transferability, high implementation costs, and cybersecurity concerns.

Based on comprehensive analysis, this review offers actionable guidance for manufacturers contemplating DT adoption, emphasizing pilot-scale implementations, modular architectures, cross-functional collaboration, and workforce upskilling as manufacturing transitions toward cyber-physical systems.

**Keywords:** Digital Twin, Smart Manufacturing, Industry 4.0, Predictive Maintenance, Real-time Monitoring, Fault Diagnosis, Process Control, Cyber-Physical Systems, IoT, Manufacturing Digitalization

## Introduction

Digital manufacturing technologies have witnessed unprecedented growth in recent years globally through the integration of cyber physical systems in the traditional manufacturing. According to market analyses, the global digital twin market will exceed USD 73.5 billion by 2027 due to the rapid adoption of smart factory within developed and emerging economy (1). In regions engaged in advanced automation, digital connectivity, and predictive analytics to boost industrial productivity and competitiveness this transformation is particularly evident.

In this context, digital twins (DTs) are the fastest growing backbone of industrial innovation as applications proliferate in every industry from aerospace, energy to manufacturing (2). As clearly shown in studies (3,4), benefit of DTs in maintenance, design optimization, and real time monitoring has been shown and demonstrated with use cases both in high end engineering and in resource constrained environments.

A digital twin is defined as a continuously synchronized virtual replica of a physical system, enabling two-way data exchange to support simulation, prediction, and control (1,5). Evolving from early aerospace simulations (6), DTs now form the backbone of smart manufacturing ecosystems through their integration with cyber-physical systems, IoT, AI, and cloud platforms (7,8).

Despite a growing body of research on DT use cases, a fragmented understanding persists, with limited synthesis across diverse manufacturing applications and functional challenges (2). Emerging technologies such as AI, big data analytics, and edge/cloud computing are rapidly accelerating DT adoption, yet they also introduce new technical, economic, and organizational barriers (9,10). These dynamics are particularly important for emerging economies, where DTs have the potential to democratize high-efficiency production and anticipatory maintenance (3,11).

In order to maximize the potential of DTs, it is crucial to learn about their diverse applications—various predictive maintenance to design optimization—and how these affect different manufacturing ecosystem functions. Equally vital is a critical examination of the constraints hindering real-world applicability, namely data quality, complexity of integration, and non-standardization (12).

Therefore, this study aims to investigate the role of digital twins in enhancing manufacturing operations, predictive maintenance, design management, and process control, and the extent to which they can optimize various functions for operational benefits.

More specifically, the study addresses the following research questions:
*RQ1: What are the specific applications and measurable impacts of digital twins in different areas of manufacturing processes?*
*RQ2: What are the challenges faced in the implementation of digital twins in manufacturing processes?*

**The rest of the paper is organized as follows. The second section is about an in-depth literature review of digital twins in manufacturing, and the evolution of digital twins. Then, the applications of digital twin are examined in detail in key manufacturing functions, such as predictive maintenance, design management, real-time monitoring, fault diagnosis etc. We then look at the issues and constraints that occur during the implementation of digital twins for manufacturing. The conclusion section finishes by a**

**summary of findings and practical implications from the study, shortcomings and further research ideas.**

**Digital Twins and Their Evolution**

The concept of the digital twin (DT) refers to a virtual replica of a physical asset, system, or process that is kept in continuous synchronization with its real-world counterpart through the real-time flow of operational and sensor data (1). In contrast to the conventional digital models, DTs are dynamic in that they do not just reflect the present state of a system but develop along with it, providing simulation, prediction, and optimization capabilities throughout the life cycle of the system (1). For Kritzinger et al. (5), only virtual models capable of receiving and sending data from and to the physical world qualify as a correct digital twin. Such systems are being seen more and more as essential drivers of intelligent, data-informed decision-making within complex industrial and manufacturing contexts (13,14).

The digital twin concept has its roots in the aerospace sector, where NASA came up with the concept as a way of enhancing mission reliability using digital replicas of spacecraft that were based on real-time sensor readings and past data (6). These initial DTs combined multi-physics simulation and probabilistic computation to replicate the health of aircraft systems over an assortment of mission profiles (15). With increasingly capable digital engineering tools like Computer-Aided Design (CAD), they paved the way for expanding the DT concept to other areas. Grieves (16) explains that this initial modeling ability was one of the dual ideological foundations of DTs, the other being simulation-based methodologies. With the emergence of Industry 4.0 technologies such as the Internet of Things (IoT), cloud computing, and big data analytics, DTs have now evolved as an integral part of intelligent manufacturing environments (1,7). In the future, Digital Twins will have a similarly important function in Industry 5.0, where emphasis will be on human-centered, sustainable, and resilient production.

