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Research Article

Harnessing Digital Twins: Advancing Virtual Replicas for Optimized System Performance and Sustainable Innovation

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ABSTRACT

Digital twins (DTs) have recently become an extremely influential and disruptive concept in engineering and technology. They are characterized as dynamic virtual replicas of physical systems used for real-time monitoring, simulation, and optimization. In the face of growing complexity in modern industries, digital twins offer the capacity to aggregate data from IoT sensors, utilize AI-based analytics, and provide predictive and prescriptive decision-making to achieve operational excellence and drive sustainable innovation.

This review presents an in-depth overview of the state-of-the-art in digital twin technologies, covering their conceptual foundations, enabling technologies, application domains, theoretical frameworks, as well as the key challenges and future potential of digital twins. The review highlights how digital twins are enabling progress in diverse sectors, including manufacturing, healthcare, construction, energy, supply chains, and emerging fields such as 6G networks and autonomous systems.

Beyond summarizing technological advancements, this review emphasizes the importance of socio-technical perspectives, ethical considerations, and interdisciplinary collaboration in shaping the future trajectory of digital twin development. Finally, it identifies key areas for future research and practice, including standardization, human-centered design, governance, and the evolving role of digital twins in advancing Industry 5.0 and sustainable innovation.

The primary goal of this review is to empower researchers, practitioners, and policymakers to leverage the potential of digital twins for intelligent and adaptive systems, by providing an integrated and critical perspective.

1. INTRODUCTION

1.1 Definition and Scope of Digital Twins

Our focus here is on Digital Twins (DTs) in the context of CPSs (e.g., industrial automation, automotive systems, aerospace, energy systems, etc.). Digital Twins (DTs) are a transformative paradigm at the convergence of engineering, data science, and information technology. Digital Twins have recently been introduced as a dynamic and virtual model of a physical process, that receives and integrates continuously data from real-world systems to simulate, analyze, and optimize their functionalities and performance in real time [1]. Compared to conventional static models or classic simulations, digital twins utilize modern sensors, artificial intelligence (AI), and Internet of Things (IoT) architectures to facilitate bidirectional communication between the real world and the cyber environment [2]. This ongoing synchronization enables digital twins to not only mirror the operation of a system but also to forecast future behaviors, consider alternative scenarios, and facilitate autonomous decision-making [3].

Digital twins have applicability in a variety of industries and application domains including manufacturing, aerospace, healthcare, energy, and smart cities [4]. In industrial environments, such as manufacturing or the process industry, digital twins provide predictive maintenance, process optimization, and real-time monitoring of the production line [5]. In a medical context, digital twins enable patient-specific simulations for targeted personalized medicine and surgical planning [6]. Furthermore, as edge computing, cloud services, and AI-based analytics continue to merge, the capability of digital twins to enable large-scale distributed and autonomous systems is quickly increasing [7]. In this review, we take a wide yet

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organized view of digital twins, including technology background as well as cross-sectoral applications, focusing on their impact on system performance and on the generation of innovation.

1.2 Evolution and Increasing Relevance in Engineering and Technology

The concept of digital twin was proposed in the early 2000s and introduced in product lifecycle management and aerospace engineering [8]. The term gained increasing popularity in the context of high-fidelity simulations of spacecraft systems developed by NASA for mission assurance and predictive maintenance [9]. In the last 20 years, the development of enabling technologies, including IoT, AI, big data analytics, and cloud computing, has expanded the capabilities and scope of digital twins [10].

CPS began to merge with industrial IoT during the 2010s, which can be perceived as the tipping point in the evolution of digital twins [11]. Academics and practitioners started to investigate the potential of real-time data integration for dynamic simulation and continuous monitoring of complex systems [12]. Recent developments in machine learning and edge intelligence have also improved the analytics capabilities of digital twins, enabling adaptive learning and autonomous decision-making [13]. Today, digital twins are more commonly considered to be strategic enablers for innovation, operational excellence, and sustainability rather than only tools for monitoring and simulation [14].

The relevance of digital twins is also reflected in international industry initiatives and standardization activities. Organizations such as the International Organization for Standardization (ISO) and Industrial Internet Consortium (IIC) are currently developing interoperability standards and reference architectures to facilitate the adoption of digital twins across industries [15]. In addition, the relevance of the digital twin and its relationship with emergent concepts, like Industry 5.0, metaverse, and 6G networks, demonstrates its leading role in the development of engineering and technology [16].

1.3 Aim and Structure of the Review

In view of the rapid developments and multidisciplinary nature of digital twin research, it becomes necessary to have a holistic review addressing the state-of-the-art, trends, and challenges in digital twin technology. The current literature presents much valuable specific application and technical development, but a holistic view of the relationship between methodological, theoretical, and practical aspects is still lacking [17]. In addition, important aspects like data privacy, governance, ethical considerations, and socioeconomic implications of digital twins are usually treated in a scattered way [18].

