Exploring the Synergy Between Digital Twin Technology and Artificial Intelligence: A Comprehensive Survey

Wael Y. Alghamdi, Rayan M. Alshamrani, Ruba K. Aloufi,
Shaikhah O. Ba Lhamar, Retaj A. Altwirqi, Fatimah S. Alotaibi,
Shahad M. Althobaiti, Hadeel M. Altalhi, Shatha A. Alshamrani, Atouf S Alazwari
College of Computers and Information Technology, Taif University, P.O.Box 11099, 21944 Taif, Saudi Arabia

Abstract—**The integration of Digital Twin Technology with Artificial Intelligence (AI) represents a transformative advancement across multiple domains. Digital twins are dynamic, real-time virtual representations of physical systems, leveraging technologies such as Internet of Things (IoT), augmented and virtual reality (AR/VR), big data analytics, 3D modeling, and cloud computing. Initially conceptualized by Michael Grieves in 2003 and further developed by organizations such as NASA, digital twins have been widely adopted in manufacturing, healthcare, smart cities, and energy systems. This paper provides a comprehensive analysis of how real-time data streams, continuous feedback loops, and predictive analytics within digital twins enhance AI capabilities, enabling anomaly detection, predictive maintenance, and data-driven decision-making. Additionally, the study examines technical and operational challenges, including data integration, sensor accuracy, cybersecurity, and computational overhead. By evaluating current methodologies and identifying future research directions, this survey underscores the potential of digital twins to drive adaptive, intelligent, and resilient systems in an increasingly data-driven world.**

Keywords*—*Digital twin; artificial intelligence; internet of things; big data; predictive analytics; real-time monitoring

I. Introduction

The rapid evolution of digital twin technology represents a pivotal advancement in the Industry 4.0 paradigm, enabling real-time virtual representations of physical systems that dynamically interact with their real-world counterparts. Initially conceptualized by Michael Grieves in 2003 and later refined by organizations such as NASA, digital twins have transcended their origins as static simulations to become intelligent, data-driven models that integrate Internet of Things (IoT) sensors, augmented reality (AR), and big data analytics. These systems facilitate continuous synchronization between the physical and digital domains, allowing for real-time monitoring, predictive maintenance, and enhanced decision-making. By leveraging adaptive learning and advanced analytics, digital twins are transforming industries by optimizing efficiency, resilience, and innovation across manufacturing, healthcare, smart cities, and energy. This paper explores the foundational principles, technological enablers, and emerging applications of digital twin technology, while addressing key challenges such as data integration, cybersecurity, and computational scalability. The findings underscore the transformative potential of digital twins in creating self-optimizing, intelligent systems that drive the next generation of industrial and operational efficiency [1].

In parallel with the evolution of digital twin technology, the field of Artificial Intelligence (AI) has undergone exponential growth, with machine learning algorithms and AI-driven models becoming integral to decision-making, predictive maintenance, and operational optimization. The convergence of digital twins and AI represents a natural progression, wherein the real-time, high-fidelity data streams provided by digital twins significantly enhance AI's predictive accuracy, adaptability, and responsiveness [2]. This paper provides a comprehensive survey of the current landscape of digital twin applications, exploring how their integration with AI enables the simulation of rare events, reinforcement of adaptive learning mechanisms, and support for human-in-the-loop decision-making. By critically analyzing enabling technologies, application domains, and real-world implementations—ranging from industrial automation and healthcare to urban management—this study aims to elucidate the transformative role of digital twins in advancing AI capabilities. Additionally, it addresses key challenges, including data heterogeneity, system scalability, and cybersecurity, offering insights into future research directions and potential solutions [3].

The remainder of this paper is structured as follows: Section 2 defines the concept of a digital twin, explores its historical evolution, distinguishes between digital twins and simulations, and highlights major misconceptions about digital twins. Section 3 examines the integration and interaction of digital twins with modern technologies by describing the roles of AI, IoT, ML, and big data in enhancing digital twins. Section 4 presents the applications of digital twins in the modern healthcare industry. Section 5 discusses the major challenges of digital twins as an emerging technology. Finally, Section 6 concludes the paper.

II. Definition of Digital Twin

This section presents the findings derived from the analysis of selected literature that define the digital twin concept. Additionally, it examines the enabling technologies that enhance its intelligence and capabilities, while critically reviewing common misconceptions surrounding the framework.

A. Historical Evolution of the Digital Twin

A digital twin is a dynamic virtual model that replicates a physical system in real-time, facilitated through bidirectional data exchange. This enables continuous monitoring, predictive analysis, and performance optimization [4]. It relies on live sensor data, directly linking the digital model to its physical counterpart, allowing it to adapt and evolve in response to changing environmental and operational conditions [4].

The concept of the digital twin was first introduced by Michael Grieves in 2003, who identified three fundamental components: the physical space, the virtual space, and the data-linking mechanism that enables seamless information exchange between them [5]. In 2012, NASA further refined this concept, defining the digital twin as "an integrated multi-physics, multiscale simulation of a system or vehicle as built, continuously updated using the best available physical models, sensor data, fleet history, and other inputs to accurately reflect the actual life of its physical counterpart" [6], [4].

The definition of digital twins has evolved over time, with researchers offering different perspectives depending on the field of application. Ríos et al. (2015) describe the digital twin as an integrated multiphysics and multiscale simulation, continuously updated using the best available physical models and sensor data [7]. In contrast, Parrott and Warshaw (2017) take a business-oriented approach, defining it as "**an advanced digital file that captures and reflects the historical and current behavior of a physical entity or process, thereby improving operational efficiency and decision-making" [7].

From a dynamic systems perspective, Liu et al. (2018) describe the digital twin as "a living model of a physical asset or system that continuously adapts to operational changes based on real-time data and can predict future performance" [8]. Similarly, Madni et al. (2019) characterize it as "a continuously updated virtual representation of a physical system that integrates performance, maintenance, and health status data throughout its lifecycle" [8].

Other researchers offer more detailed perspectives on digital twin technology. Zheng et al. (2018) define it as "**a set of virtual information structures that fully describe a potential or actual physical product, covering all aspects from the micro-atomic level to the macro-geometrical level" [8]. VRABIČ et al. (2018) highlight its role in predictive analytics and real-time service data, stating that a digital twin represents a physical entity or a group of entities through integrated simulations and continuous data exchange [8], [9].

