DIGITAL TWINS FOR INTELLIGENT COMPUTING: MODELS, APPLICATIONS, AND CHALLENGES

Jagadeesh Sundaramoorthy[1], Yasmani Vitulas-Quille (Yasmani Teófilo Vitulas Quille)[2], Ms. Aarya Devendra Joshi[3]

[1]Technical Architect, US Digital Transformation, Company Name: Infosys Ltd, Location: Raleigh, NC, United States of America,
Email ID: s.jaga87@gmail.com, ORCID ID: 0009-0000-1012-2034
[2]University Professor, Design and Construction, ORCID ID: 0000-0002-7507-0308, National University of the Altiplano, Country: Peru,
Email Id: yvitulas@unap.edu[3]Dr Saba Amin Khan, Assistant Professor, Department of Biochemistry, Indira Gandhi Government Medical College, Nagpur, India, Email id - drsaba2112@gmail.com
[3]Assistant professor BSc IT, Thakur Ramnarayan College of Arts and Commerce, Dahisar East, Mumbai, Email id: joshiaarya3@gmail.com

ABSTRACT
Digital Twins (DTs) have emerged as a transformative technology for bridging physical and virtual systems, enabling real-time monitoring, predictive analytics, and intelligent decision-making across diverse application domains. Recent advances in artificial intelligence (AI), machine learning, the Internet of Things (IoT), cloud-edge computing, and cyber–physical systems have accelerated the evolution of conventional DTs into Intelligent Digital Twins (IDTs), capable of adaptive learning and autonomous operation. This narrative review synthesizes recent developments in DT research by examining their conceptual evolution, modeling paradigms, integration with intelligent computing techniques, and representative applications in manufacturing, healthcare, smart cities, infrastructure, supply chains, and energy systems. The review further discusses physics-based, data-driven, and hybrid modeling approaches, highlighting their respective strengths and limitations in developing reliable and intelligent DT frameworks. In addition, key challenges related to interoperability, scalability, cybersecurity, data governance, and model reliability are critically analyzed, together with emerging research opportunities involving explainable AI, federated learning, and edge intelligence. The findings demonstrate that Intelligent Digital Twins are evolving beyond digital representations into intelligent computational ecosystems that support autonomous, data-driven, and resilient operations. This review provides researchers and practitioners with a comprehensive understanding of current advances, identifies critical research gaps, and outlines future directions for realizing the full potential of Intelligent Digital Twins in next-generation intelligent computing.

KEYWORDS: Digital Twins; Intelligent Computing; Artificial Intelligence; Digital Twin Modeling; Cyber–Physical Systems

1. INTRODUCTION
In today's fast-evolving and digitalizing world, the speed of digital technological development has revolutionized systems in industries and societies, where intelligent computing is becoming central for data-driven decision making, autonomous operation and real time optimization. Physical assets, through the advent of artificial intelligence (AI), the Internet of Things (IoT), cloud and edge computing, cyber–physical systems (CPS), and big data analytics, now have the capacity to communicate, learn and adapt in interconnected digital environments (Fuller et al., 2020; Zayed et al., 2023). With the growing pace of digital transformation, organizations require frameworks that are smarter and capable of accurately capturing physical systems and continuously monitoring, predicting, simulating, and optimizing them. In this context, the DT (Digital Twin) has become a paradigm changing approach which enables two-way interactions between the real physical object and the virtual one and allows the continuous synchronization of information and the ability to make informed decisions (Barricelli et al., 2019).
The Digital Twin concept was originally based on a virtual copy of a physical object, but has come a long way in the past decade. Today's Digital Twins are not just digital replicas, but are used to exchange information with their physical counterparts, throughout the system lifecycle, to give real-time visibility into operational state (VanDerHorn & Mahadevan, 2021). This transformation has led to new uses beyond visualization and simulation, to predictive maintenance, operational optimization, and intelligent decision support (Fuller et al., 2020). Rasheed et al., (2019) explain that the true value of Digital Twins lies in the ability to combine the physical knowledge with the data being constantly collected by the system, which allows systems to adjust to changes in their environment and optimize their performance over time. As a result, Digital Twins have emerged as an integral part of smart Cyber–Physical Systems (CPS) that can be used for data-driven and adaptive operation.
Digital Twins are becoming more and more capable largely because of advancements in intelligent computing technologies. The rise of AI, machine learning, IoT-based sensing, cloud platforms and edge intelligence has made it much more possible to process heterogeneous data, forecast the future state of the system and optimize system operations in real-time with Digital Twins (Hu et al., 2021). In recent years, Digital Twins have evolved from mere replicas to entities with learning and reasoning capabilities, enabling them to make predictions, identify anomalies and make autonomous

decisions (Kreuzer et al., 2024). Moreover, the use of artificial intelligence (AI) and the internet of things (IoT) has made Digital Twins an intelligent computational ecosystem that can learn from data and adaptively optimize their performance over time (Zayed et al., 2023). These advancements put Digital Twins at the forefront as a key technology that will enable the next generation of intelligent computing systems.

