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Digital Twin Technology: A Comprehensive Overview of Concepts, Applications, and Innovations

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Abstract
Introduction: Digital Twin (DT) refers to a real-time virtual representation of a physical object, system, or process, maintained through continuous data exchange between physical and digital spaces. Originating from NASA's early simulation models and formally conceptualized in the early 2000s, DTs have become foundational to digital transformation, particularly in Industry 4.0. Supported by developments in Internet of Things (IoT), machine learning, and cloud computing, DTs are now widely adopted across sectors including manufacturing, infrastructure, and environmental management.
Body: The operational mechanism of DTs involves data collection from physical entities through IoT sensors, followed by model construction using geometric, behavioral, and contextual data. These models are continuously synchronized via real-time networks and analyzed through anomaly detection, state estimation, and predictive analytics. A dynamic feedback loop enables performance optimization and failure prevention in physical systems. Visualization is achieved through dashboards, 3D models, and AR interfaces. Current applications include wildfire prediction through ROM and UAV integration, as well as building performance monitoring via BIM and MBSE frameworks. Despite rapid expansion, limitations persist in data standardization, cybersecurity, system orchestration, and governance. Future directions focus on adopting interoperability standards (e.g., ISO 23247), implementing blockchain-based data integrity solutions, and enhancing real-time control through 5G networks. These developments aim to improve DT scalability, security, and cross-sector adaptability.

Keywords: digital twin; real-time simulation; internet of things; predictive analytics; reduced-order modeling; UAV swarms; smart infrastructure; building information modeling; data interoperability; climate resilience

Introduction and History

Definition

A digital twin (DT) is a virtual representation of a physical object, system, or process that mirrors its real-world counterpart in real time. In 2024, Information Technology for European Advancement (ITEA) defined DTs as "a digital representation of a real-world system that bi-directionally sends and receives updates with its counterpart at a frequency and fidelity befitting the use case" [1]. The concept of DTs has evolved into a cornerstone of digital transformation, particularly in the era of Industry 4.0. By establishing a dynamic, data-driven link between the physical and virtual worlds, DTs empower industries to simulate, predict, and optimize performance [2]. The technology is widely applied in complex and unpredictable scenarios in modern industrial and technological fields. The definition of a DT remains inconsistent across academic and industrial literature, often tailored to specific fields or use cases. International standards organizations are working to develop frameworks that ensure interoperability and consistent application [3].

Origins

The early idea of DT originated in the 1960s when National Aeronautics and Space Administration (NASA) created physically duplicated systems at ground level to match the systems in space. These earthbound versions allowed for monitoring, assessment, and simulation of conditions in spacecraft. After the launch of Apollo 13 in April 1970, an oxygen tank exploded early into the mission. To resolve critical technical issues from up to 200,000 miles away, NASA used a physical replica of Apollo 13 on Earth, which allowed engineers to test and simulate possible solutions from ground level. This incident inspired the creation of DTs to test real-time survival solutions in the 1980s [4].

Conceptualization

The concept of DTs was first proposed by Dr. Michael Grieves in 2002 at a conference on Product Lifecycle Management (PLM) at the University of Michigan, where he described them as "virtual representations of physical products or systems that allow real-time monitoring, simulation, and analysis throughout their lifecycle" [5]. At the time, the idea of virtual representations of physical products was considered relatively novel and immature. Grieves envisioned a system where virtual models of physical products could provide a solid foundation for lifecycle management, addressing limitations in data collection and enabling smoother processes [3].

Grieves initially described the DT as comprising three key elements: the physical product, its virtual counterpart, and bi-directional data connections between the two, which was then referred to as 'Mirrored Spaces Model" [3]. This cyclical process, often referred to as "mirroring" or "twinning," allowed information to flow seamlessly between the physical and virtual environments [3]. NASA later expanded upon this concept in the early 2010s, redefining the DT as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, and fleet history to mirror the life of its flying twin" [6]. Over time, additional frameworks were introduced—such as the Digital Twin Prototype (DTP), Digital Twin Instance (DTI), Digital Twin Aggregate (DTA), and Digital Twin Environment (DTE)—each serving a distinct role in the digital twin lifecycle: DTP focuses on virtual development and testing, DTI on real-time operation and monitoring, DTA on integrating multiple twins into complex systems, and DTE on managing the broader digital ecosystem that connects and supports them all [3]. These variants expanded the concept across the product lifecycle, ensuring applicability from the design phase to disposal [3]. In 2011, NASA included the term "Digital Twin" in its technology roadmap, solidifying its role in aerospace applications. By 2012, the U.S. Air Force adopted the concept for aircraft structural integrity programs [3].