A comprehensive definition proposed by Singh et al. (2021) describes the digital twin as "a self-evolving, dynamic virtual model that accurately represents its physical counterpart at any given moment through real-time data exchange while maintaining historical records. Unlike static models or simulations, a digital twin not only mirrors its physical entity but also allows changes in the digital model to influence and optimize the real-world system" [9].

The definition of the digital twin varies based on its application domain. In this study, we provide a comprehensive overview of digital twin definitions across different sectors, highlighting its diverse implementations and transformative potential.

In the industrial sector, digital twin technology is a scalable and transformative innovation that plays a critical role in driving digital transformation. By creating real-time virtual replicas of physical assets, processes, and systems, digital twins enable enhanced operational efficiency, predictive maintenance, and data-driven decision-making. This technology is a cornerstone of Industry 4.0, facilitating seamless integration between cyber-physical systems, IoT-enabled manufacturing, and AI-driven analytics [10]. Through continuous monitoring and simulation, digital twins optimize production workflows, reduce downtime, improve resource utilization, and support adaptive manufacturing strategies. By bridging the gap between physical and digital environments, digital twins empower industries to transition towards smart, autonomous, and self-optimizing manufacturing ecosystems.

In the healthcare sector, digital twin technology serves as an advanced virtual model that integrates real-time patient data, biomedical simulations, and predictive analytics to enhance patient care, disease prevention, and clinical decision-making. By leveraging AI-driven diagnostics, sensor-based monitoring, and personalized treatment simulations, digital twins enable precision medicine, allowing healthcare providers to model individual patient responses to treatments and surgical procedures before real-world application. Additionally, digital twins support clinical operations optimization, resource management, and medical training, providing immersive simulations for healthcare professionals. This technology has significant potential in early disease detection, remote patient monitoring, and personalized therapy, thereby improving healthcare outcomes and operational efficiency [11].

In the manufacturing and engineering sector, digital twin technology provides a high-fidelity virtual representation of physical products, processes, and systems. By integrating real-time sensor data, AI-driven analytics, and IoT-enabled monitoring, digital twins enable direct access to manufacturing data, allowing for optimized production workflows, predictive maintenance, and quality control. This technology enhances design, prototyping, and lifecycle management by simulating product performance under various operational conditions, reducing the need for physical testing and accelerating time-to-market. Furthermore, digital twins facilitate adaptive manufacturing, ensuring efficient resource utilization and minimizing production downtime through continuous monitoring and simulation-based decision-making [12].

In the smart cities sector, digital twin technology functions as a dynamic, data-driven model that integrates real-time urban data, IoT-enabled infrastructure, and AI-powered analytics to enhance urban management, decision-making, and sustainability. By continuously collecting and analyzing data from traffic systems, energy grids, environmental sensors, and public services, digital twins enable predictive modeling, scenario testing, and resource optimization. This technology supports efficient transportation planning, smart energy distribution, disaster resilience, and sustainable urban development, fostering more resilient, livable, and intelligent cities. Through simulation and real-time monitoring, digital twins empower city planners and policymakers to make informed decisions that improve infrastructure efficiency, environmental impact, and citizen well-being [13].

In the construction sector, a digital twin is a dynamic model that combines real-time data with Building Information Modeling (BIM) to facilitate asset monitoring, enhance decision-making processes, and enable cyber-physical integration [14].

In general, a digital twin is a software model that replicates a physical entity, utilizing real-time data for simulation, prediction, and optimization of efficiency through the integration of Internet of Things (IoT) and Artificial Intelligence (AI) technologies [15]. Moreover, the digital twin is a technology that simulates physical objects in real-time, enabling performance analysis, exploration, and future prediction.[16]

In the energy and utilities sector, a digital twin is a dynamic virtual model that simulates energy systems in real-time, facilitating improvements in efficiency, balancing supply and demand, and enabling predictive maintenance [17].

In the cybersecurity sector, a digital twin safeguards data and infrastructure from threats by employing encryption, access control, and intrusion detection, thereby ensuring secure communication between digital and physical systems [18].

In the agriculture and environment sector, a digital twin is a virtual model that optimizes productivity and sustainability by analyzing real-time data, monitoring resources, and predicting environmental changes [19].

In the supply chain sector, a digital twin is a dynamic virtual model that simulates material flows and logistical processes using real-time data, thereby enhancing efficiency, reducing costs, and improving risk management and demand forecasting [20].

B. Enabling Technologies

A digital twin is an advanced concept that leverages a suite of enabling technologies to create dynamic digital models that mirror physical systems in real-time, thereby enhancing monitoring, analysis, prediction, and data-driven decision-making [21]. This technology predominantly relies on the Internet of Things (IoT) and wireless communications [21]. Furthermore, augmented reality (AR) and virtual reality (VR) technologies are integrated into digital twins to create interactive simulation environments, facilitating improvements in design processes, maintenance, and training within industrial and engineering settings [4].

Big Data Analytics plays a crucial role in the operation of digital twins, enabling the processing of vast quantities of data collected from sensors. This facilitates the optimization of operational processes, identification of trends, and enhanced decision-making through more accurate and proactive data analysis. The technology relies on artificial intelligence (AI) algorithms and predictive analytics models to extract meaningful insights from raw data [22].

3D modeling and simulation are fundamental in the development of digital twins, enabling the creation of precise digital models that replicate the behavior and performance of physical systems. This technology supports engineers and developers in testing and analyzing designs prior to implementation, thereby improving operational efficiency and reducing errors and costs [23]. Additionally, AI and machine learning (ML) techniques are instrumental in analyzing the vast datasets generated by digital twins. Deep learning algorithms and artificial neural networks contribute to pattern recognition, failure prediction, and autonomous optimization of system performance, thereby improving decision-making accuracy and reducing operational costs by anticipating potential issues before they occur [21].

The Internet of Things (IoT) is integral to the development of digital twins, ensuring continuous connectivity between physical systems and their corresponding digital models. IoT-connected devices collect real-time data from various operational environments, which can then be analyzed and interpreted to support monitoring, control, and intelligent decision-making. IoT technologies are widely applied in digital twin systems across numerous industries, including manufacturing, healthcare, and smart cities [24].

Cloud computing provides a vital infrastructure for digital twins, offering a platform for large-scale data storage and processing that enables real-time simulations and analytics. The integration of deep learning with cloud computing enhances the accuracy of digital models by supporting continuous data analysis and improving proactive maintenance strategies [25]. Finally, blockchain technology plays a critical role in ensuring the security and integrity of data exchanged within digital twin systems. By providing immutable records, blockchain technology guarantees data security and reduces the risk of manipulation or cyberattacks. This capability is particularly important in industrial and medical applications where data security is paramount [23].