The intention of this review is to deliver an up-to-date and structured overview of digital twin research and practice. In particular, this review aims at (1) structuring the conceptual roots and technological underpinnings of digital twins; (2) characterizing their applications in major industrial and societal areas; (3) examining emerging methodologies and theoretical viewpoints; (4) expounding the main challenges and adoption obstacles; and (5) outlining promising directions for research and opportunities for innovation.

We organize the review as follows to achieve these objectives:

- In Section 2, we cover the theoretical fundamentals of digital twins, mapping their evolution and explaining central concepts.
- In Section 3, we describe how this review was carried out, including the selection criteria of the searched literature, the analysis used, and the extent of the literature examined.
- Section 4 presents a detailed overview of digital twin implementations across a variety of industries, exemplified by use cases.
- The underpinning enabling technologies of digital twin systems are detailed in Section 5.
- Section 6 addresses theoretical foundations and interdisciplinary perspectives on digital twin research.
- The key challenges and barriers to adoption are discussed in Section 7.
- Section 8 highlights opportunities and future research directions for advancing digital twins.
- The final Section 9 presents the conclusion, summarizing key findings and offering recommendations for future innovation in digital twin technologies.

2. CONCEPTUAL FOUNDATIONS OF DIGITAL TWINS

2.1 Historical Evolution

Digital Twins (DTs), as a concept, originate from a rich history of technological advancement and interdisciplinary developments. Their earliest conceptual origins are rooted in the product lifecycle management (PLM) field, where the idea of building a detailed digital artifact of a physical item was introduced to improve manufacturing and maintenance processes [17]. One of the initial formal descriptions of the digital twin was by NASA to describe the simulation of high-fidelity models of machines and systems for monitoring system health and for troubleshooting problems in space [18]. The initial applications resulted mainly from the necessity of risk management and the requirement for robustness in aerospace engineering.

In the last decade, the rapid spread of enabling technologies such as Internet of Things (IoT), cloud computing, and big data analytics has triggered the wider diffusion of digital twins within a diversity of industrial fields [19]. The combination of live sensor information and advanced modeling was a paradigm shift, enabling digital twins to do more than just replicate behavior in static simulations — as dynamic, self-updating entities [20]. This evolution coincided with the birth of Industry 4.0, which stressed the fusion between physical and digital worlds to enable operational excellence and innovation [21].

Digital twins now have a much more mature and multidimensional technological base. They provide the basis for numerous applications, ranging from predictive maintenance in manufacturing to personalized healthcare and smart city administration [22]. As shown in Figure 1, the architecture for a digital twin system often includes several layers, such as data collection, processing layer, AI-based modeling layer, and user interface elements, connected through two-way data exchange between the physical and virtual worlds.

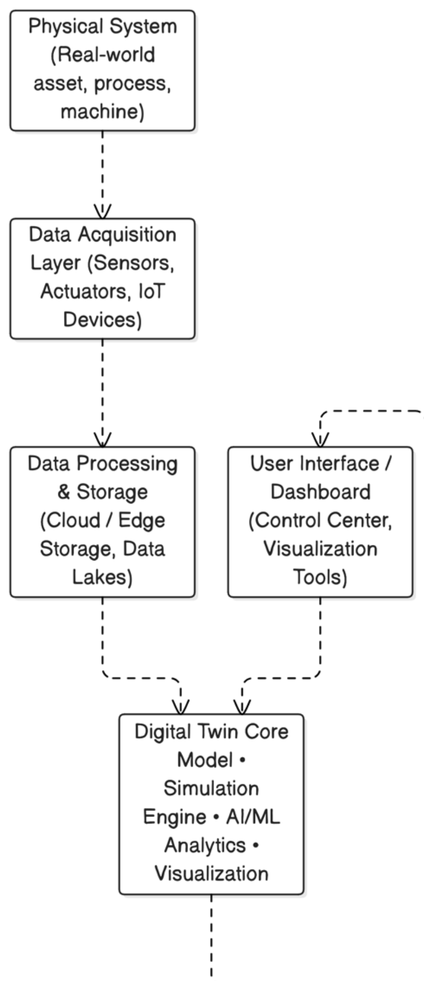

Fig. 1. Architecture of a Digital Twin System: Layers and Data Flow between Physical and Virtual Domains

2.2 Definitions and Typologies

Although the concept of a digital twin is widely accepted in academia and industry, diverse interpretations and classifications exist depending on use cases. Conceptually, a digital twin is a digital replica of something that exists physically and is updated in real time to reflect how it changes or is used [23]. This definition emphasizes two important features of a digital twin: (1) its dynamic behavior realized by continuously synchronized data and (2) its capability for simulation and prediction in the decision-making process [24].