Due to the fast growth of Digital Twin research, great advances have been achieved in many fields and industries. Definitions, characteristics, design principles and implementation frameworks for DT have been explored in detail in comprehensive reviews and have helped to create a more uniform understanding of the paradigm (Barricelli et al., 2019; Jones et al., 2020). Other studies have reviewed the development of the Digital Twin concept, and have pointed out that it is becoming increasingly important in manufacturing, industrial automation and lifecycle management (Semeraro et al., 2021). Digital Twins have also become a hot topic in the architecture, engineering, construction, and operations (AECO) industry, where they can be used to intelligently manage infrastructure, monitor assets, and improve operational efficiency (Al-Sehrawy & Kumar, 2020). Altogether, these studies show that Digital Twins have turned out to be a flexible platform to enable intelligent computing for a vast domain of applications.

Nevertheless, current literature on Digital Twins is still scattered in the treatment of Digital Twins from an intelligent computing point of view. Most reviews are related to conceptual definitions, enabling technologies, or application in a specific domain without an in-depth analysis of how intelligent computing is transforming the Digital Twin abilities (Jones et al., 2020; Hu et al., 2021). Similarly, while there have been recent reviews on the role of AI in Digital Twin Systems, these reviews typically focus on a specific technology and do not offer a consolidated overview of the Digital Twin models, intelligent computing approaches, applications, and related challenges (Kreuzer et al., 2024; Zayed et al., 2023). This disjointed view does not provide a broad picture of the evolution of Digital Twins toward adaptive, autonomous and cognitive systems.

To overcome these limitations, this review attempts to present a narrative form of Digital Twins for Intelligent Computing, their conceptual evolution, modelling paradigms, intelligent computing techniques, representative applications, and emerging challenges. This article takes an integrated approach to reviewing the latest developments in Digital Twin models and intelligent computational approaches and their application in the real world, which differs from previous reviews largely focussed on individual technologies or application domains. This review aims to offer researchers and practitioners a thorough understanding of the status of Digital Twins and recent advances to help them recognize crucial research gaps and devise future directions to foster the next generation of intelligent, autonomous, and data-driven systems.

2. From Conventional Digital Twins to Intelligent Digital Twins

2.1 Evolution of the Digital Twin Concept

The Digital Twin (DT) concept has gone far beyond merely modelling physical resources digitally, it now comprises an intelligent computational framework that can support autonomous decision making. At first, DTs have been added to create a dynamic relationship between a physical system and a virtual one, so as to monitor and manage the lifecycle of a system in an industrial environment (Lu et al., 2020). As industrial systems became more and more data-intensive and connected, the use of Digital Twins went beyond visualization to simulation, prediction, and optimization of operations. As pointed out by Leng et al. (2021), this development has been closely linked to the advent of Industry 4.0, in which Digital Twins can be regarded as one of the key enablers of intelligent manufacturing systems. Similarly, Liu et al. (2021) highlighted how the advancements of the sensing technologies, data integration, and computational capabilities have made Digital Twins dynamic systems that can continuously adapt to the changing operational conditions. Finally, a transformation has led to the creation of Intelligent Digital Twins, where real-time data is combined with intelligence and analytics to enable predictive and autonomous system behaviour (Singh et al., 2021).

2.2 Characteristics of Intelligent Digital Twins

Intelligent Digital Twins also have adaptive capabilities, unlike conventional Digital Twins, so they can be more than real-time. They are constantly gathering and processing diverse data to provide predictive insights, intelligent decision support, and automatic optimization across the system's lifecycle (Liu et al., 2024). They have some key characteristics such as bi-directional exchange between physical and virtual objects, continuous data synchronization, self-awareness of operational status, predictive reasoning and adaptive learning. These capabilities enable Intelligent Digital Twins to identify anomalies, assess potential alternative operational strategies and take proactive action to meet the changing environment in real time (Liu et al., 2021). In addition, Melesse et al. (2021) asserted that combining intelligent analytics to the Digital Twin models can improve the efficiency of operations and enable resilient industrial operations that can adapt to uncertainties with minimal or no human intervention.