The creation and utilization of digital twins have been facilitated by the convergence of multiple enabling technologies. Cyber-physical systems (CPS), Internet of Things (IoT) networks, artificial intelligence (AI), and cloud computational infrastructure at scale collectively enable the bidirectional data exchange between the physical and digital realms (1,17). These infrastructures allow DTs not just to simulate real-world behavior in cyberspace but also to drive physical outcomes based on predictive and prescriptive knowledge. Alam and El Saddik (18) point out that real-time interaction between model and reality is what makes a digital model a digital twin, and the feedback loop provides for adaptive behavior and intelligent control. With this in mind, Rasheed et al. (19) emphasize that a digital twin is essentially a unification of a physical object, a virtual model, and the data link allowing feedback and adjustment. This makes DTs particularly useful in industries like manufacturing, where they allow end-to-end visibility and control throughout the product life cycle—design and prototyping, production, and maintenance (1,20).

In the real-world applications, and arguably one of the most significant uses by digital twin technology is in the area of prediction maintenance. DTs can leverage real time monitoring along with physics based and data driven models to not only forecast future breakdowns but also optimize maintenance interventions before failures (1,7,19). It provides substantially more predictive capacity for critical asset downtime and renders it much more efficient and trustworthy in the process. DTs also provide a powerful decision-making support structure that allows stakeholders to simulate and analyze situations prior to the implementation of changes physically within the physical environment (17). Notwithstanding the introduction of DTs in industrial environments, issues, including standardization, integration of different systems, and absence of a well-defined road map of development into DTs remain (9). The DTV envisions full synchronization and predictive automation, while in most real-world DTs the technological and organizational limitations do not permit (9). Therefore, digital twins are not digital simulacra, but working tools which combine modeling, sensing, analysis and control to shake up the traditional approaches of monitoring, managing and eradicating the contemporary systems.

## Applications of Digital Twins in Manufacturing

### *Predictive Maintenance*

Digital twins (DTs) are a revolutionary technology in predictive maintenance (PdM) that allows real-time monitoring, failure prediction, and lifecycle optimization of industrial equipment. In various industrial settings, scholars have illustrated how DTs integrate sensor measurements, simulation models, and smart algorithms to optimize maintenance methods and minimize unplanned downtime.

One of the key uses of DTs in PdM is real-time monitoring and diagnosis. Zhong et al. (21) highlight that DT-based maintenance systems are distinguished from conventional methods by their real-time perception, regulation, and prediction, which overcome shortcomings of partial data usage. Through the integration of physical asset data streams, DT architectures support ongoing condition evaluation (22). Real-time synchronization of the virtual and physical worlds also allows faults to be detected using simulation models based on electrical and mechanical signals (23). Sensors are also combined with simulation environments to form intelligent systems that can perform on-the-fly diagnostics (24).

Another key area of utilization is the prediction of remaining useful life (RUL). Precise prediction of RUL facilitates timely interventions and cost-effective maintenance plans. Several studies have introduced the contribution of DTs to predicting future degradation trends and facilitating simulation-based forecasting (25, 26). As Chryssolouris et al. (4) observe, RUL is the key parameter to plan maintenance for, and DTs are increasingly being utilized to estimate it in real-time. The accuracy of these models has been repeatedly established across several studies; for example, Mayr et al. (27) used a DT-based RUL model on 510 industrial equipment and obtained substantial predictions in all instances. These methods tend to couple data-driven and physics-based approaches, like Archard's equation, to account for component-specific wear behavior.

To enhance predictive accuracy even more, DT frameworks are typically augmented with artificial AI, ML, and IoT technologies in most cases. You et al. (28) emphasize how DTs may create synthetic training data for ML algorithms to increase their performance under real-world variability. ML methods are utilized to determine condition indicators from past sensor data and to make predictions for future degradation behaviors (26,28). In settings where sensor data can be limited, D'Urso et al. (10) recommend employing reliability-based DTs to model degradation data, providing continuous learning for AI predictors.