Industrial Adoption and Expansion

The development of Internet of Things (IoT) platforms in the 2010s significantly reduced costs and improved accessibility for DTs, marking a pivotal shift in their adoption. Between 2015 and 2016, DTs gained substantial traction in industrial settings, fueled by the rise of Industry 4.0 initiatives [7]. During this period, major technology companies such as Siemens, General Electric Company (GEC), and International Business Machines Corporation (IBM) began developing commercial DT platforms, expanding their applications beyond aerospace into sectors like manufacturing, energy, and infrastructure [6, 7]. By 2017, DTs were widely recognized as one of the top strategic technology trends, underscoring their transformative impact on industrial operations and beyond [6, 7].

From 2020 onward, DTs transcended industrial domains to address broader societal challenges. Today, the concept is applied in areas such as healthcare, urban planning, and disaster management [8]. The outbreak of Coronavirus disease 2019 (COVID-19) pandemic further accelerated DT adoption, as organizations sought virtual alternatives to physical operations and monitoring [3]. The global DT market size is expected to reach United States Dollar (USD) 110.1 billion by 2028 from USD 10.1 Billion in 2023, growing at a Compound Annual Growth Rate (CAGR) of 61.3% during the forecast period from 2023 and 2028 [9].

Operational Mechanisms

Data Collection and Transmission

The DT mechanism begins with the physical entity, such as a machine, building, supply chain, or an entire city. This entity is equipped with sensors, IoT devices, or other data collection tools that monitor its state, performance, and environment. These tools capture critical real-time data along with historical data, maintenance records, and external environmental factors. The data is transmitted to the DT platform via networks such as cloud computing, edge computing, or local servers, allowing for large scalability of DTs in scenarios requiring high-frequency updates or global collaboration [10]. Physical-to-virtual connections rely on sensors to capture the state of the physical entity and transfer it to the virtual counterpart. Conversely, virtual-to-physical connections involve transferring optimized parameters from simulations to the physical realm using actuators [3, 6].

Model Construction

The DT model is constructed using machine learning algorithms by testing "what-if" situations. This model integrates three critical types of data to ensure a comprehensive reflection of the physical counterpart [11]. Geometric data captures the physical shape and structure of the entity. Behavioral data describes how the entity operates or responds to various inputs, enabling the simulation of its dynamic interactions and performance. Contextual data encompasses environmental or operational conditions that influence the entity's behavior. By combining these data types, the DT model synchronizes the states of the physical and virtual entities [3, 12]. Meanwhile, the twinning rate specifies how frequently this synchronization occurs, ranging from periodic updates to near real-time adjustments [3, 12].

Data Analysis, Feedback and Control

At this stage, the DT integrates real-time data with its virtual model, using anomaly detection and predictive analytics to detect deviations from expected behaviors and forecast future conditions, ensuring proactive decision-making and maintenance [13]. When measurements are incomplete or noisy, state estimation algorithms assess the

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state of physical entities, ensuring an accurate representation of the system [3]. Insights generated by the DT are fed back to the physical entity to enable real-time adjustments, creating a dynamic feedback loop that enhances performance and reliability. This loop can trigger maintenance or repairs to prevent failures, reducing downtime and extending the lifespan of the entity [3].

Visualization and User Interface

The DT is often visualized through dashboards, 3-Dimensional (3D) models, or augmented reality (AR) interfaces. These visualization tools allow users to interact with the DT and monitor its performance. For example, a dashboard could display key performance indicators (KPIs) for decision-making [14].

Current Research and Applications

DTs are currently transforming wildfire management through advanced data integration and predictive modeling. These systems integrate IoT networks and satellite imagery to link virtual models with real-world conditions [15]. Unmanned Aerial Vehicle (UAV) swarms deliver real-time data to DTs, ensuring dynamic simulations and timely emergency responses [16]. Reduced-order modeling (ROM) has already enhanced computational efficiency, enabling the rapid processing of wildfire datasets for real-time predictions [17]. Innovative hybrid modeling approaches have achieved remarkable progress and have enhanced predictive accuracy by approximately 50% [18]. Recent findings highlight the success of DTs in emergency response planning, where predictive modeling has significantly improved cities' ability to adapt to evolving wildfire conditions. DTs are also used to simulate the impacts of climate change on wildfire frequency and intensity, which provide actionable insights into long-term ecological recovery and sustainability [19, 20]. By modeling complex environmental systems, DTs play a vital role in addressing the challenges of a changing climate, helping policymakers and stakeholders develop strategies for preparation and mitigation. With optimized decision-making and resource deployment, economic losses are minimized.