2.3 Enabling Technologies Driving Intelligent Digital Twins

The convergence of various digital technologies has paved the way for the evolution toward Intelligent Digital Twins, all of which contribute to continuous connectivity, intelligent analytics and distributed computation. IoT infrastructures enable real-time sensing and data acquisition from physical assets while cyber–physical systems enable seamless interactions between physical processes and their digital counterparts (Minerva et al., 2020). Cloud computing provides scalable storage and computational resources for processing large amounts of Digital Twin data, while edge computing allows for low-latency processing closer to the data sources, enhancing responsiveness in time-critical applications (Lu et al., 2020). Moreover, Digital Twin networks have become a significant achievement to promote multiple Digital Twins communication and collaboration, which supports distributed intelligence in complex industrial ecosystems (Wu et al., 2021). As a whole, these technologies form the technological backbone needed to move from traditional Digital Twins towards intelligent systems that enable real-time prediction, optimization, and autonomous decision-making.

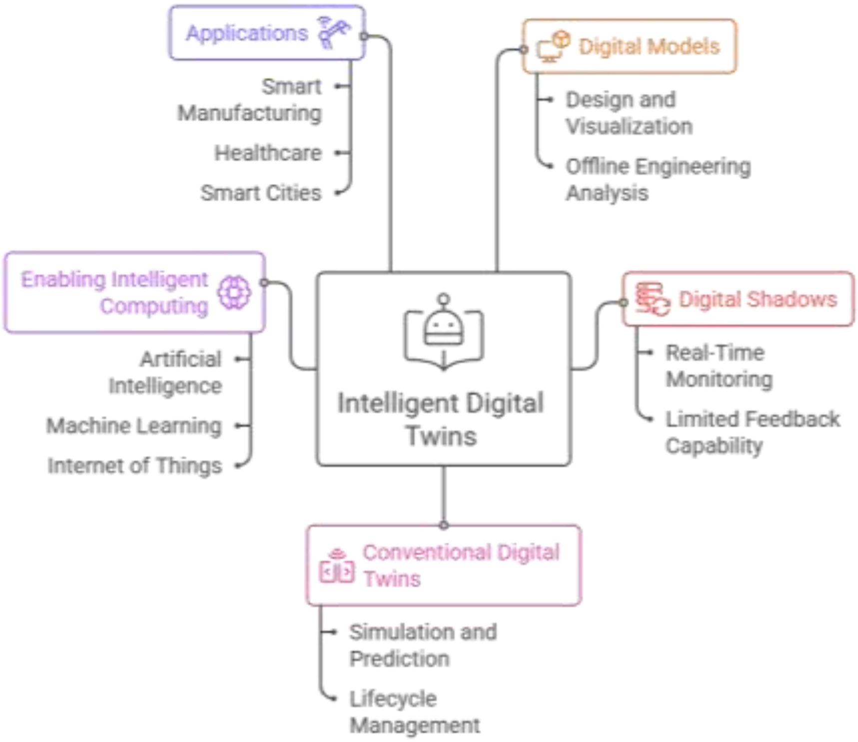

Figure 1. Conceptual evolution of the Digital Twin paradigm from conventional virtual models to Intelligent Digital Twins (IDTs).

Figure 1 illustrates the conceptual evolution of the Digital Twin paradigm from conventional virtual representations to Intelligent Digital Twins empowered by intelligent computing technologies.

2.4 Comparative Evolution of Digital Twins

A clear path can be seen from descriptive Digital Twins to Digital computational ecosystems, as illustrated by the progressive enhancement of Digital Twin capabilities. As summarised in Table 1, the levels of connectivity, synchronisation, intelligence and decision-making capability increase as the evolutionary stage is increased, demonstrating the increasing role of Digital Twins in intelligent industrial systems.

Table 1. Comparative evolution from conventional Digital Twins to Intelligent Digital Twins

Evolution Stage	Key Characteristics	Primary Capability	Representative Focus	References
Digital Model	Static virtual representation	Visualization and design	Product representation	Singh et al. (2021)
Conventional Digital Twin	Bidirectional synchronization with physical assets	Monitoring and simulation	Lifecycle management	Lu et al. (2020); Liu et al. (2021)
Intelligent Digital Twin	AI-enabled, adaptive, and self-learning system	Prediction, optimization, and autonomous decision-making	Intelligent manufacturing and industrial operations	Leng et al. (2021); Liu et al. (2024); Melesse et al. (2021)