C. Distinction Between Digital Twin, Simulation

A digital twin is a dynamic digital model that replicates physical systems in real-time, leveraging enabling technologies such as the Internet of Things (IoT), augmented reality (AR), virtual reality (VR), and artificial intelligence (AI) for enhanced monitoring, analysis, prediction, and decision-making [21]. IoT enables continuous data collection from operational environments, while AR and VR enhance design, maintenance, and training through interactive simulations [4].

Big Data Analytics facilitates the processing of large datasets from sensors, supporting proactive decision-making through predictive analytics and AI algorithms [22]. Furthermore, 3D modeling and simulation are integral to creating accurate digital replicas of physical systems, optimizing efficiency and reducing errors [23]. AI and machine learning (ML) algorithms, such as deep learning, enable pattern recognition and failure prediction, further improving operational performance [21].

Cloud computing offers scalable data storage and processing for real-time simulations, while blockchain ensures data integrity and security, critical in industrial and medical applications [23].

D. Misconceptions about Digital Twin

Despite the growing adoption of Digital Twin technology across various industries, several misconceptions persist regarding its true nature and capabilities. Many individuals and organizations mistakenly equate a Digital Twin with other digital representations, such as digital models, digital shadows, or 3D models. However, these concepts differ significantly in terms of data flow, real-time interaction, and functionality as shown in Figure 1.

1) Digital model: A common misconception is that a Digital Twin is simply a digital model representing a physical entity. However, this is incorrect, as a digital model lacks the capability for real-time data exchange between the virtual representation and its physical counterpart. In contrast, a Digital Twin continuously reflects changes occurring in the physical system, enabling dynamic interaction, while a digital model remains static and does not adapt to such changes [4].

2) Digital shadow: A Digital Shadow is a digital representation of a physical entity, where the data flow is one-way from the physical entity to the digital model without any reverse impact[4]. Any change in the physical entity is reflected in the digital model, but modifications in the digital model do not affect the physical system[26].

3) 3D Model: Some assume that a Digital Twin is simply a 3D model of a physical object. While a 3D model provides a visual representation, a Digital Twin is far more advanced. It requires continuous data updates, operational simulation, and performance analysis based on real-time data rather than merely serving as a static visual model[4][27].

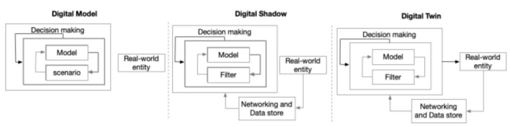

Fig. 1. From digital model to digital twin based on Kritzinger et al.'s classification. [28].

III. Integration and Interaction of Digital Twin with Modern Technologies

The convergence of Digital Twins (DTs) with Artificial Intelligence (AI) has significantly advanced data-driven decision-making across various sectors. This integration enhances predictive analytics, real-time monitoring, and optimization processes, thereby improving operational efficiency and strategic planning. As a result, organizations are better equipped to adapt to dynamic market conditions and improve overall performance [29]. Digital Twins serve as virtual representations of physical systems, enabling real-time monitoring, predictive maintenance, and process optimization. Their integration into industrial applications has led to substantial improvements in operational efficiency and decision-making, transforming contemporary approaches to system management and performance enhancement [30].

The convergence of the Internet of Things (IoT), Big Data, AI, and Machine Learning (ML) further augments the capabilities of Digital Twins. This synergy facilitates the development of more adaptive and intelligent decision-making frameworks, optimizing operational efficiency and predictive analytics. As these technologies continue to evolve, their combined impact is set to revolutionize various sectors, fostering innovation and delivering improved outcomes [31].

The synergistic integration of dynamic, data-driven insights enhances operational efficiency and strategic planning. This approach streamlines processes and enables organizations to adapt effectively to evolving market conditions, fostering a proactive operational framework crucial for sustained competitive advantage [32]. As industries increasingly adopt advanced technologies to improve performance and reduce costs, the integration of these innovations fosters a culture of continuous improvement and adaptability, supporting a strategic response to complex challenges. This shift not only enhances cost efficiency but also drives innovation, positioning businesses to effectively navigate a dynamic market landscape [33].

The convergence of Artificial Intelligence (AI) and Digital Twins (DTs) facilitates significant advancements in modeling and identifying rare events and outliers, areas where traditional AI models often face limitations due to data constraints. By leveraging the real-time capabilities of Digital Twins, AI systems can improve anomaly detection accuracy and reliability, enhancing decision-making and predictive analytics across various sectors [34]. This study explores the complex interactions among digital technologies, the Internet of Things (IoT), Big Data, AI, and machine learning, emphasizing the unique advantages of AI-enhanced digital technologies in contemporary applications and innovation strategies [35]. The integration of IoT-derived data further enhances advanced models for rare event modeling and anomaly detection, enabling more accurate predictions and timely interventions across diverse domains.

This study investigates the efficacy of artificial intelligence-driven digital twins (DTs) in mitigating the limitations posed by data scarcity in traditional analytical methodologies. By elucidating the potential of these advanced technologies, the research aims to enhance the accuracy, adaptability, and efficiency of digital twin applications. The findings are anticipated to contribute significantly to the field, providing insights that may revolutionize data-driven decision-making processes in various sectors.

A. The Role of Artificial Intelligence in Enhancing Digital Twins

1) AI for Cognitive and predictive capabilities: Artificial Intelligence (AI) is pivotal in enhancing the cognitive and predictive functionalities of Digital Twins (DTs) by facilitating their capacity to assimilate insights from both historical and real-time datasets. The integration of Machine Learning (ML) and Deep Learning (DL) algorithms serves to significantly bolster the predictive accuracy of DTs. These advanced computational techniques enable DTs to discern patterns, identify anomalies, and generate forecasts based on extensive datasets, thereby improving decision-making processes across various domains. By leveraging AI, DTs can continuously adapt and refine their models, resulting in enhanced performance and reliability. Consequently, the incorporation of AI-driven methodologies not only optimizes the operational efficiency of DTs but also fosters innovation in fields such as manufacturing, healthcare, and urban planning, marking a transformative shift in how complex systems are monitored and managed [36],[8]. Digital twins (DTs) leverage advanced algorithms to simulate intricate scenarios, facilitating accurate failure predictions and automating decision-making processes. By efficiently processing extensive data inputs, these algorithms enhance operational insights, thereby improving system reliability and performance in various applications across industries. This integration of technology represents a significant advancement in data-driven decision-making methodologies.