In the literature, different typologies of digital twins have been defined **to** distinguish the degree of sophistication and functionality of such models. A common taxonomy identifies three categories: digital models, digital shadows, and digital twins [25]. Digital models are stand-ins for physical systems that do not incorporate real-time data. Digital shadows integrate unidirectional data flow from the physical to the digital system, allowing occasional updates. In contrast, true digital twins feature bidirectional data exchange, enabling interaction and mutual influence between the physical and digital domains in real time [26].

Furthermore, digital twins can also be classified according to their level of representation. These are component-level twins (focusing on parts), system-level twins (representing complex assemblies or entire systems), and process-level twins (modeling workflows or operational processes) [27]. Digital twins can be applied across various industries and scenarios, with varying abstraction levels and degrees of integration depending on specific applications.

2.3 Correlation to Cyber-Physical Systems (CPS), IoT, AI, Industry 4.0/5.0

The introduction and application of DTs are closely linked to several core technology paradigms, including Cyber-Physical Systems (CPS), the Internet of Things (IoT), artificial intelligence (AI), and Industry 4.0 and 5.0 frameworks. CPS form the architectural basis of digital twins, enabling continuous interfacing between computational models and physical objects via embedded sensors and actuators [28]. This tight integration of the cyber and physical worlds enables digital twins to attain high levels of realism and real-time fidelity in simulating real-world phenomena.

The IoT's role is equally important. IoT devices are the main sources of real-time data that drive digital twin models. By collecting fine-grained data on the performance of physical assets, IoT networks enable digital twins to maintain an accurate and current representation of the system of interest [29]. The scale and granularity of IoT data further support the development of multi-scale digital twins, capable of modeling phenomena from component-level behavior to system-wide interactions [30].

Digital twins benefit significantly from the powerful analytics and predictive capabilities of artificial intelligence. Through machine learning algorithms and sophisticated data analytics, digital twins can uncover patterns, generate predictions, and support autonomous decision-making [31]. The integration of AI enables digital twins to evolve over time, transforming them from static representations into adaptive, intelligent systems [32].

Finally, the emergence of the 4th Industrial Revolution and the newer Industry 5.0 paradigm provides the socio-technical context for the rapid diffusion of digital twins. Industry 4.0 emphasizes the digitization of manufacturing and industrial processes through CPS, IoT, and AI [33]. Digitization is essential for creating self-optimizing, predictive, and intelligent systems, with digital twins at the core. Meanwhile, Industry 5.0 focuses on human-centered, sustainable, and resilient industrial systems enabled by digital twins — where the goal is not only efficiency but also enhanced human-machine collaboration and environmental stewardship [34].

To summarize, the conceptual foundations of digital twins rest on a dynamic equilibrium between historical evolution, definitional clarity, and synergy with allied technological paradigms. As this review will explore in greater depth, these foundations support a wide range of applications and innovations that are revolutionizing engineering and technological landscapes across many sectors.

3. METHODOLOGY OF THE REVIEW

The methodological approach in this review is intended to facilitate an extensive and organized overview of the existing research on digital twins. Because of the multifaceted nature of the field, a variety of literature from engineering, computer science, healthcare delivery, urban planning, and organizational studies has been cited in the review. The aim is to survey both the width and depth of applications, frameworks, and nascent theoretical perspectives of digital twins.

3.1 Review Papers Selection Criteria

We performed a systematic search on academic databases, which are Scopus, Web of Science, IEEE Xplore, SpringerLink, and ScienceDirect. These databases were selected because they comprehensively index peer-reviewed journal and conference literature and research theses on the topic of digital twins.

To facilitate the search, a number of basic keywords and their combinations were used: "digital twin", "digital twins", "digital twin framework", "cyber-physical systems", "digital twin and Industry 4.0", "AI-enabled digital twin", "IoT-based digital twin", "digital twin in manufacturing", "digital twin in healthcare", "digital twin architecture", and "digital twin applications". Searches were further refined through the application of Boolean operators to achieve as complete a coverage as possible of relevant studies.

The first stage of the search covered the period of 2015–2025 to concentrate on the most recent and influential work while capturing seminal work over the last decade [35]. A further manual search of reference lists of pivotal articles was undertaken to locate landmark texts that may have been missed in the database search.

3.2 Inclusion and Exclusion Criteria

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The following inclusion criteria were adopted to choose the studies for this review: (1) peer-reviewed papers, conference papers, and authoritative reports; (2) works directly discussing the concept, framework, or application of digital twins; (3) studies contributing theoretical, methodological, and practical knowledge on digital twin technologies; and (4) papers written in English.

By contrast, the exclusion criteria were designed to maintain focus and quality. Exclusion criteria were: (1) articles that merely referred to digital twins without any substantive content; (2) papers that were purely speculative or theoretical without empirical or methodological underpinnings; (3) duplicate reports from different databases; and (4) non-peer-reviewed content such as editorials, opinion articles, and trade magazines.