2.5 Digital Twins as an Intelligent Computing Paradigm

The development of Digital Twins is part of a general trend where intelligent computing is the key enabler of future cyber–physical systems. Intelligent Digital Twins are not simply digital copies; they are systems that learn and adapt, continuously collecting data, performing intelligent analyses, and making autonomous decisions to optimize performance in real-time. The usage of this paradigm is not limited to manufacturing, and Sacks et al. (2020) showed how it can be applied in the field of intelligent infrastructure and construction management with decision support based on data. Likewise, Digital Twin networks can be used for the collaborative intelligence of distributed systems in scalable and interconnected industrial environments (Wu et al., 2021). As a result, Intelligent Digital Twins are now gaining momentum as an important paradigm of intelligent computing that can be used to combine physical assets, computational intelligence, and real-time analytics into single digital ecosystems. This conceptual change lays the groundwork for the understanding of how various modelling paradigms augment the intelligence, adaptability and operation capabilities of Digital Twin systems, as discussed in the next section.

3. Modeling Paradigms for Intelligent Digital Twins

3.1 Evolution of Digital Twin Modeling

In fact, Digital Twin (DT) modeling has evolved beyond just the virtual "twin" of a physical entity to a full smart and intelligent modelling system that can simulate and even predict real-time in-sync with the physical asset. DTs have become an integral part of smart manufacturing and Industry 4.0 (Tao et al., 2019) by using them in combination with Cyber–Physical Systems, which have enabled the continuous interaction with the physical asset and its DT. Moreover, engineering knowledge, lifecycle information and business intelligence are included in modern DTs to drive adaptive and data-driven operations (Lim et al., 2020). This evolution has turned DT modeling from descriptive visualization to intelligent computational models that help optimize system performance.

3.2 Physics-Based Modeling

Physics-based models are based on mathematical expressions and engineering principles that model the physical behavior of systems with high reliability. They are very interpretable and consistent with physical laws, which are well suited for the design optimization, the process analysis and the safety-critical applications (Tao et al., 2019). The creation of such models, however, can be quite challenging as they typically demand a lot of domain expertise and computing complexity and are therefore difficult to apply in highly dynamic environments (Perno et al., 2022). However, physics based Digital Twins are still beneficial for engineering optimisation and industrial planning. For example, Lee et al. (2022) used them to optimize the design of production lines and Wang et al. (2019) utilized Digital Twin modeling for rotating machinery fault diagnosis in smart manufacturing.

3.3 Data-Driven Modeling

The use of data-driven Digital Twin models is growing rapidly due to the development of industrial sensing and data acquisition. These models do not require physical equations to be defined and can learn the behavior of the system directly from the operational data, and the model can be used to accurately predict the behavior of the system in the case of complex and nonlinear systems (Qi & Tao, 2019). The concept of continuously updating predictions with the use of cloud, fog and edge computing infrastructures is highly scalable, and suitable for intelligent manufacturing environments that demand real-time adaptability and optimization of operations (Qi & Tao, 2019).