DT technology is widely applied in architecture and construction. During the design phase, a data-rich 3D Building Information Modeling (BIM) model is created to simulate the building's performance. Model-Based Systems Engineering (MBSE) formalizes DT development via Systems Modeling Language (SysML) diagrams. The V-model maps the lifecycle of a system such as a building to ensure traceability from requirements to physical implementation [21]. Construction Monitoring is achieved with IoT sensors (vibration, temperature) and RFID (Radio-Frequency Identification) tags (material tracking), which provide real-time data sync with the DT, reducing delays by 25% [22, 23, 24]. During the operational phase, the DT ingests live data from heating, ventilation, air conditioning (HVAC), lighting, and occupancy sensors to predict failures and optimize energy use [25]. Scenario testing such as retrofits is performed in the DT to validate decisions before physical execution [26].

DTs are transforming marketing through consumer analytics and operational optimization. Recent studies demonstrate that DTs integrating IoT data with machine learning can predict individual purchase behaviors, enabling precision targeting that reduces customer acquisition costs [27, 28]. This transformative potential extends across retail sectors, providing retailers with unprecedented capabilities to visualize, analyze, and simulate their physical spaces without disrupting ongoing operations [29]. Consumer goods research documents reduction in product return rates when AR-enabled virtual twins are deployed for pre-purchase testing [30], as AR features reduce uncertainty by enhancing perceived informativeness, sense of presence, and mental imagery [31].

Limitations and Future Directions

Limitations

Despite growing interest in DT ecosystems, several persistent challenges continue to hinder their broader deployment and scalability. A primary challenge lies in the lack of standardized data models and communication protocols, which hinders interoperability between heterogeneous systems. This is particularly problematic in complex engineering domains where multiple subsystems must be integrated into a single cohesive digital environment [10, 16, 32]. In such cases, fragmented or siloed data sources obstruct the seamless flow of information necessary for real-time synchronization between physical and virtual counterparts [33]. Second, cybersecurity presents significant risks due to the continuous exchange of real-time operational data, making DTs vulnerable to attacks that could compromise both digital and physical assets. Third, data governance and sharing remain complex, particularly in multi-actor environments where issues of data ownership, privacy, and access control are not clearly defined. Finally, system orchestration—the coordination of various digital and physical components—remains a technical and organizational challenge, especially in large-scale, dynamic environments like urban infrastructure or industrial networks [34, 35].

Future Directions

Overcoming current limitations in DT ecosystems will require targeted advancements across several key areas. Improving interoperability is fundamental and can be achieved through the wider adoption of shared ontologies and international standards such as ISO 23247 and OPC UA39. These frameworks will allow digital twins to operate across systems and domains, enabling more modular, scalable applications. To address cybersecurity risks, the integration of blockchain technologies presents a promising direction.

Blockchain's decentralized and tamper-resistant architecture enhances trust, data integrity, and secure multi-stakeholder collaboration [37, 38]. This is particularly relevant in sectors like supply chain management or critical infrastructure, where secure real-time data sharing is essential.

The challenge of data governance and sharing will require the design of transparent and adaptable governance models. These should define data ownership, access protocols, and usage rights, while also accommodating dynamic consent and evolving regulatory requirements [36]. Such frameworks are necessary for fostering data trustworthiness and encouraging broader participation across stakeholders.

For improved system orchestration, the adoption of 5G technology will be instrumental. With its low-latency and high-throughput capabilities, 5G will enable real-time communication and synchronization between physical assets and their digital counterparts, supporting complex, time-sensitive applications such as smart manufacturing and city-scale operations [39].

Collectively, these advancements will expand the capabilities of DTs by directly addressing current limitations—making them more robust in handling security and governance challenges, and more adaptable to complex, dynamic environments through improved technical and organizational integration.

List of Abbreviations

3D: 3-dimensional
5G: fifth generation mobile network
AR: augmented reality
BIM: building information modeling
CAGR: compound annual growth rate
COVID-19: coronavirus disease 2019
DT: digital twin
DTA: digital twin aggregate
DTE: digital twin environment
DTI: digital twin instance
DTP: digital twin prototype
GEC: General Electric company
HVAC: heating, ventilation, air conditioning
IBM: international business machines corporation
IoT: internet of things
ITEA: information technology for European advancement
KPI: key performance indicator
MBSE: model-based systems engineering
NASA: national aeronautics and space administration
PLM: product lifecycle management
RFID: radio-frequency identification
ROM: reduced-order modeling
SysML: systems modeling language
UAV: unmanned aerial vehicle
USD: United States dollar

Conflicts of Interest

We declare that we have no conflict of interests.

Authors' Contributions

ZM: Contributed to topic selection, structured the outline, planned the project, conducted literature search and review, participated in writing, and gave final approval of the version to be published.
SZ: Contributed to topic selection, structured the outline, planned the project, conducted literature search and review, participated in writing, and gave final approval of the version to be published.
ZL: Contributed to topic selection, structured the outline, planned the project, conducted literature search and review, participated in writing, and gave final approval of the version to be published.

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