Artificial Intelligence (AI) plays a pivotal role in the seamless integration of physical and digital systems by leveraging advanced analytics of sensor data. Through the identification

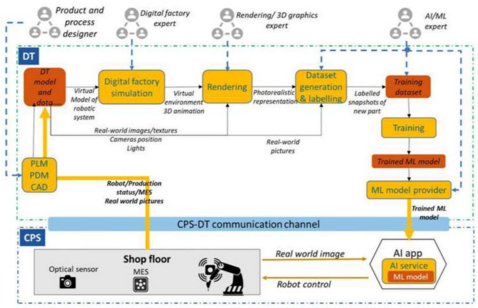

Fig. 2. DT-Driven ML for self-adaptable handling of product variations by an industrial robot [39].

of trends and the generation of real-time recommendations, AI significantly enhances operational efficiency. The capacity to process diverse data sources, such as Internet of Things (IoT) sensor readings, historical trends, and simulation data, not only improves accuracy but also fosters adaptability within dynamic environments. This capability is crucial for optimizing decision-making processes across various sectors [37] [38].

2) AI for Predictive maintenance and fault detection: The integration of artificial intelligence (AI) in digital twins (DTs) presents substantial benefits in the realms of predictive maintenance and fault detection, especially within the industrial and manufacturing sectors. The capability for early anomaly detection plays a crucial role in minimizing operational downtime and enhancing overall efficiency. Research indicates that AI algorithms not only reduce the incidence of false alarms but also elevate the precision of decision-making processes. This transition from traditional reactive maintenance paradigms to more proactive predictive maintenance models signifies a transformative shift in industrial operations. By harnessing the power of AI-driven DTs, industries can achieve optimized resource utilization, improved reliability, and a more sustainable operational framework, ultimately leading to significant economic and operational advantages. Such advancements underscore the critical importance of AI in future industrial practices[33] [35]. Figure 2 illustrates the capacity of data-driven (DT) machine learning (ML) to facilitate adaptive handling of product variations by industrial robots. This advancement significantly improves automation efficiency while minimizing the necessity for manual intervention. By leveraging AI-driven predictive analysis, the approach enables real-time adjustments, fostering continuous optimization of industrial processes. Consequently, the integration of ML into robotic systems represents a transformative development in enhancing operational capabilities within manufacturing environments.

B. IoT as the Backbone of Digital Twin Data Acquisition

1) Real-time data collection and system synchronization: The Internet of Things (IoT) serves as a crucial component within Digital Twin (DT) ecosystems, delivering continuous and real-time sensor data that underpins the digital representations of physical assets. By leveraging IoT technologies, digital twins enhance data collection across diverse sectors such as industrial automation, smart cities, and healthcare. This integration allows organizations to achieve operational optimization through the implementation of real-time monitoring and predictive analytics. The ability to receive instantaneous data not only enhances decision-making processes but also fosters improved efficiency and resource management. Consequently, the synergistic relationship between IoT and digital twins signifies a pivotal advancement in the realm of data-driven strategies, positioning organizations to navigate complexities and drive innovation in an increasingly interconnected digital landscape [40][41].

2) The Bidirectional feedback loop of IoT and DTs: The convergence of the Internet of Things (IoT) with Digital Twins (DTs) facilitates a bidirectional feedback mechanism, which is crucial for ensuring that digital representations accurately mirror the conditions of their physical counterparts. This integration enhances the fidelity and responsiveness of digital models in real-time applications. Moreover, the data generated by IoT devices is characterized by its substantial volume, heterogeneity, and complexity. As a result, effective analysis of this data requires the implementation of Big Data analytics and artificial intelligence (AI)-driven models. These advanced methodologies are essential for extracting meaningful insights from the vast datasets, enabling organizations to make informed decisions and optimize operational efficiency. Consequently, the interplay between IoT, DTs, and advanced analytics is pivotal for advancing technological applications across various sectors [42][43] . The synchronization and model enhancement process within Digital Twin technology is exemplified in Figure 4. This figure elucidates the interaction between real-world data and simulated digital environments, facilitated by iterative learning and feedback loops. Such an approach ensures the ongoing refinement of predictive models, which significantly enhances the system's capacity for real-time adaptation. Consequently, this iterative methodology contributes to improved accuracy in anomaly detection and overall system optimization, thereby underscoring the efficacy of Digital Twin technology in advanced data-driven applications.

C. The Role of Big Data in Digital Twin Intelligence

1) Big data-driven decision making in DTs: Big Data significantly contributes to the advancement of artificial intelligence (AI) model training within Digital Twin frameworks. The integration of these frameworks with Internet of Things (IoT) systems results in the generation of vast amounts of data characterized by high volume, velocity, and variety. Such characteristics necessitate the implementation of sophisticated data processing techniques to ensure the reliability and accuracy of predictive modeling and system diagnostics. The ability to effectively analyze and interpret this data is crucial, as it enables the optimization of AI algorithms used in Digital Twins, thereby enhancing their performance and predictive capabilities. Furthermore, the continuous influx of real-time data from IoT devices supports dynamic updates to the AI models, promoting adaptive learning and improved decision-making processes. Consequently, the interplay between Big Data and AI within Digital Twin frameworks underscores the importance of advanced data processing methodologies in achieving optimal results in modern technological applications [44][45]. Figure 3 presents a detailed visualization of the fundamental components of Big Data, namely volume, velocity, and variety, in conjunction with its principal sources, which

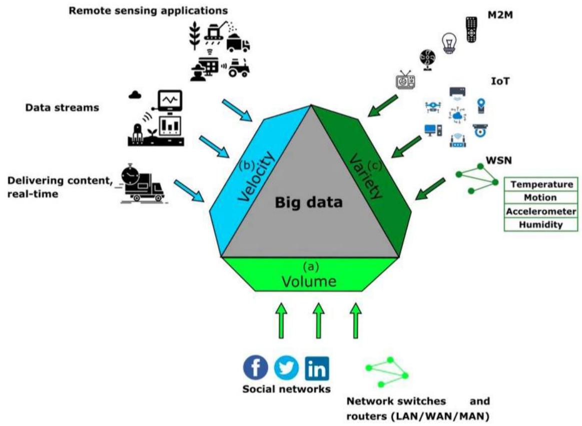

Fig. 3. Big data definition [46].