Aside from algorithmic innovations, DTs have also shown utility in real-world industrial applications. Some papers present case-specific applications of DTs. For instance, Chryssolouris et al. (4) present a simulation tuning system that dynamically adjusts the digital model in real time to fit observed machine behavior. Falekas and Karlis (24) introduce an extended DT concept tailor-made for electrical machine control and PdM. At the same time, Werner et al. (29) present a holistic approach that combines measured and simulated data to develop an overall predictive maintenance strategy.

Finally, most contributions have aimed at specifying and formalizing architectural frameworks of DT-driven PdM. Such frameworks generally differentiate between layers of physical modeling, data analytics, and decision orchestration (22). Alghamdi et al. (25) emphasize the potential benefits of integrating data-driven and physics-based approaches in order to improve accuracy and resilience. Other researchers suggest multi-level or hybrid structures that real-time optimize maintenance scheduling (30), while You et al. (28) outline a DT-based PdM framework that incorporates predictive knowledge within the digital model itself.

In conclusion, the current literature collectively validates the efficacy of digital twins as a first technology for predictive maintenance. By means of real-time monitoring, RUL estimation, AI integration, practical deployments, and layered system architectures, DTs are transforming the manner in which industrial systems are maintained and optimized.

### *Design Management*

The incorporation of DTs into design management has brought about a new paradigm in engineering. Fu et al. (2) highlight that "digital twins enable the seamless fusion of physical and virtual equipment data to support not only the design process but also manufacturing and maintenance throughout a product's lifecycle" (p. 4). The incorporation of DTs promotes efficiency and creates real-time, bidirectional feedback between physical assets and their virtual equivalents.

In design optimization and evaluation, DTs enable engineers to quickly evaluate a number of alternative designs, determine potential defects at the early stage of the cycle, and consequently minimize time-to-market. The modularity of DT systems makes it easier to be flexible since design teams can easily simulate cases and modify parameters (2). These features are very useful in high-end engineering applications like aerospace.

Some authors also emphasize the necessity of formal DT-driven frameworks. Fu et al. (2) point out that a sound DT architecture should be able to deal with huge, heterogeneous data across product development phases. These frameworks enable the "integration of design, manufacturing, and maintenance information under a single digital-physical loop" (31).

Central to this integration is the interaction between virtual simulation and physical model. The high fidelity and cross-dimensional character of DTs arise from the embracement of next-generation sensing technologies, big data analytics, and the industrial internet (2). Such capabilities enable predictive modeling, status monitoring, and real-time optimization, such that the digital environment accurately mirrors the physical system.

Additionally, the adoption of cloud computing and AI vastly increases the capability of DTs to improve the efficacy of design management. The application of machine learning algorithms on simulations enhances performance results, with scalable data handling and storage provision by cloud technology. These tools, apart from hastening DT simulations' computationally intensive task performance, facilitate more accessibility and dependability of these simulations (31).

Lastly, the authors emphasize that an end-to-end implementation of digital twin design models must include multiple digital assets such as digital product, design, manufacturing, and performance models to facilitate transparency and systematic management of the design-manufacture-performance chain (31). Such comprehensive modeling is the basis for smart design practices that are responsive to sophisticated industrial requirements.

***Real Time Monitoring***

DTs are increasingly being deployed as necessary devices for real-time monitoring in manufacturing environments, providing a linkage between physical systems and their digital twins. Wang et al. (3) and Wang, Lee, and Angelica (32) both present case studies illustrating how DTs allow for constant, data-driven oversight of operating conditions across various industries.

The cornerstone in facilitating the real-time monitoring using DTs is in coming up with highly structured frameworks encompassing multiple capabilities. For example, Wang, Lee, and Angelica (32) came up with a DT framework for typical machinery, featuring sub-modules of machine monitoring in real-time, order scheduling, as well as OEE. Their framework focused on converting individual stand-alone machines to networked intelligent systems without capital-intensive expenditure. Likewise, Wang et al. (3) introduced a full DT system for pipeline condition monitoring that incorporates several cutting-edge technologies like IoT, finite element simulation, cloud computing, and virtual reality to provide high-fidelity simulation, real-time status tracking, and predictive diagnosis.