The screening and selection followed a multistage strategy, starting with title and abstract screening, followed by full-text review to evaluate eligible studies. A PRISMA-style flowchart (Figure 2) outlines this process, illustrating the number of records considered, screened, and included in the final synthesis.

3.3 Analytical Approach

A qualitative synthesis of findings was used as the main analytical strategy owing to the heterogeneity of fields and research designs covered in the body of digital twin work. The selected articles were thematically reviewed according to prevailing trends, conceptual frameworks, enabling technologies, sectoral applications, and open challenges. Special emphasis was placed on cross-sectoral trends and new interdisciplinary approaches that are advancing the field of digital twins.

When possible, a bibliometric trend analysis was also performed to complement and frame the qualitative synthesis. Using Scopus-derived data, the yearly publication trends, top contributing journals, most-cited articles, and top contributing nations/institutions were established. While this part of the bibliometric analysis is exploratory, it offers a more detailed understanding of the maturity and global distribution of digital twin research [36].

Through the combination of thematic synthesis and bibliometric trend analysis, a comprehensive and integrated review is achieved, allowing for depth and breadth of understanding of the current field. Moreover, this approach is consistent with best practices for modern literature reviews and contributes to the strength, transparency, and replicability of this study [37].

4. DIGITAL TWIN USE CASES BY INDUSTRY

Digital twin (DT) has been recognized as an enabling technology that brings groundbreaking changes to various industries in the areas of system optimization, predictive maintenance, and decision support. Their distinctive capability to offer data-driven and real-time-informed views makes digital twins one of the leading drivers of digital transformation in sectors ranging from manufacturing and healthcare to construction, transportation, energy, and beyond. In this section, the current status of applications in major sectors is synthesized, with particular attention to trends observed across and within sectors.

4.1 Manufacturing and Industry 4.0

Industry 4.0 is expected to revolutionize manufacturing and industry, transforming the way products are created and brought to market.

The manufacturing industry is one of the most advanced domains to adopt the concept of digital twins. In the context of Industry 4.0, digital twins are widely used to optimize the production phase, realize predictive maintenance, and reinforce quality control [38]. Through persistently synchronizing real-time sensing information with virtual models of machinery, production lines, or even entire plants, manufacturers are capable of predicting breakdowns, reconfiguring process parameters online, and optimizing operational flow [39].

Promising case studies have shown that implementing digital twins in manufacturing can significantly reduce unplanned downtime and maintenance costs while increasing yield and energy efficiency [40]. Furthermore, the fusion of AI with digital twins facilitates adaptive learning from both historical and real-time data, promoting continuous process excellence [41].

4.2 Healthcare

In medical applications, digital twins are emerging as a powerful tool for patient-specific modeling, predictive diagnostics, and personalized treatment planning [42]. Applications include anatomical modeling for surgical planning and physiological modeling that facilitates continuous patient monitoring in intensive care units (ICUs) [43].

For example, virtual hearts — digital twins — have been employed to model the electrophysiological properties of the heart, helping to design treatments for arrhythmias [44]. In orthopedics, digital twins allow for the design of customized prosthetic implants based on individual biomechanics [45]. Research in this field was further catalyzed by the COVID-19 pandemic, which spurred the use of digital twins for decision-making, hospital resource allocation, and modeling of infectious disease spread [46]. The healthcare domain is highly suitable for precision medicine and enhanced patient care.

4.3 Building and Smart Cities

Digital twins are gaining momentum in the building and construction industry, as well as in urban planning for sustainable infrastructure and smart city projects [47]. Building Information Modeling (BIM), a precursor to digital twins in civil engineering, has evolved to incorporate live data feeds and enable real-time monitoring of building performance, structural health, and energy consumption [48].
In smart cities, urban digital twins collect data from transportation systems, utilities, environmental sensors, and citizen interactions to provide an integrated view of the city for governance [49]. Recent implementations in cities such as Singapore and Helsinki demonstrate the potential of urban digital twins to optimize traffic flow, reduce energy consumption, and enhance disaster response capabilities [50]. Scalable digital twins in this context are essential elements for building future urban resilience.

4.4 Aerospace and Automotive

Digital twins are well established in the aerospace and automotive sectors, where they support the entire product lifecycle — from design and testing to operation and maintenance [51]. In aeronautics, they provide real-time simulation of components and systems, supporting predictive maintenance by accounting for stress and other factors to prolong component life and enhance flight safety [52].
In the automotive industry, digital twin technology enables virtual prototyping and vehicle simulation under varying operational conditions, accelerating development and reducing reliance on physical tests [53]. With the emergence of self-driving vehicles, digital twins play a key role by simulating complex test scenarios and training AI driving algorithms [54].