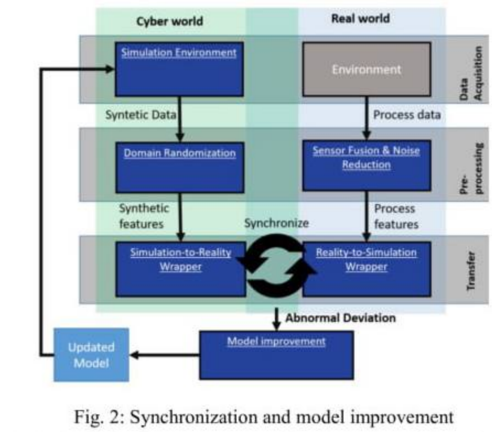

Fig. 4. Synchronization and model improvement process in digital twin technology [48].

include the Internet of Things (IoT), machine-to-machine (M2M) communications, and remote sensing applications. This illustration underscores the significant role that diverse data streams play in generating artificial intelligence-driven insights within Digital Twin frameworks. Such integration facilitates real-time content delivery and sophisticated analytics, ultimately enhancing the decision-making processes. The interplay between these elements exemplifies the transformative potential of Big Data technologies in optimizing operational efficiency and responsiveness in various sectors.

2) Synthetic data for training AI models in DTs: The integration of Big Data analytics within digital twins (DTs) offers significant advancements in anomaly detection and predictive capabilities. By leveraging vast datasets, DTs can identify latent correlations that may not be immediately observable, thus enabling the extraction of meaningful insights that inform decision-making processes. Furthermore, the application of synthetic data generation emerges as a crucial technique for augmenting training datasets. This strategy enhances the performance of artificial intelligence (AI) models, particularly in their capacity to recognize low-frequency anomalies, which are often challenging to detect in conventional datasets. The ability to simulate realistic scenarios through synthetic data not only bolsters the robustness of AI models but also facilitates the continuous refinement of predictive analytics within DT frameworks. Consequently, the convergence of Big Data analytics and synthetic data generation positions digital twins at the forefront of technological innovation, ultimately contributing to more accurate and reliable predictive modeling in various domains[47] [45].

D. Machine Learning and Digital Twin Training for Rare Events

1) Addressing data imbalance through synthetic training: The development of artificial intelligence (AI) faces notable challenges, particularly in the context of training models to identify rare events and outliers. Traditional AI models frequently encounter difficulties when dealing with imbalanced datasets, which can lead to suboptimal performance and reduced accuracy in real-world applications. However, the innovative concept of Digital Twins presents a promising solution to this issue. By simulating rare scenarios and generating synthetic data, Digital Twins effectively augment the training process for machine learning (ML) models. This approach not only increases the availability of diverse training examples but also enhances the robustness and generalizability of the models. As a result, the integration of Digital Twin technology into AI development offers a transformative avenue for overcoming the limitations associated with rare event detection, ultimately contributing to more reliable and effective AI systems capable of addressing complex, real-world challenges. The exploration of this synergy between Digital Twins and AI holds significant implications for future research and application[49][50].

2) AI-Powered DTs for smart cities and healthcare: The application of Artificial Intelligence (AI) in Digital Twins (DTs) has emerged as a transformative approach in the context of smart cities and healthcare. In urban settings, AI-enhanced DTs play a crucial role in simulating low-probability yet high-impact urban events, such as traffic congestion, infrastructure failures, and energy grid disruptions. This predictive capability significantly contributes to the enhancement of urban resilience and the optimization of strategic planning initiatives. By leveraging advanced algorithms and real-time data analytics, urban planners can devise more effective responses to potential crises, thereby fostering a more sustainable and adaptive urban environment. In the realm of healthcare, AI-integrated DTs offer substantial advancements in the prediction of rare medical conditions. By training predictive models on synthetic patient data, these systems facilitate early disease diagnosis and personalized treatment strategies. The synthesis of comprehensive patient profiles enables healthcare providers to identify potential health risks proactively and tailor interventions to individual patient needs. Consequently, this innovative application of AI and DTs not only improves patient outcomes but also promotes a more efficient healthcare delivery system. The utilization of AI-powered DTs, therefore, represents a significant leap forward in both urban management and healthcare practices, with the potential to yield substantial societal benefits [50].

E. Conclusion

The Transformative Role of AI-Powered Digital Twins in Smart Cities and Industry 4.0, Digital twin technology (DT) has witnessed significant advancements, particularly with the integration of artificial intelligence (AI) in various sectors, including urban planning and healthcare. In smart cities, AI-powered digital twins are utilized to simulate low-probability urban events such as traffic congestion, infrastructure failures, and energy grid disruptions. These simulations not only enhance urban resilience but also facilitate strategic planning (Santos et al., 2020; Zhang et al., 2021). For instance, by harnessing large datasets, urban planners can predict and devise effective strategies to mitigate the impact of such events. Similarly, in the healthcare sector, AI-integrated digital twins are proving instrumental in anticipating rare medical conditions. By training on synthetic patient data, these systems advance early disease diagnosis and enable personalized treatment plans, thus demonstrating the versatility and importance of digital twin technology across multiple domains. The expansion of digital twin technology's adoption across various industries reflects its increasing significance in the modern technological landscape. Within the context of Industry 4.0, digital twins are positioned as crucial innovations that empower organizations to predict outcomes, optimize processes, and facilitate real-time decision-making. The strategic implementation of digital twins allows organizations to enhance efficiency, reduce operational costs, and improve product lifecycle management. This optimization is particularly evident in industrial applications, where digital twins play a pivotal role in refining manufacturing processes and logistics management. In the industrial sector, the convergence of IoT, AI, and Big Data has transformed traditional manufacturing paradigms. The integration of these technologies enables the development of precise, adaptive, and intelligent systems capable of predictive maintenance and real-time monitoring. For example, manufacturers can leverage digital twins to monitor the condition of machinery and predict potential failures before they occur. This proactive approach minimizes downtime, enhances operational efficiency, and mitigates risks associated with equipment failure, ultimately leading to increased productivity and reduced costs. However, despite the numerous advantages associated with digital twin technology, several challenges remain. Issues related to data integrity, cybersecurity, and system scalability pose significant hurdles for organizations seeking to implement digital twins effectively. Data integrity concerns arise from the dependency on accurate and reliable data inputs for effective simulations and predictions. Furthermore, as digital twins become more interconnected, vulnerabilities to cyberattacks increase, necessitating robust cybersecurity measures. Finally, scaling digital twin systems to accommodate growing datasets and complex operations requires careful planning and resource allocation. To address these challenges, the development of robust frameworks that ensure secure, reliable, and efficient digital twin implementation across industries is essential. Organizations must prioritize investment in cybersecurity protocols, data management strategies, and scalable infrastructure to harness the full potential of digital twin technology. By fostering collaboration among stakeholders, including technology providers, researchers, and industry practitioners, the path toward successful digital twin integration can be paved. In conclusion, the application of AI-powered digital twins in smart cities and industrial settings exemplifies their transformative potential. As their role in manufacturing, predictive maintenance, and logistics management becomes increasingly pronounced, understanding the practical implications of digital twins will provide valuable insights into how this technology is revolutionizing operations and shaping the future of smart factories. The continued exploration and development of digital twin technology will be vital for advancing efficiency, resilience, and innovation in the rapidly evolving landscape of Industry 4.0.