Sensor integration and data acquisition are central to such frameworks. Wang, Lee, and Angelica (31) explained how real-time operational data from the die cutting machine were collected via a programmable logic controller (PLC) and presented on a human-machine interface (HMI), which interfaced with a digital dashboard for remote monitoring. Conversely, Wang et al. (2) utilized a sensor network, such as guided-wave sensors and strain gauges, to obtain operational data as well as inspection results from pipelines. These inputs were utilized by a Bayesian inference engine to update the digital twin in real time and keep the physical system aligned with its virtual model.

Visualization of current data is also essential for actionable insights. The digital dashboards developed by Wang, Lee, and Angelica (32) granted operators real-time access to machine parameters, status indicators, and OEE calculations. Similarly, Wang et al. (2) highlighted the usefulness of graphical user interfaces and augmented reality (AR) for delivering real-time DT states, enabling operators to determine pipeline health and schedule maintenance without having to conduct physical inspections.

As far as predictive potential is concerned, both studies demonstrate how DTs can transcend passive observation to enable proactive decision-making. For instance, Wang et al.'s (2) pipeline DT employs uncertainty modeling and prediction algorithms to forecast future degradation and plan sensor reactivation accordingly. This forecasting capability is crucial for predicting failures and reducing downtime, a mission shared by Wang, Lee, and Angelica (32), who also discuss how DTs can be expanded to incorporate predictive maintenance through sensor-based analytics.

The real-world applications outlined in these studies illustrate the agility and versatility of digital twins for real-time monitoring. From monitoring high-risk infrastructure such as pipelines to monitoring a manufacturing-floor machine such as a die cutter, DT systems were found to deliver real-time feedback, historical record tracking, and predictive analysis, greatly improving operations visibility and responsiveness (2,32).

***Fault Diagnosis***

Digital twin technology has been a revolutionary method in fault diagnosis, allowing real-time monitoring and predictive analytics in various industrial applications. One of the greatest advantages of digital twins is that they can provide continuous, real-time monitoring of physical systems. For example, Wang et al. (2) explain how virtual models of physical assembly workshops enable managers to track key bottleneck stations in real time, utilizing real-time data to predict and react to unusual occurrences. Such real-time synchronization is also seen within chiller systems, with DTs making possible 3D visualization as well as real-time status monitoring, dramatically increasing the responsiveness and accuracy of fault diagnostics (28). Ranpariya and Sharma (33) also highlight the ability of DTs to sustain real-time system monitoring and behavior forecasting in time-critical IIoT settings. In machining, Liu et al. (34) show how sensor-integrated DTs use real-time vibration and control information to dynamically analyze cutting tool condition, showing excellent potential for adaptive fault detection during operation.

In addition to monitoring, DTs are being used more and more for predictive fault detection, using historical and real-time data to predict system failures. In product assembly lines with complex products, Wang et al. (2) suggest a digital twin-based model that predicts equipment faults, especially at production bottlenecks, by analyzing data gathered from the physical and virtual environments. In HVAC systems, a DT model based on stacked sparse autoencoders and transfer learning was proposed by Ma et al. (35), which achieves fault diagnosis and result verification by conducting data-driven simulations. Their model successfully solves issues of a lack of training data and varying operating conditions. Similarly, Ranpariya and Sharma (33) offer a strategy that integrates lightweight machine learning into a DT structure to realize predictive maintenance and timely fault detection with low latency. For rotating equipment, Wang et al. (2) propose a benchmark DT model developed specifically for fault detection and tracking of degradation that demonstrates its applicability and reliability through experimental proof.

The architecture of these DT systems differs based on their planned application but typically consists of both physical and virtual representations, a real-time data flow system, and a predictive analytics system. Wang et al. (36) present in their research on complex product assembly a multi-layered architecture consisting of a physical workshop, virtual environment, twin data platform, and an abnormal event prediction system that together enable real-time analytics and rescheduling functions. Ranpariya and Sharma (33) suggest a two-innovation architecture with a cloud-edge collaborative framework and a machine learning ensemble model, specific to resource-limited IIoT environments. Liu et al. (34) present a new modeling framework in machining where the virtual twin models dynamic behaviors by extracting vibration signals and frequency-domain features to detect anomalies. Wang et al. (2) emphasize the need to synchronize digital twin models with the physical conditions of the actual system, employing physics-based simulations and data-driven intelligence to improve diagnostic accuracy and model flexibility.