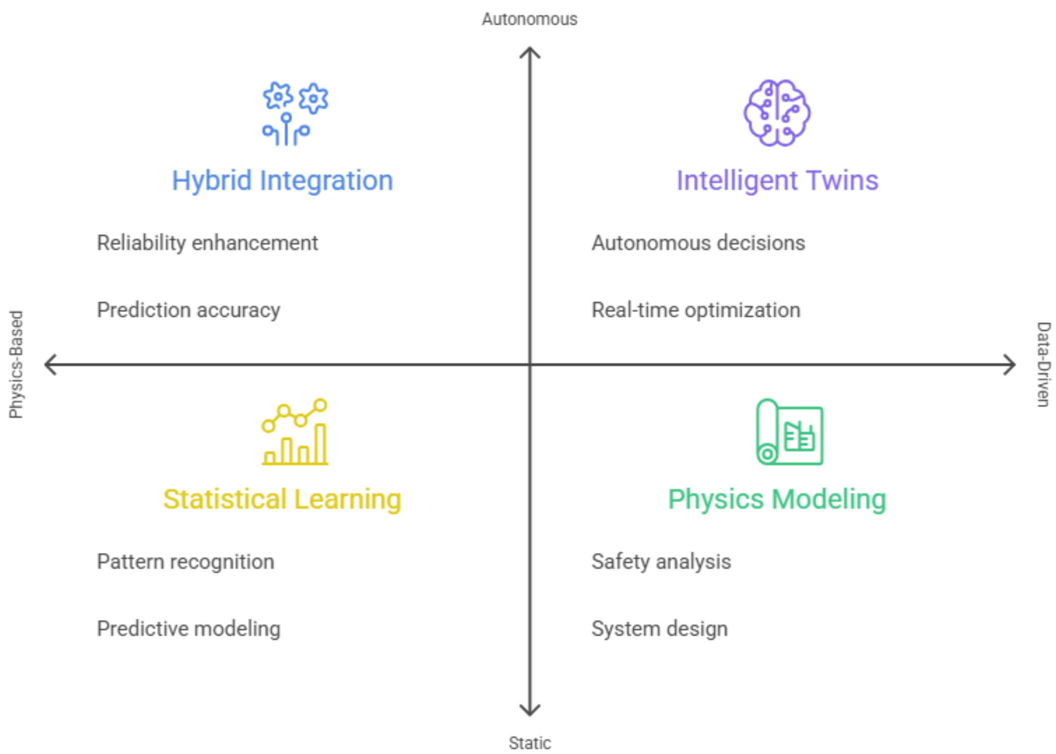

Figure 2. Evolution of Digital Twin modeling paradigms from physics-based approaches to data-driven and intelligent computational models.

3.4 Hybrid Modeling Approaches

While physics-based and data-driven models have their own merits, they each have their own drawbacks when used as the only approach for Digital Twins, limiting their adaptability and reliability. The limitation can be overcome by hybrid modeling, which combines physics-informed knowledge with data-driven learning, thus achieving model interpretability and predictive accuracy. Hybrid models allow for corrective mechanisms that continuously correct the model output based on the operational data, and hence increase the model reliability, as shown by Blakseth et al. (2022). Likewise, Lai et al.

(2023) revealed that combining computational models with measurements is a powerful tool for structural health monitoring, as it can greatly increase the accuracy of damage detection and prediction. As a result, hybrid Digital Twins are currently considered to be the most promising paradigm for modelling intelligent systems with varying and unpredictable conditions.

3.5 Comparative Perspective on Modeling Paradigms

The development of Digital Twin modeling can be seen as a gradual shift from deterministic engineering models to adaptive and intelligent computational models. Table 2 summarizes the different advantages that each modeling paradigm offers based on the need of the application, data availability and computational complexity. Physics-based models are required to be interpretable, data-driven models are more flexible, and hybrid models combine the advantages of both paradigms to yield more reliable and operationally intelligent models (Botín-Sanabria et al., 2022).

Table 2. Comparative analysis of Digital Twin modeling paradigms

Modeling Paradigm	Strengths	Limitations	Representative Applications	References
Physics-based	High interpretability and engineering consistency	High computational cost; requires domain expertise	Engineering design, production planning, fault diagnosis	Tao et al. (2019); Lee et al. (2022); Wang et al. (2019)
Data-driven	Learns complex patterns from operational data; adaptive	Dependent on data quality and quantity	Smart manufacturing, intelligent services	Qi & Tao (2019)
Hybrid	Combines physical knowledge with data-driven learning; high prediction accuracy	Higher implementation complexity	Structural health monitoring, predictive maintenance	Blakseth et al. (2022); Lai et al. (2023)

Thoroughly, the applicability of these paradigms is also different when it comes to industrial sectors. For instance, a process industry may depend on a hybrid or physics-informed model for a reliable model performance even when operating under complex conditions (Perno et al., 2022), while large-scale infrastructures like smart ports are increasingly relying on data-driven Digital Twins, which are able to incorporate different operational data for intelligent management of the infrastructure (Wang et al., 2021). Further, extensive reviews highlight that there is no universal solution to model a system and the choice of the appropriate modelling paradigm depends on the complexity of the system, computational resources and the desired level of operational intelligence (Botín-Sanabria et al., 2022).

3.6 Transition Toward Intelligent Computing

As Digital Twin (DT) modeling continues to be developed, the basis for the inclusion of intelligent computing techniques in modern DT systems has been laid. Digital Twins are moving beyond simply predicting data to becoming computational ecosystems with adaptive capabilities, including autonomous reasoning and decision-making, through the integration of robust modeling techniques and AI-powered analytics. This convergence has radically increased the capabilities of Digital Twins and also led the way towards the integration of machine learning technologies, deep learning, federated learning and edge intelligence, which are examined in the next section.

4. Intelligent Computing as the Core of Modern Digital Twins

4.1 Intelligent Computing in Digital Twins

Digital Twins (DTs) have developed in close relation with progress in intelligent computing and have evolved from being a monitoring and simulation system to an adaptive system that can learn and make decisions autonomously. DTs (nowadays) involve AI/ML, deep learning, edge intelligence and federated learning to continuously process data from the operation process, optimize performance and improve prediction capabilities (Kreuzer et al., 2024). This convergence has paved the way for Digital Twins to become smart computational ecosystems that reflect the physical assets and provide insights for real-time decision-making. Furthermore, Zhang et al. (2024) pointed out the importance of intelligent computing for enhancing the autonomous, precise, and adaptable manufacturing systems that rely on Digital Twins.