IV. Application of Digital Twin

A. Industry

In the era of Industry 4.0, digital twins are one of the leading innovations reshaping the management of industrial processes. This virtual model serves as an accurate Digital Replica of Real-World Objects, such as machines and systems, enabling manufacturers to monitor performance and analyze data in real-time. By leveraging real-world data collected from connected sensors, digital twins can enhance efficiency, reduce costs, and improve strategic decision-making.

By integrating digital twins into their operations, manufacturers can gain deeper insights, optimize processes, and adapt more quickly to changing conditions in the industry.

Digital twins have numerous applications at various stages of the product lifecycle, from design and simulation to predictive maintenance and process management. However, they face challenges related to data integrity and cybersecurity, necessitating effective strategies to overcome these obstacles.

1) Definition: A Digital Twin is a virtual model of physical entities, like machines and systems, that relies on real-world data from connected sensors. It enables performance analysis, enhances efficiency, reduces costs, and improves decision-making with real-time information. Additionally, digital twins optimize maintenance by predicting issues and minimizing downtime. Utilizing technologies such as the Internet of Things (IoT) and big data, they are essential for innovation in manufacturing, enhancing the efficiency of industrial operations [51][52][53].

2) The Role of digital twins in industry: The digital twin serves as a pivotal tool in various stages of the manufacturing process, used for virtually verifying and enhancing product designs based on data derived from previous products. Digital twins contribute to selecting optimal materials through accurate simulations of properties and costs, thereby enhancing the effectiveness of the design process.

During the manufacturing phase, digital twins enhance resource management, production planning, and process control, reducing downtime by implementing predictive maintenance strategies. Post-sale, digital twins provide real-time monitoring of product operational status, aiding companies in developing effective data-driven maintenance strategies. Moreover, they improve productivity by analyzing root causes of failures and enhance transparency in the supply chain through accurate tracking of logistics.

Digital twins are essential in the digital transformation of factories, providing deeper insights into operations and enhancing operational efficiency. In transportation, they foster the use of digital technologies and artificial intelligence by integrating big data, contributing to future planning of transportation systems like high-speed trains. Thus, digital twins are strategic tools that enhance innovation and efficiency in the industrial sector [51][52][54].

3) Building a digital twin: The integration of a set of essential details into the framework of Industry 4.0 places the Internet of Things (IoT) as the backbone of this concept, providing a network of devices equipped with sensors with much data in the commercial reality, which is still in the creation of digital models of the current state of production. The digital one is thus built from three basic elements: the physical world, which includes tangible objects and sensing; the virtual world, which includes the digital twin itself and technologies such as learning and databases; and the observable, especially between the two worlds via protocols such as WiFi and Bluetooth, which enables the exchange of new data. Cloud computing completes this system by storing data extracted from the IoT, providing valuable insights and facilitating access to information, leading to digital balance. Multiple digital technologies are presented on various boards such as Microsoft Azure, which offers a range of services to support advanced digital models, including Azure IoT and Azure Big Compute, which contribute to enhancing the efficiency and effectiveness of industrial processes. In addition, AI produces a versatile ability to analyze digital data and decode complex processes, enabling accurate predictions and potential performance and capabilities distribution. Data also envisions an optional aspect in this context, allowing users to customize and monitor information, creating interaction between the world and facilitating better decision-making on available data analytics.[53][55]

4) Examples of digital twin implementation in leading companies: Digital twin technologies are showcased on various platforms, such as Microsoft Azure, which offers a range of services to support the creation of advanced digital models, including Azure IoT and Azure Big Compute. Furthermore Siemens is a leading company in industrial manufacturing in Germany, leveraging digital twin solutions to enhance strategic decision-making regarding its fleet of gas turbines. This system relies on analyzing large amounts of available data, allowing for the integration of information related to customers, supply chains, production, and maintenance. This integration contributes to improved productivity and asset management. The technology gathers accurate data on turbine performance, repairability, renewability, and spare parts inventory, processing this data within dynamic simulation models. This enables engineers to make informed decisions about fleet management, enhancing operational efficiency and overall performance [53].

In the context of digital twin applications, a company in Germany has introduced an advanced solution known as Tunnelware. This system enables the diagnosis of the working condition of underground engineering equipment through effective collaboration between tunnel designers, owners, and technical staff. This collaboration enhances operational efficiency and addresses the complex challenges associated with underground work environments. To improve operational efficiency, the University of California, San Francisco, developed an advanced model by implementing diagnostic and repair technologies at the Bay Mission Hospital branch. These technologies have reduced the time for diagnosing and repairing building pipes from two to three days to just a few hours, reflecting the effectiveness of modern technology in enhancing efficiency and reducing response times in maintenance operations, thereby improving the quality of service provided to patients[56].

General Electric (GE) is a leader in the digital twin (DT) market within the energy sector, with its solutions reducing startup time by 50%, cutting maintenance costs by 10%, and saving up to 5 million dollar per megawatt-hour. Additionally, GE's solutions help reduce power outage costs by up to 150 million dollar annually, showcasing their significant impact on economic efficiency and energy system reliability [56].

In a collaboration with Microsoft, Thyssenkrupp developed a digital twin framework for an advanced elevator system in a high-rise building in Rottweil, Germany. This system, which integrates IoT technology for vertical and horizontal movement, reduces elevator downtime and enhances service levels. It also provides real-time data on elevator usage, ensuring efficient operation for over 10,000 users daily, highlighting the role of digital innovation in improving vertical transportation systems [56].

Regarding marine structures, Axelos has developed a comprehensive digital twin (DT) framework in conjunction with parallel cloud computing. This framework allows for risk-based decision-making in real-time, responding to the varying uncertainties faced in marine structural engineering. It addresses the effects of waves, winds, marine environments, and other factors, contributing to the improved performance and sustainability of marine structures[56].