Practical applications of DTs for fault diagnosis vary widely across industrial applications, ranging from manufacturing systems to HVAC and rotating equipment. In chillers, Ma et al. (35) show that their DT framework can well diagnose various levels of fault severity, enhancing decision-making for maintenance staff. In machining, Liu et al. (2024) illustrate how DTs are especially useful in monitoring the wear of cutting tools, particularly in dynamic and intricate operating conditions, by detecting differences in vibration signatures that are related to tool deterioration. In rotating equipment, Wang et al. (2) built a rotor system model to experiment on the performance of their digital twin, obtaining accurate fault localization and degradation prediction. Lastly, in the field of complex product assembly, the use of DT technology to forecast faults in EMU bogie workshops not only enhanced fault forecast accuracy but also enabled better production planning and minimized operational disruption (36).

### *Process Control*

DTs have become an essential element in control of the manufacturing process, providing the ability for adaptive behavior and nearly real-time responsiveness. Here, the DT is not just a passive model of the system but actively acts as a control and optimization method to act upon the physical process. It incorporates control theory to manage uncertainties and dynamically feeds back useful information to the physical process to improve responsiveness and robustness (37). These attributes also make DTs facilitators of lifecycle-based manufacturing approaches, e.g., remanufacturing and recycling, through self-adaptive capabilities and enabling informed decision-making by the operators (37). Integration of DTs into Cyber-Physical Systems (CPS) and IoT infrastructures, though, poses key challenges, particularly communication latency and cybersecurity. Networked Control Systems (NCS) frequently incur signal delays in transmission, which can reduce manufacturing accuracy and cause out-of-tolerance outputs (37). At the same time, digital signal communication makes the system vulnerable to cybersecurity risks with the potential of signal corruption causing physical damage. In response to these threats, encryption mechanisms—in the form of the RSA cryptosystem—are used for protection of control as well as feedback signals, providing "end-to-end confidentiality and authenticity as signals travel through IoT-connected modules" (37). This approach was tested in a case study of laser welding, a temperature- and energy-sensitive process. Through the use of compression and RSA encryption in the control architecture, and simulation via a DT framework, the study demonstrated that decrypted signals were identical to the original inputs and caused minimal delays (37). Critical performance parameters like temperature, laser power, and welding speed were effectively controlled, which suggests the real-world applicability of encrypted DT-controlled systems in real-time manufacturing processes (37).

The examination also considered compound delays imposed by multi-layer encryption, compression, and error correction procedures, illustrating that the combined delay was still "within tolerable bounds of the system's sampling rate" (37). Other cryptographic algorithms like AES and DES were also suggested for further research, as well as blockchain methods for auditability and trust confirmation (37). This entire control architecture is underpinned by a finite element method (FEM)-based thermal model, from which a dynamic system was extracted via system identification. A discrete-time $H\infty$ controller was utilized, optimized via Linear Matrix Inequality (LMI) optimization to have robust performance for all different types of disturbance and delay scenarios (37). While the static controller was strong enough for normal uncertainties and delays, computational stiffness and system controllability were found to have limitations when the delays were on the rise, particularly with regard to matrix augmentation (37). In spite of such limitations, the encrypted control system performed well in tracking and stabilization and thus concluded that the use of robust DT-based controllers is a promising way to ensure secure, real-time process control in advanced manufacturing settings.

**Challenges in Application of DTs**

The fundamental modeling strategies employed in PMx—data-driven, physics-based, and knowledge-based—each pose their own drawbacks. Data-driven models are plagued by poor explainability and inefficiency as a result of sparse failure data, while physics-based models may be extremely complex and resource-hungry. Knowledge-based approaches tend to lack scalability and generalizability outside their initial context (35).

Additionally, there is significant fragmentation in the existing application of DTs, with applications being mostly limited to particular industries like aerospace or manufacturing. Such sector-specific targeting hinders broader applicability and cross-industry learning (35). The heterogeneity of assets within industries also makes it harder to develop standard DT-PMx systems, especially when trying to guarantee scalability and flexibility across diverse use cases.

Other barriers are issues pertaining to data quality, system security, and the unavailability of skilled human resources that can design and maintain DT systems optimally. These issues combined deter the complete exploitation of DTs' potential in predictive maintenance (35).