4.5 Supply Chain and Logistics

Supply chains are becoming increasingly dynamic and complex, requiring advanced tools for real-time visibility and optimization. Supply chain digital twins provide virtual representations of inventory flows, transport networks, and demand models [55]. By aggregating data from IoT-enabled logistics assets, enterprise resource planning (ERP) systems, and external market signals, digital twins enable predictive analytics and scenario-based planning [56].
These capabilities have proven especially valuable in overcoming supply chain disruptions and enhancing resilience, particularly during recent global crises [57]. Furthermore, AI-powered digital twins can autonomously optimize routing, inventory management, and supplier selection [58].

4.6 Energy and Utilities

In the energy sector, digital twins of complex systems are used for smart grids, power plants, and wind farms to perform load analysis and performance management [59]. Real-time simulations of grid dynamics support load balancing, fault detection, and predictive maintenance, improving the reliability and efficiency of energy infrastructure [60].
For renewable energy, digital twins of wind turbines and solar farms support condition monitoring and adaptive control strategies to maximize power production [61]. In the utilities sector, digital twin technology enhances operational optimization and regulatory compliance monitoring of water and wastewater treatment plants [62]. These applications, contribute to the transition toward sustainable and resilient energy systems.

4.7 Novel Applications: 6G, Autonomy, and Sustainability

Beyond established sectors, digital twins are enabling innovations in 6G networks, autonomous systems, and sustainability initiatives. Network digital twins are being explored in telecommunications to enhance the design, deployment, and management of future-generation 6G networks [63].
In robotics and autonomous systems, digital twins are used to simulate and validate the behavior of complex multi-agent systems in dynamic environments [64]. Additionally, digital twins are increasingly viewed as facilitators of sustainability through support for circular economy practices, lifecycle assessment, and environmental impact analysis [65].
As digital twin technologies continue to evolve, their potential to address global challenges such as climate change, public health, and urbanization is becoming clear. These emerging applications are highlighted in Table 1.

TABLE I. SUMMARY OF KEY DIGITAL TWIN APPLICATIONS ACROSS SECTORS

Sector / Domain	Example Applications	Reported Benefits	References
Manufacturing	Predictive maintenance, process optimization, real-time monitoring of production lines	Reduced downtime, improved efficiency, cost savings	[3],[5], [14]
Healthcare	Patient-specific simulations, surgical planning, digital patient monitoring	Personalized treatment, risk reduction, better outcomes	[6], [17]
Construction & Smart Cities	Structural monitoring, energy optimization in buildings, urban planning	Increased safety, energy savings, enhanced decision-making	[4],[9], [15]
Aerospace & Automotive	Virtual prototyping, testing of aircraft/vehicles, fleet management	Faster development cycles, improved reliability, safety	[8], [12]
Supply Chain & Logistics	Autonomous supply chains, real-time inventory management, demand forecasting	Agility, transparency, resilience	[13], [16]
Energy & Utilities	Smart grid management, predictive maintenance of infrastructure	Grid stability, optimized resource use, sustainability	[7], [10]
Emerging: 6G / Autonomous Systems	Digital twins for network optimization, autonomous vehicles, robotics	Performance optimization, adaptive learning	[11], [18]

5. KEY ENABLING TECHNOLOGIES

The rapid development and continuous proliferation of DTs are mainly inspired by the confluence of a set of enabling technologies. These technologies not only furnish the infrastructure for constructing and deploying digital twins but also enrich the analytical power, scalability, and reliability of digital twins. In this section, we discuss four key technological infrastructures supporting digital twin implementation: (a) IoT integration, (b) AI and ML, (c) big data and cloud architectures, and (d) blockchain for data integrity and security.

5.1 IoT Integration

IoT forms the bottom layer to support digital twins by facilitating real-world data streams that generate shadows and observe physical objects in reality [66]. We refer to sensors, actuators, and embedded controllers that collect fine-grained data on system states, environmental conditions, and operational parameters as IoT devices. These data are sent to the digital twin, which is continuously updated and simulated.

The development of IoT has greatly increased the range and scale of digital twins. In production environments, IoT-enabled sensing on the shop floor enables condition monitoring and predictive maintenance [67]. In smart cities, IoT endpoints aggregate data from transportation systems, energy grids, public infrastructure, and other sources to fuel urban digital twins [68]. Digital twins are not dynamic or real-time without IoT integration. The interaction between IoT and digital twins, forms the foundation of cyber-physical convergence in modern industrial systems.

5.2 Digital Twin Enhanced Capabilities through AI and Machine Learning

AI and ML are instrumental in advancing digital twins from descriptive models to predictive and prescriptive systems [69]. AI-driven digital twins can analyze past and current data, identify patterns, predict future behavior, and recommend optimal actions.