5) Challenges in the industry: The challenges associated with the application of digital twins in the industry encompass several key aspects. First, many organizations face difficulties in data integration, as information is collected from multiple sources, complicating the linkage between systems and affecting operational effectiveness. Second, the risks related to cybersecurity increase due to the growing connectivity between devices, necessitating the adoption of robust security strategies to protect data and systems. Additionally, digital twins suffer from a lack of integration with Internet of Things (IoT) systems, where weaknesses in security and reliability during synchronization negatively impact performance and operational safety. The high costs of implementing and maintaining digital twins also present a significant barrier for small and medium-sized enterprises, limiting their ability to adopt this advanced technology. Moreover, there is a shortage of specialized skills related to data analysis and information technology, hindering the ability to fully leverage digital twins. Organizations also face resistance to organizational change, affecting the acceptance of new technologies. Integrating digital twins with existing systems requires a substantial investment of time and effort, along with the need for ongoing updates and maintenance to maintain accuracy and effectiveness. These challenges demand well-thought-out and integrated strategies to ensure success in implementing digital twins and achieving the desired benefits.[52][57] The digital twin is a critically important strategic tool that redefines the management of industrial operations. By enabling the virtual model to rely on real data, organizations can achieve significant improvements in efficiency, reduce costs, and enhance decision-making based on accurate information.However, the potential benefits of digital twins require addressing the challenges associated with data integration and cybersecurity, necessitating the development of effective strategies. Investing in this technology represents a fundamental step for organizations towards achieving innovation and sustainability in evolving industrial work environments.

B. Healthcare

The Digital Twin in healthcare is an innovative technology designed to create a dynamic virtual model that accurately reflects an individual's health status or the performance of medical systems by integrating and analyzing data from multiple sources. This model relies on clinical data, including electronic health records, laboratory tests, and medical imaging, alongside genomic and molecular data that enhance precision medicine by tailoring treatments to patients' biological characteristics. Additionally, physiological data from wearable sensors play a crucial role in real-time health monitoring, while environmental and behavioral data contribute to a comprehensive understanding of factors influencing patient health. The Digital Twin is characterized by key features such as realtime data synchronization for continuous updates, the use of artificial intelligence and predictive analytics to improve diagnosis and treatment, and virtual simulation models that allow testing therapeutic strategies before clinical application. The development of a Digital Twin follows a structured process, beginning with data collection and processing to ensure accuracy and integration, followed by the creation of a virtual model using AI and IoT technologies, and then linking it to real-time data for continuous updates and health monitoring. Furthermore, data analysis helps identify disease patterns and predict health conditions, thereby enhancing clinical decision-making and optimizing hospital operations. Through these capabilities, the Digital Twin strengthens healthcare by enabling personalized and precise treatments, reducing risks, and improving patient outcomes, making it a transformative solution in the digital evolution of healthcare [58],[59],[60].

1) Applications in the health field: Digital Twin (DT) is used in medicine to enhance diagnosis and treatment through imaging and data analysis [61]. In cardiovascular diseases, DT aids in accurate diagnosing heart and artery conditions [62]. While in cancer treatment, patient data has been integrated for early diagnosis and risk prediction[63]. In orthopedics, a DT predicts lumbar spine biomechanics in real-time [64].

2) Challenges:

a) Data collection and integration: Standardizing health records poses considerable challenges, further exacerbated by the absence of automated systems for handling unstructured data. Moreover, the integration of diverse data sources remains intricate, necessitating sophisticated approaches to achieve seamless interoperability and ensure data accuracy [65].

b) Data privacy in digital systems: Protecting patient data is a critical challenge amid the expansion of artificial intelligence and big data. This necessitates the implementation of encryption, secure storage, and access control mechanisms to prevent breaches and data misuse. Striking a balance between data accessibility for research and ensuring patient privacy is essential to fostering trust in digital health technologies[66].

C. Smart Cities

The concept of digital twins revolves around creating virtual counterparts of real-world entities, including people, objects, connections, and processes. This virtual representation enables the analysis, monitoring, and management of physical systems by simulating their digital models. In the context of urban transportation and smart city development, digital twins provide significant advantages by enhancing operational efficiency and decision-making [3].

The Digital Twin City model is characterized by four key elements: Accurate Mapping, Virtual-Real Interaction, Software Definition, and Intelligent Feedback. By deploying sensors across multiple layers of the urban environment—including air, ground, underground, and waterways—a digital twin city can establish a comprehensive digital model of urban infrastructure, encompassing roads, bridges, manhole covers, lamp posts, and buildings. This facilitates real-time monitoring and full perception of the city's operational status, ensuring precise information exchange between the virtual and physical city within the digital ecosystem [67].

A fundamental advantage of Virtual-Real Interaction is the ability to track and analyze traces left by people, vehicles, and logistics within the virtual city as soon as they are generated in the physical world. Meanwhile, Software Definition allows for the creation of a dynamic digital model that replicates urban systems, enabling simulations of behaviors, events, and objects within the virtual environment. Lastly, Intelligent Feedback provides early warnings regarding potential risks, conflicts, or adverse effects in urban areas. Through planning, design, and simulation within the digital twin, cities can develop proactive countermeasures to mitigate potential challenges before they arise, fostering more efficient, resilient, and data-driven urban management [67].

The Digital Twin City model serves as the foundation for integrating advanced technologies such as the Internet of Things (IoT), cloud computing, big data, artificial intelligence (AI), and other next- generation IT solutions. This integration plays a crucial role in optimizing urban planning and management, improving the efficiency of physical city operations, and enhancing the delivery of citizen services, ultimately accelerating the development of smart cities [68].

The Internet of Things (IoT) is a rapidly evolving field with significant technical, social, and economic implications. By leveraging strong internet connectivity and advanced data analytics, IoT enables a vast array of connected devices—including consumer products, durable goods, automobiles, industrial components, and sensors—to revolutionize both daily life and professional sectors. The synergy between IoT and digital twin technology strengthens urban management by enabling real- time monitoring, predictive analytics, and data-driven decision-making, leading to more resilient and adaptive smart cities [69].

Recognizing these benefits, many countries have already initiated the adoption of digital twin technologies in their cities, setting the stage for more efficient, data-driven urban management strategies. Figure 5 adapted from [70], illustrates a selection of cities that have begun implementing digital twin solutions, providing a clearer perspective on the global adoption and evolution of this transformative technology.