***Challenges in Manufacturing***

The deployment of DTs in production encounters a spectrum of interrelated technical and operational issues. The most visible among these is the quality and reliability of the data employed to build and refine the digital models. Digital twins rely on real-time sensor feeds and historical data to stay in synch with their physical counterparts. But if this information is low quality, badly formatted, or inconsistent, it can restrict the twin's ability to represent or respond to actual conditions accurately (38,11).

Interoperability and complexity are also essential issues. DT models tend to cross multiple domains, require regular updates, and are constructed from heterogeneous tools, all of which add to challenges in ensuring consistency and integration (39). Synchronization between virtual and physical elements is an ongoing challenge, compounded by the sheer amount and variety of industrial data sources (40).

The reliance on networked, real-time data streams also raises serious issues of cybersecurity and privacy. Factory systems are becoming more interconnected, and weaknesses in the digital twin's architecture could allow sensitive information to be compromised or the manufacturing process opened up to outside attacks. The use of secure communication procedures, encryption, and other privacy-protection techniques is therefore a condition of any factory-scale rollout (41,11).

Similarly important is the economic and human capital expense of creating and sustaining digital twins. The technology is capital-intensive, frequently demanding substantial initial investment in software infrastructure and expert staff. For most companies, particularly small and medium-sized businesses, the choice to implement digital twins hinges on a tangible return on investment, which is not always straightforward to measure (41;42).

Insufficient standardization and non-compatibility with the installed base of manufacturing capital also pose insurmountable obstacles. Heterogeneous systems abound in industrial environments, often operating with multiple communication protocols. Deploying a digital twin on these environments either needs middleware approaches or brand new hardware, which both add to complexity (11,42).

In terms of technical modeling, the greatest technical challenge among the most complicated ones is that DTs must be functional on multiple scales—anywhere from material behavior at the micro scale to full-scale production line dynamics. This multiscale necessity presents challenges in model fidelity, consistency, and simulation speed. Existing methods of integrating cross-domain models are underdevelopment, especially when there are differences between virtual predictions and physical results (11,42).

Lastly, communication latency still impacts the responsiveness of DTs, particularly when there is a need for real-time feedback in adaptive control. Even with high-end hardware, latency in data transmission between physical and digital spaces can result in stale simulations or delayed system corrections (42). This constrains the DT's applicability in high-speed or high-precision manufacturing applications.

***Challenges in Predictive Maintenance***

Use of digital twins (DTs) in predictive maintenance (PMx) is one promising direction toward improving operational performance and system durability. The adoption of DTs in this application, though, is plagued with complex challenges. One major restraint is the lack of a formal definition of DTs, with the result being varied interpretations that impede cooperative development across sectors (35). Adding to this is the heterogeneity in stakeholder needs, which hinders designing PMx DT systems that can be applied across all settings.

The second significant limitation is the shortage of data—specifically, failure data because of proactive repairs, which limits the performance of AI and machine learning models (10,26). The problem is exacerbated by the expense and feasibility limitations of installing required sensors, particularly in individual components or large-scale systems (10,23). Furthermore, the creation and verification of precise digital twin models rely significantly on high-fidelity data, which tends to be hard to come by or unreliable because of sensor noise (34; 27).

Aside from data-related issues, integration and standardization also present considerable challenges. The absence of common frameworks, reference models, and interoperability across hardware/software platforms prevents the scalability and cross-industry take-up of DT-based PdM (43; 28; 44). In addition, current enterprise systems are not compatible enough to facilitate complete DT deployment (45), and most firms continue to grapple with developing systematic implementation plans (29).

Real-time precision and model flexibility are another fundamental problem. Most existing PdM models cannot adjust for dynamically shifting machine parameters, lowering the precision and effectiveness of conclusions derived from the DT (Zhong et al., 2023). In complicated systems, the problem of deciding the right amount of model detail and maintaining real-time updates restricts reliability and performance in the long term (Yakhni et al., 2022; You et al., 2022). In addition, as systems grow more complex—with stacked layers of equipment and disparate production environments—generalized DT models have difficulty adapting to diverse operational environments (21; 30; 27).

Finally, even though DT and PdM methodologies are conceptually aligned, there is a reported absence of integration between the two in existing literature, along with no performance benchmarks and explicit definitions for next-generation digital twin (nexDT) frameworks (24). Overall, these shortcomings highlight the necessity for more resilient, standardized, and responsive digital twin strategies that can break through technical, infrastructural, and data-based hurdles in predictive maintenance.