4.2 Artificial Intelligence and Machine Learning in Digital Twins

AI and ML algorithms are the computational backbone of Intelligent Digital Twins, enabling the identification of patterns, prediction of future trends, detection of anomalies, and optimization of processes based on the real-time data flow. AI-driven DTs continuously update and refine their predictive models, incorporating new data to improve the responsiveness of the system and operational efficiency, unlike conventional analytical methods, which rely on periodic updates to the predictive models (Kreuzer et al., 2024). Min et al. (2019) created the Digital Twin framework for production optimization using machine learning, which enhanced production optimization in the petrochemical industry through real-time industrial data and predictive learning algorithms. In the same vein, Zayed et al. (2023) highlighted how AI and IoT systems can boost the intelligence of Digital Twins, allowing for intelligent monitoring, autonomous control, and adaptive decision-making in complex industrial settings.

4.3 Emerging Intelligent Computing Techniques

Recently, some works have extended the concept of Intelligent Digital Twins to distributed and collaborative computing. Physics-guided federated learning allows multiple Digital Twins to cooperate in the construction of predictive models without having to share sensitive operational data, which improves model reliability, privacy and scalability (Stadtmann et al., 2024). Similarly, by moving data closer to the physical resources, edge intelligence can minimize latency in data processing and enable Digital Twins to make informed decisions and detect anomalies in real time in time-sensitive industrial settings (Huang et al., 2021). These new methods make the IDT more responsive and robust, and enable their usage in geographically distributed, resource-constrained systems.

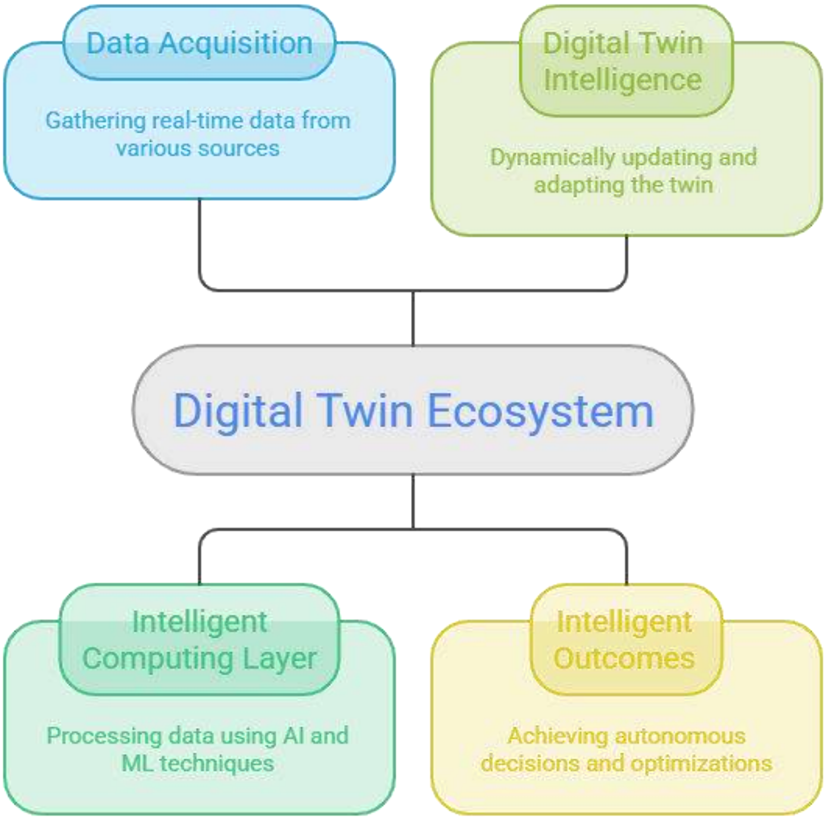

Figure 3. Integration of intelligent computing technologies within the Digital Twin ecosystem for continuous learning and autonomous decision-making.

4.4 Comparative Perspective on Intelligent Computing Techniques

Digital Twins' capabilities have been enhanced by the increasing variety of intelligent computing techniques. Table 3 offers a summary of the different benefits of the techniques in terms of computational advantages, according to the requirements of the application, the availability of data and the objective of the operation.