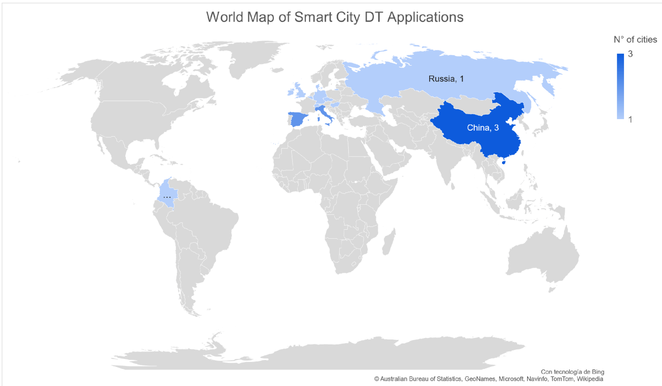

Fig. 5. Worldwide Map of digital twin implementations in smart cities [71].

1) Applications: One of the notable applications of digital twins is the integration of Building Information Modeling (BIM) and digital twin technology to manage the construction, operation, and maintenance of smart buildings. A digital model is created to simulate the building before and during construction, enabling the anticipation of technical issues and the development of effective construction management plans. For instance, BIM technology allows for simulating different construction stages, detecting potential errors and logistical obstacles, and making timely adjustments to construction plans. Consequently, this technology not only supports the design of smart buildings that meet sustainability and innovation standards but also helps increase productivity and reduce costs and waste [30].

Beyond their role in smart building management, digital twins play a crucial part in optimizing transportation systems, further demonstrating their versatility and impact on developing efficient and sustainable smart cities. Recent scientific studies and reviews highlight a growing interest in digital twin applications for transportation, covering various modes, including air, maritime, and land transport. The increasing adoption of this technology is driven by its capability to enhance efficiency, safety, and sustainability. Simultaneously, evolving customer demands have placed significant pressure on transportation companies, necessitating rapid, flexible, and secure services while maintaining high quality across all stages of transportation. Achieving these goals requires modern fleets, advanced maintenance systems, and swift emergency response capabilities.

In this context, digital twins emerge as a promising solution for predicting potential malfunctions, proactively managing maintenance schedules, and coordinating repair procedures using real-time data. These capabilities enhance the efficiency of transportation systems, ensuring that they can meet evolving demands while supporting the broader vision of smart cities [72].

Beyond transportation, digital twins play a transformative role in smart infrastructure, leveraging real-time data to boost efficiency, lower costs, and improve sustainability. However, as adoption is still in its early stages, challenges such as technology integration, cultural adaptation, and workforce skill gaps persist. Addressing these challenges through digital upskilling and innovation can accelerate adoption and unlock the full potential of digital twins in urban development. Despite these hurdles, digital twins offer substantial opportunities to revolutionize infrastructure management and drive sustainable, data-driven city development [73].

2) Challenges of digital twins in smart cities: Despite advancements, digital twins (DTs) in smart cities face key challenges, including data availability and ownership, as datasets are often fragmented among stakeholders, complicating integration. Data standards and interoperability remain critical, requiring unified frameworks for seamless adoption. Stakeholder collaboration is essential, demanding co-creation models between public and private sectors. Additionally, cost and scalability pose hurdles due to hidden infrastructure expenses. The complexity of urban environments necessitates modular solutions, while edge computing and distributed intelligence can optimize resources but require balanced computational loads. Addressing these issues is crucial for maximizing DTs' impact on urban development and sustainability [74].

V. General Challenges of Digital Twin Technology

Digital twin technology faces a set of challenges that require precise handling to ensure its effectiveness. First, the spatial-temporal accuracy of sensor data emerges as a critical factor in achieving effective communication between physical assets and digital twins, necessitating the assurance of real-time data accuracy. Additionally, response time in communications is essential, requiring quick and effective responses to ensure seamless interaction. Systems also face challenges related to large data volumes and high data generation rates, demanding the capability to process vast amounts of information periodically. Furthermore, managing data diversity and maintaining data integrity is crucial for ensuring the reliability of incoming information. Rapid retrieval for archiving is also vital for improving operational efficiency. On the other hand, digital models need to evolve in tandem with physical assets to ensure compatibility with ongoing changes. Finally, the importance of security and safety is highlighted, necessitating high levels of protection, as well as transparency and interpretability of decisions made, which calls for the design of interpretable models that align with ethical standards [10].

VI. Conclusion

The convergence of Digital Twin technology with Artificial Intelligence (AI) represents a paradigm shift in the design and operation of intelligent systems. This integration, evident in applications across industries such as manufacturing, healthcare, and urban management, transforms traditional static models into dynamic, adaptive systems that provide real-time insights and continuous feedback. By supplying AI systems with live data streams and realistic simulation environments, Digital Twins significantly enhance the predictive capabilities and decision-making accuracy of AI, thereby improving operational efficiency and enabling proactive maintenance strategies.

However, challenges persist, primarily related to the need for accurate sensor data, seamless data integration, and robust cybersecurity measures. Addressing these challenges is essential for fully leveraging the potential of AI-powered Digital Twins. Future research should focus on developing standardized frameworks, scalable architectures, and advanced security protocols to accommodate the growing complexity of interconnected systems. Ultimately, the integration of Digital Twins with AI not only advances technological capabilities but also fosters innovative solutions that have the potential to redefine efficiency and sustainability in complex, real-world environments.

Future research should focus on addressing the key challenges associated with digital twin technology to enhance its reliability, efficiency, and security. One critical area for exploration is improving the spatial-temporal accuracy of sensor data to ensure precise and real-time synchronization between physical assets and their digital counterparts. Additionally, optimizing response times in digital twin communications remains crucial for achieving seamless interactions, particularly in time-sensitive applications. Given the exponential growth in data generation, future studies should investigate scalable data processing techniques capable of handling large volumes of diverse information while maintaining integrity and reliability. Efficient data retrieval and archiving mechanisms should also be explored to enhance operational efficiency and decision-making processes.

Moreover, the continuous evolution of digital models in alignment with physical assets necessitates the development of adaptive frameworks that can accommodate structural and functional changes over time. Security and privacy concerns must also be addressed through advanced encryption methods, robust authentication mechanisms, and interpretable AI models that ensure transparency and ethical decision-making. Furthermore, integrating digital twins with AI presents new opportunities for predictive analytics, intelligent automation, and proactive maintenance strategies across various industries. To fully leverage these benefits, future work should focus on developing standardized interoperability frameworks, scalable architectures, and robust cybersecurity measures to support the increasing complexity of interconnected systems. Ultimately, advancing digital twin technology will not only improve system efficiency but also contribute to the broader goals of sustainability and intelligent system design in real-world applications.

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