***Challenges in Design Management***

Digital twins encounter some remarkable challenges when implemented in design management.

First, data integration is still a major bottleneck. While the design process creates enormous amounts of useful information, much of it is isolated because of inconsistent standards and lack of interoperability, which prevents collaborative development and reuse of design data (31).

Second, growing product personalization needs impose a large load on digital design structures. With customers desiring more individualized products, DT systems will have to fit more variables, configurations, and exceptions, which makes design optimization and automation complicated (2).

Third, the absence of real-time feedback from other lifecycle phases—particularly from manufacturing and end-use—hinders the capacity of digital twin platforms to inform and iterate on design choices. This lack of connection results in ineffective reuse of prior design effort and constrains the effectiveness of cross-functional collaboration (2).

Ultimately, the requirement for precise scientific modeling is a significant barrier. For reliability and safety purposes, DTs have to include comprehensive simulations that consider complex, multi-mechanism failure modes. This entails high-fidelity, physics-based lifetime models that are still challenging to incorporate with today's tools and data limitations (2).

***Challenges in Real Time Monitoring***

Real-time monitoring systems based on DTs are challenged greatly by the limited IoT capability of most traditional machines. It is expensive and challenging for small- and medium-sized manufacturing companies to be able to afford complete sensor upgrades (32). Even with real-time connectivity through technologies like cloud computing and AR interfaces, hardware constraints create problems of latency, weight, and restricted display scope, all of which diminish operational efficiency and user comfort (2). Another key issue is the modeling of uncertainty. Without accurate quantitation and variability control over physical properties and measurement methods, there are risks of costly overcorrection or unsafe undervaluation (2). Moreover, implementational limitations in the form of data access prohibition to secure customer-side activities have the result of many digital twins being only passive shadows instead of active controllers (32). Lastly, the lack of mature, standardized frameworks still inhibits reliability and scalability across various industrial environments (32).

***Challenges in Fault Diagnosis***

DT fault diagnosis systems are confronted with a number of serious challenges that limit their complete effectiveness in all industrial applications. One of the key challenges is the insufficiency of fault data. Most fault diagnosis models are trained on limited, offline data, which makes them less accurate in real-world applications involving new or changing faults (47, 34). Also, deep learning methods such as CNNs tend to demand huge amounts of data and strong computing resources, which are not always within reach (34).

Poor model transferability between systems is another hindrance. Models learned in one setting cannot be safely used in another due to differences in data distribution and system configurations (47).

Computational requirements and latency are also of pressing concern, particularly in real-time IIoT applications. Industrial settings utilize edge devices with limited processing capabilities, so it's necessary for models to be accurate yet computationally efficient (33).

Finally, generalization in dynamic or noisy environments is still an open problem. Models such as stacked sparse autoencoders may not perform well with changing data streams (47), and signal-based monitoring systems tend to fail under changing environmental conditions (34). Seamless real-time adaptability is still a developing area (33).

### *Challenges in Process Control*

DTs in process control systems are challenged by a range of issues primarily linked to real-time communication and system reactivity. Delays caused by IoT-based NCSs and cryptography modules can impair system performance, potentially driving outputs beyond tolerance boundaries (37). These delays, while occasionally tolerable using system design, are a continuous risk to control accuracy (37). Cybersecurity also arises as a pressing issue; unauthenticated or hacked control signals threaten not only data integrity but also possible physical damage, particularly in safety-critical applications such as laser welding (37). Furthermore, technical constraints in control systems add another level of sophistication. They comprise the fact that certain machines cannot handle negative flux signals and the computational stiffness due to delay-enhanced system matrices (37). Even deployment of resilient controllers—conceived to counteract such issues—has, on occasion, led to reduced performance (37). These collectively illustrate the technical and operational frailties to be overcome for DT-based process control systems to effectively operate within manufacturing contexts.

## Conclusion

This review analysis aimed to investigate the development, uses, and constraints of DT technologies in manufacturing contexts, including predictive maintenance, design management, real-time monitoring, fault diagnosis, and process control. The inquiry was motivated by the following questions: (1) What are the uses and quantifiable effects of DTs in various domains of manufacturing? (2) What limitations prevent their general deployment?

In all areas of manufacturing investigated, DTs possess various and disruptive characteristics. In predictive maintenance (PdM), DTs enable real-time condition monitoring, fault detection ahead of time, and RUL estimation (25,26,27). Coupling with AI and machine learning also further improves these models to allow for adaptive action based on historical and synthetic data (48).