Table 3. Intelligent computing techniques enabling modern Digital Twins

Technique	Primary Role	Major Benefit	Representative Application	References
Artificial Intelligence	Intelligent reasoning and autonomous decision-making	Adaptive system behavior	Manufacturing and industrial intelligence	Kreuzer et al. (2024); Zayed et al. (2023)
Machine Learning	Prediction and process optimization	Improved operational efficiency	Petrochemical production optimization	Min et al. (2019)
Federated Learning	Collaborative distributed learning	Privacy-preserving model development	Distributed Digital Twin systems	Stadtmann et al. (2024)
Edge Intelligence	Localized real-time analytics	Low-latency anomaly detection	Industrial automation	Huang et al. (2021)

In addition to industrial automation, the use of Digital Twins has been extended to the healthcare sector and smart service environment. Digital Twin frameworks have been used for cloud-assisted elderly care through intelligent health services, combining continuous health monitoring with intelligent health services (Liu et al., 2019). In addition, there is a recent surge of interest in healthcare Digital Twins, in which AI can be used to analyze data and support disease monitoring, clinical decision making, and personalized healthcare applications (Sheng et al., 2023). All these developments highlight that intelligent computing is no longer a supplementary ability of Digital Twins but rather the ability that allows their development into adaptive, cognitive and autonomous systems in multiple applications.

5. Intelligent Digital Twins Across Application Domains

5.1 Manufacturing and Industrial Systems

Intelligent Computing has greatly broadened the scope of applications of Digital Twins (DTs) in manufacturing and industrial systems. Intelligent DTs can continuously synchronize operational data with virtual models, allowing for predictive maintenance, production optimization and real-time decision-making for improving productivity and operational reliability (Errandonea et al., 2020). In addition, RL algorithms have been applied to boost manufacturing intelligence, where Digital Twins are used to train autonomous agents for optimizing manufacturing processes in a dynamic environment (Xia et al., 2021). These have made DTs a crucial technology for industrial digital transformation and smart manufacturing initiatives (Erol et al., 2020).

5.2 Healthcare and Smart Infrastructure

One of the fastest growing application areas for Intelligent Digital Twins is healthcare where they can be used to integrate patient-specific information with predictions. Cloud-based DT frameworks are beneficial in consistent wellbeing monitoring and customized care, such as elderly care (Liu et al., 2019). In the field of precision medicine, disease prediction, and clinical decision support, significant progress has been made in cardiovascular applications and other digital health use cases (Coorey et al., 2022; Katsoulakis et al., 2024), which can be supported by Health Digital Twins. In addition to healthcare, DTs also enhance infrastructure management by providing continuous monitoring, structural assessment and predictive maintenance, which helps to build resilient and sustainable infrastructure systems (Broo et al., 2022).

5.3 Smart Cities and Cross-Domain Applications

The combination of geospatial data, Internet of Things (IoT), and smart analytics has helped boost the use of Digital Twins in smart cities. By synchronizing the physical and digital environments in real-time, these systems can support efficient urban planning, monitoring of infrastructure, traffic management, and resource optimization (Deren et al., 2021). In a like manner, Digital Twins have also backed the supply chain by enhancing visibility, coordination and operational resilience through continuous integration of data (Marmolejo-Saucedo, 2020). Within the energy industry, especially for oil and gas, DTs enable predictive maintenance, asset integrity management and operational optimization in complex industrial settings (Wanasinghe et al., 2020).

5.4 Comparative Perspective on Application Domains

A large number of Intelligent Digital Twins are already in use, which shows their flexibility for various operational needs. While the applications have varying purpose, they all require ongoing data synchronization, intelligent analytics and predictive decisions, as summarized in Table 4.

Table 4. Representative application domains of Intelligent Digital Twins

Application Domain	Primary Objective	Intelligent Capability	References
Manufacturing	Production optimization and predictive maintenance	Reinforcement learning and intelligent monitoring	Errandonea et al. (2020); Xia et al. (2021); Erol et al. (2020)
Healthcare	Personalized healthcare and disease prediction	AI-assisted monitoring and clinical decision support	Liu et al. (2019); Coorey et al. (2022); Katsoulakis et al. (2024)
Smart Cities	Urban planning and resource optimization	Intelligent analytics and real-time decision-making	Deren et al. (2021)
Infrastructure	Asset lifecycle management	Predictive maintenance and structural monitoring	Broo et al. (2022)
Supply Chain	Operational visibility and coordination	Real-time synchronization and optimization	Marmolejo-Saucedo (2020)
Oil & Gas	Asset integrity and operational reliability	Predictive maintenance and risk management	Wanasinghe et al. (2020)

These challenges have helped the Intelligent Digital Twins (IDTs) move from a domain specific tool to a cross-disciplinary digital transformation technology, which is increasingly adopted by various sectors. Although they are already proven to be beneficial, interoperability, scalability, data security, and implementation complexity are still challenges that hinder their widespread adoption, and more research on IDTs challenges and future directions are needed.