In manufacturing, ML algorithms combined with digital twins can identify anomalies, predict equipment malfunctions, and recommend process adjustments [70]. In healthcare, AI-enhanced digital twins allow for tailoring treatment planning by simulating patient-specific responses to medical interventions [71]. In addition, reinforcement learning is being studied to enable autonomous decision-making in digital twins for autonomous vehicles and robotics [72]. As AI becomes increasingly integrated with digital twins, they evolve from being merely monitoring tools to becoming intelligent agents, introducing new possibilities for system optimization and innovation.

5.3 Big Data and Cloud-Centric Architectures

To operate effectively, digital twins require reliable big data and cloud-based architectures capable of handling the volume and variety of IoT data generated [73]. Big data platforms enable the ingestion, storage, and processing of large datasets used as input for digital twin models. Sophisticated data analytics pipelines extract actionable insights for real-time and predictive simulations.

Cloud computing offers the scalability and computational power needed to manage complex digital twin ecosystems [74]. Cloud-based digital twin systems can leverage distributed computing resources to run high-fidelity simulations and manage geographically distributed assets. Moreover, cloud platforms facilitate integration with other enterprise systems and enable workflows across organizational boundaries [75]. The intersection of cloud architectures and big data thus supports the scalability and distributed operation of digital twins.

5.4 Blockchain in DTs for Data Integrity and Security

As digital twins play an increasingly critical role in infrastructure and business operations, ensuring the integrity, transparency, and trustworthiness of data becomes paramount. Blockchain has the potential to provide secure, decentralized, and immutable ledgers for recording and authenticating transactions related to digital twins [76].

In supply chains, blockchain can enhance the trustworthiness of digital twins for products and assets that require reliable provenance records across multiple parties [77]. In healthcare, blockchain can safeguard patient data in digital twin systems by improving privacy and compliance with data protection regulations [78]. Moreover, blockchain can support secure interoperability between distributed and cross-organizational digital twins [79].

By improving data integrity and trust, blockchain helps address some of the most critical barriers to broader adoption of digital twins, particularly in environments where regulatory compliance and multi-party collaboration are essential. As digital twins evolve toward more open and collaborative ecosystems, blockchain is emerging as a key enabler of secure and trustworthy digital twin networks.

6. THEORETICAL BACKGROUNDS AND CONCEPTS

As DTs advance to the next generation of complex systems, it is essential to explore the theoretical underpinnings of their development, implementation, and implications. Although much of the current literature focuses on technological applications, a growing body of research examines digital twins through systems engineering, socio-technical, human-centered, and governance perspectives. This section integrates these theoretical perspectives to provide a general framework for digital twins in current and future systems.

6.1 Approaches Based on Systems Engineering

Digital twin development draws heavily from the foundations of systems engineering, which emphasizes holistic design, analysis, and management of complex systems [80]. From a systems engineering perspective, a digital twin is a dynamic model used for continuous verification and validation of system performance across the entire lifecycle — from inception to decommissioning [81].

In digital twins, system models are iteratively updated using real-world data in the context of model-based systems engineering (MBSE) [82]. This supports engineers in managing complexity, enhancing performance, and maintaining traceability of design decisions. Feedback loops are an explicit feature of systems engineering-driven digital twin architectures, where real-time data flows drive adaptive system behavior [83]. This perspective positions digital twins within lifecycle-based, resilient, and adaptive engineering paradigms.

6.2 Socio-Technical Models

Beyond technical considerations, digital twins are increasingly recognized as socio-technical systems that both shape and are shaped by human, organizational, and social contexts [84]. Socio-technical frameworks highlight the co-evolution of technology and society and emphasize that effective digital twin implementation requires attention to organizational culture, user engagement, and inter-organizational collaboration [85].

For example, urban digital twins in smart cities are not merely technical platforms but also collaborative tools involving government agencies, businesses, and citizens [86]. Similarly, in healthcare, digital twins influence clinical decision-making and must align with ethical and professional standards [87]. Socio-technical perspectives expand the scope of digital twin research, fostering interdisciplinary collaboration across engineering, management, social sciences, and ethics.

6.3 Human-in-the-Loop vs. Fully Autonomous DTs

A key point of debate in the digital twin literature concerns the extent of human agency versus system autonomy [88]. Traditional IoT-based digital twins typically adopt a human-in-the-loop model, where users interpret digital twin outputs and make decisions accordingly [89]. This approach promotes transparency, accountability, and user control, particularly in safety-critical contexts such as healthcare and aviation [90].

However, recent advances in AI and machine learning enable the development of fully autonomous digital twins that can make decisions and actuate responses without human intervention [91]. While this enhances system responsiveness and scalability, it also raises challenges related to explainability, trust, and governance [92]. The balance between human-in-the-loop and autonomous approaches is a key theoretical axis in digital twin research, influencing system design, user experience, and ethical oversight.