In design management, DTs act as feedback-capable platforms that bring real-time information from working environments into the design process so that iterative tuning and performance enhancement are possible and facilitate data-based decision-making for design teams in the early stages of the product development process. Furthermore, end-to-end DT frameworks encompassing digital models of manufacturing and use conditions provide an integrated model for product lifecycle optimization (31).

Real-time monitoring applications showcase DTs as dynamic decision-support tools. Existing studies such as Wang, Lee, and Angelica (32) and Wang et al. (36) highlight how digital dashboards, AR interfaces, and Bayesian inference engines collectively enable live feedback, performance tracking, and predictive diagnostics and can transform conventional systems into smart, responsive infrastructures without significant capital reinvestment.

In fault diagnosis, DTs enable real-time anomaly detection and predictive maintenance using layered architectures. Various studies have demonstrated the viability of DT based fault detection systems that effectively tackle data variability and improve responsiveness as well as support synchronized prediction and rescheduling, reducing downtime and improving production planning (34,35,36).

For process control, DTs integrated with control theory can facilitate self-regulating systems that operate under uncertainty. They are particularly applicable in precision manufacturing environments where being responsive in real-time is absolutely necessary (37).

In all these fields, some measurable advantages of DTs arise, such as: minimized unplanned downtime by predicting RUL precisely (27), improved design flexibility and feedback by integrated platforms (31), real-time process optimization through sensor-based monitoring (22), and enhanced diagnostic accuracy through adaptive twin frameworks (34).

Even with the revolutionary potential of DTs, several limitations limit their large-scale adoption. Some of the key challenges are data availability and quality (10; 27) that impacts the performance of AI-augmented DTs (34); non-generalizability that prevents the scalability and transferability of current models (35); low portability due to dependence on domain-specific rules (35); non-standardization due to the lack of common frameworks for data formatting, communication protocols, and model architectures (44); high hardware, skilled personnel, and IT infrastructure investment (41); cybersecurity issues pertaining to the real-time transmission of control signals and operational data (37,11); and low real-time responsiveness due to communication delays and computational bottlenecks (37).

For production companies evaluating DT adoption, a number of real-world implications arise from this review. Firms should first implement pilot scales in high-leverage applications like predictive maintenance or bottleneck monitoring to test ROI prior to scaling up, as it can reduce downtime and maximize output without system-level overhauls (2,4). Companies must invest in modular, hybrid DT architectures integrating physics-based modeling with data-driven inference to weigh the computational expenses against predictive precision with cloud-based platforms and elastic analytics solutions (31). Cross-functional collaboration channels between design, operations, and IT teams are essential, particularly for integrating feedback from downstream processes through interoperable platforms and common data environments (31). Cybersecurity frameworks must be prioritized, following the example of encrypted control architectures demonstrated in studies such as Papacharalampopoulos et al. (37). Finally, workforce upskilling in sensor integration, data analytics, and control systems becomes increasingly critical as manufacturing shifts toward cyber-physical systems.

Several directions for future research emerge from gaps identified in this study. Future studies can focus on developing standardized reference models and ontologies for DT architectures across manufacturing domains to facilitate interoperability, benchmarking, and collaborative innovation. Secondly, emerging technologies such as blockchain for auditability, edge computing for reduced latency, and federated learning for privacy-preserving model updates, which can address challenges in data security, responsiveness, and collaboration need to be examined in the context of DTs for manufacturing. Finally, performance benchmarking frameworks with standard KPIs such as latency, prediction accuracy, and system adaptability need to be integrated into research studies to enable comparative evaluation across industries.

Digital twins have evolved from conceptual tools to indispensable technologies central to Industry 4.0, fundamentally transforming manufacturing operations across multiple domains. While their benefits are substantial, DTs are not turnkey solutions and their implementation faces numerous challenges. As we transition toward Industry 5.0, digital twins are poised to extend beyond their current technical foundations by incorporating human-centric values, sustainability principles, and resilience frameworks. This evolution will enable more collaborative human-machine interactions, resource-efficient processes, and adaptive production systems that balance technological advancement with societal and environmental wellbeing. Through focused research and collaborative innovation, the transformative potential of digital twins can be fully realized as foundational, ethically-aligned tools in the human-centered manufacturing ecosystems of the future.

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