5.5 Comparative Analysis of Application Domains

Intelligent Digital Twins implementation differs from application to application based on the operational goals and the amount of computation needed. Manufacturing applications focus on predicting maintenance and optimizing production based on AI algorithms that analyze data and use reinforcement learning (Errandonea et al., 2020; Xia et al., 2021), as detailed in Table 4. The applications of Healthcare Digital Twins are largely focused on personalized medicine, disease prediction and intelligent clinical decision-making (Coorey et al., 2022; Katsoulakis et al., 2024; Liu et al., 2019). Smart city and infrastructure applications leverage IoT and intelligent analytics for urban management and optimization of the asset lifecycle (Deren et al., 2021; Broo et al., 2022), while supply chain and energy systems are focused on achieving operational visibility, integrity of assets, and predictive maintenance in order to enhance resilience (Marmolejo-Saucedo, 2020; Wanasinghe et al., 2020).

6. Challenges, Research Gaps, and Future Perspectives

While Intelligent Digital Twins (IDTs) have made significant strides, there are still some challenges to address that will prevent the technology from being widely used. One of the biggest challenges is managing the integration of data from various sensors, legacy systems, and distributed platforms, as it can be difficult to keep this data synchronized and interoperable in real-time across Digital Twin environments (Lu et al., 2020). However, to keep Digital Twins accurate and always up to date, high computational capacity is also needed, and, in complex industrial settings, it can be challenging to achieve high scalability and real-time performance (Botín-Sanabria et al., 2022). Moreover, cyber security and data privacy are other key considerations as Digital Twins increasingly rely on cloud technologies and on-going data sharing. An additional challenge is the reliability of the model. Despite the advances made in the field of intelligent computing, the performance of Digital Twin is still largely dependent on the quality of data and the accuracy of models. The prediction reliability may be reduced over time due to variations of operating conditions, incomplete data sets and data drift (Lu et al., 2020). In addition, there is a lack of standardisation of architectures, interoperability protocols, and evaluation metrics which hinder the portability and large scale adoption of Digital Twin solutions within different domains (Botín-Sanabria et al., 2022).

Research-wise, the future intelligent digital twins should evolve into computational ecosystems, which are interoperable, self-adaptive and trustworthy. All of the above mentioned require more attention to improve transparency, scalability, and reliability, especially in the case of explainable AI, federated intelligence, edge computing, and uniform validation methods. Increased collaboration between different disciplines (academic, industry and policymaker) will also be vital to facilitate speedy deployment. Digital Twins will be increasingly relevant in the adoption of healthcare systems, infrastructures, smart cities and industrial systems, and consequently, secure, intelligent and resilient frameworks will be increasingly relevant for long-term digital transformation (Errandonea et al., 2020). To realize the potential of Intelligent Digital Twins as a key enabler of next generation intelligent computing, these challenges will need to be overcome.

7. CONCLUSION

Today, Digital Twins (DTs) have evolved from the simple virtual representation to become smart computational ecosystems with the ability to include real-time data, advanced modeling, and automated decision-making. This review has demonstrated that the advent of Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), cloud-edge computing, and Cyber–Physical Systems (CPS) has transformed DTs into Intelligent Digital Twins (IDTs) that are used to support predictive analytics, adaptive optimization, and data-driven decision making. Additionally, the new modeling technologies like physics-driven, data-driven and hybrid-models have helped in the accuracy, reliability and adaptability of Digital Twin (DT) systems in a vast range of operating environments. The review also illustrates the relevance of IDTs in different industries such as manufacturing, health care, smart cities, infrastructure, supply chains, and energy systems and shows how IDTs can be used in different industries to optimize operations, forecast maintenance and make systems more resilient. However, they are still quite limited in their use due to problems with interoperability, scalability, cyber security, data governance, and the reliability of models, which require standardized architectures and robust validation processes. Future development of Intelligent Digital Twins will rely heavily on the effective integration of emerging intelligent computing technologies like explainable AI, federated learning, edge intelligence and next generation communication networks. Collaboration among academics, industry and also with policy makers will also be essential to interoperable standards development and deployment in real-world situations. Overall, it is fair to say that Intelligent Digital Twins will most likely be a technology for the next generation of smart computing that can enable an autonomous, adaptive and sustainable digital ecosystem.

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