6.4 Governance and Ethical Requirements

As digital twins become more pervasive and influential, there is a growing call for robust governance and ethical frameworks [93]. Issues related to data ownership, privacy, and interoperability must be addressed in governing digital twin ecosystems [94]. Ethical concerns also arise regarding the societal impacts of digital twins — including effects on employment, equity, and social welfare [95].

In supply chains, while transparency can be enhanced through digital twins, there is also a risk of exposing sensitive business information, necessitating governance mechanisms to manage data sharing responsibly [96]. In healthcare, digital twins have the potential to improve patient outcomes but must comply with stringent data privacy regulations and respect patient autonomy [97]. Furthermore, as digital twins increasingly influence policy decisions in areas such as urban planning and environmental management, ethical frameworks are needed to ensure responsible use and prevent unintended societal harm [98].

Some standards are emerging from organizations such as the International Organization for Standardization (ISO) and the Industrial Internet Consortium (IIC), providing initial guidance for digital twin governance [99]. However, much work remains to develop comprehensive and adaptable governance models that can keep pace with the rapid evolution of digital twin technologies.

7. BARRIERS OR CHALLENGES FOR THE UPTAKE

Digital twins (DT) are a concept that **is** increasing in popularity and has demonstrated great potential, although the degree to which they are introduced and diffused varies by sector, and there are a number of barriers to their introduction and diffusion. These difficulties are multi-faceted, involving technical, data, organizational, economic, and regulatory aspects.

7.1 Technical Problems: Interoperation and Standardization

One commonly mentioned technical challenge is the lack of interoperability among digital twin modules and platforms [100]. Another challenge arises when sharing data and models across systems or between organizations: many implementations of digital twins are proprietary and vertically integrated [101]. This piecemeal approach to development is a significant barrier to realizing open, scalable, and modular digital twin ecosystems, which are crucial for their deployment in complex domains such as smart cities and supply chains.

Standardization is a closely related issue. Although initiatives such as those by the International Organization for Standardization (ISO) and the Industrial Internet Consortium (IIC) are developing reference architectures and data models for digital twins, standards across industries have yet to mature [102]. Organizations may face higher integration costs and the risk of vendor lock-in in the absence of mature standards, leading to slower uptake [103].

7.2 Data Challenges: Quality, Integration, Privacy, Security

Equally important are the data challenges. The quality, accuracy, and timeliness of received data determine, to a great extent, the utility of a DT [104]. Yet several industries face challenges in dealing with disparate and fragmented sources, resulting in conflicting data and integration errors during digital twin simulation [105]. Furthermore, as digital twins increasingly rely on real-time IoT data, the security and trustworthiness of data streams become critical concerns [106].

Privacy is also a serious issue, especially in fields such as healthcare and smart cities, where digital twins process sensitive personal information [107]. Striking a balance between data-driven insights and compliance with regulations such as GDPR and HIPAA poses a significant governance challenge [108]. In the absence of strong data governance models, **trust** in digital twin technologies may be eroded.

7.3 Organizational and Cultural Impediments

Beyond technical and data challenges, organizational and cultural factors heavily influence the adoption of digital twins [109]. Implementing digital twins often requires new workflows, skills, and attitudes, which may face resistance due to entrenched organizational cultures [110]. Additionally, many companies are not yet digitally mature enough to take full advantage of digital twin technology [111].

This is particularly evident in industries such as aerospace and healthcare, where strict controls exist for safety reasons, and cultural barriers to AI-powered or autonomous digital twin deployment present obstacles — particularly in critical systems [112]. These barriers must be addressed not only through new technologies but also via change management, leadership support, and workforce training.

7.4 Financial and Legal Restrictions

Finally, economic and policy barriers significantly shape the diffusion trajectory of digital twins. Creating and operating high-fidelity digital counterparts — especially for complex or large-scale installations — may require substantial investments in hardware, software, and data platforms [113]. For SMEs, these costs can be prohibitive unless affordable and scalable platforms are established [114].

There is also regulatory uncertainty. In many industries, current regulations have yet to catch up with the capabilities of digital twin technology, leading to ambiguities in liability and certification contexts [115]. Clearer regulations and policies are needed to support greater and more responsible use of digital twins in key domains.

8. OPPORTUNITIES AND PERSPECTIVES

Although the challenges facing digital twin adoption are formidable, they are counterbalanced by exciting opportunities and promising future research directions. Significant advances in digital twin technologies, methodologies, and societal impacts are anticipated in the years ahead.

8.1 Standardization Efforts

Continued standardization is essential to unleash the next generation of digital twins. Various groups, including ISO, IIC, and the Digital Twin Consortium, are developing frameworks for semantic interoperability, reference architectures, and cross-domain standards [116]. As these initiatives progress, they will facilitate system interoperability, lower integration costs, and foster digital twin ecosystems across domains [117].

8.2 Ethical and Responsible Development of DT

Another key area is the advancement of ethical and responsible digital twin development. This includes embedding principles of transparency, accountability, privacy, and human-centered design into digital twin architectures [118]. Ethical considerations must also address potential biases in AI-augmented digital twins and ensure their impacts on workers, citizens, and the environment align with societal values [119].

Ethical innovation in this space will benefit from multidisciplinary collaboration involving engineers, ethicists, social scientists, and policymakers, thereby building trust and legitimacy in digital twin technologies [120].

8.3 Socio-Economic Effects and Added Value Creation

There is substantial potential to create socio-economic value through digital twins. Digital twins can deliver cost savings, productivity improvements, and sustainability outcomes by optimizing resource utilization, enabling predictive maintenance, and enhancing service delivery [121]. They can also improve the efficiency and responsiveness of urban infrastructure, healthcare systems, and transportation networks in the public sector [122].

Furthermore, digital twins can enable new business models, such as **"digital twin-as-a-service,"** providing SMEs with access to advanced capabilities that are economically viable without requiring large upfront investments [123]. Unlocking these value pathways will be a critical focus of future research and industry innovation.

8.4 Heading Toward Industry 5.0 and Sustainable Innovation

In the foreseeable future, digital twins are poised to become a cornerstone of Industry 5.0 — a paradigm that prioritizes human-centric, sustainable, and resilient production . In this context, digital twins can support collaborative human-machine systems, enable circular economy business models, and foster progress toward the UN Sustainable Development Goals (SDGs) .

For example, lifecycle digital twins can facilitate circular design and closed-loop manufacturing, thereby reducing waste and environmental impacts . In the energy sector, digital twins can drive net-zero transitions by optimizing renewable integration and grid stability . These opportunities position digital twins as key drivers of sustainable innovation in the coming decade [124].

8.5 Cross-Cutting Research Topics

Finally, realizing the full potential of digital twins will require deep, integrated collaboration across theoretical, methodological, and practical domains. Future research should draw on insights from systems engineering, AI, data science, human-computer interaction, ethics, and social sciences .

Priority areas include: (1) the development of explainable, adaptive, and trustworthy digital twin systems; (2) governance, accountability, and regulatory frameworks; (3) human-AI collaboration in digital twin environments; and (4) ecosystem-based, cross-sector digital twin platforms [125].

By embracing interdisciplinary perspectives, digital twin communities can ensure that technological advancements are both technically robust and ethically sound, aligned with societal needs, and supportive of responsible global adoption.

9. CONCLUSION

In this study, a comprehensive overview was provided on the development of digital twin (DT) technologies, including DT's theoretical background, enabling technologies, application domains, theoretical foundations, emerging challenges,

and future prospects. As the analysis shows, digital twins have evolved from static digital replicas to dynamic, intelligent systems that integrate real-time information with advanced analytics and decision-support functions. They are increasingly applied across industries such as manufacturing, healthcare, urban infrastructure, energy, and autonomous systems, delivering tangible improvements in system performance, resilience, and sustainability.
Several key conclusions emerge from this synthesis. First, the convergence of digital twins with IoT, AI, cloud computing, and blockchain technologies expands the possibilities for system monitoring, optimization, and the development of new products and services. Second, although domain-specific deployments are advancing rapidly, persistent challenges remain, including interoperability, data governance, organizational readiness, and regulatory uncertainty. Third, the growing emphasis on socio-technical and ethical considerations reflects an understanding that digital twin development must go beyond technical concerns and engage with human, organizational, and societal contexts.
To fully harness the potential of digital twins, greater interdisciplinary collaboration is essential. Engineers, computer scientists, data analysts, ethicists, policymakers, and domain experts must work together to ensure that digital twin technologies are developed, deployed, and governed in ways that respect human values, address societal needs, and promote sustainability. This will also support the creation of more adaptive, reliable, and human-centered digital twin systems.
The findings of this review suggest several implications for future research and practice. First, it is critical to prioritize the development of open standards and interoperable architectures to support scalable, cross-sector digital twin ecosystems. Second, robust ethical frameworks and governance models must be established to guide responsible innovation and protect stakeholder interests. Third, further research is needed to advance human-centered design approaches that enhance the transparency, explainability, and usability of digital twin systems. Finally, in the context of Industry 5.0 and the pursuit of sustainable socio-economic resilience, future digital twin studies should deliberately address their potential contributions to sustainable innovation and socio-economic value creation.
In conclusion, digital twins are poised to play a pivotal role in enabling intelligent, adaptive, and sustainable systems across diverse domains. By fostering interdisciplinary collaboration, maintaining critical reflection, and pursuing responsible innovation, the digital twin community can help ensure that these technologies drive not only operational excellence but also broader societal well-being and global sustainability.

Conflicts Of Interest

The author's paper explicitly states that there are no conflicts of interest to be disclosed.

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