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Chapter 3

Digital twin for healthcare, finance, agriculture, retail, manufacturing, energy, and transportation industry 4.0, 5.0, and society 5.0

Nitin Liladhar Rane [1], Shweta Shirke [2]

[1,2] *Vivekanand Education Society's College of Architecture (VESCOA), Mumbai 400074, India*
[1] *nitinrane33@gmail.com*

Abstract: Digital twins, virtual replicas of physical systems, combine real-time data, advanced analytics led by Artificial Intelligence (AI) to improve operations, forecast failure and create new products. Digital twins add value to manufacturing processes using smart automation in the industry 4.0 era and this aids predictive maintenance, real-time monitoring, and integration of Internet of things (IoT) devices. This results in more throughput, less down time and saves a bundle of money. Automation is easing transitions into Industry 5.0, where digital twins will further human-machine collaboration through individualized manufacturing and worker safety. With AI and robotics, digital twins can adaptively learn and interact between users and machines, enabling a high-rate of innovation and customization. If the concept of digital twins can be further broadened to social systems., such as individual people and industrial systems in Society 4.0 becoming part of Society 5.0, this eventually leads to a concept of Society 5.0. Healthcare applications includes digital twins of human patients for personalized medicine and continuous health monitoring and predictive maintenance of health. In addition, digital twins help to improve environmental sustainability by simulating ecosystems and forecasting the effects of global climate change for strategic planning on wildlife conservation. Digital Twins in association with AI, IoT, Big Data analytics catapult the road from Industry 4.0 to Society 5.0 The integration of these systems not just improve industrial productivity, rather it also helps the society to uplift their living standards and contribute to building a sustainable and smart future.

Keywords: Digital twins, Internet of things, Artificial intelligence, Machine learning, Deep learning, Industry 4.0

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3.1 Introduction

Digital Twins provides a sophisticated technology used in industry that enables a physical object to be represented dynamically in a digital space and simulated this way, for the purpose of being able to predict future maintenance scenarios and to reduce production friction through optimization (Javaid et l., 2023; Su et al., 2023; Wang et al., 2024). With industries moving towards Industry 5.0 human centric solution becomes, mixing human intelligence and creativity, along with sophisticated tools (Leng et al., 2023; Wang et al., 2024; Rane et al., 2024a). Digital Twins in this view enable enhanced human-machine collaboration that will promote innovation with sustainable calibrations (Wang et al., 2023; Papacharalampopoulos, et al., 2023). Information derived from Digital Twins can be used to create smarter cities, healthcare, and public services ensuring higher quality of life, making digital twins a foundational element in urban planning (Utku et al., 2023; Kataria et al., 2024; Paramesha et al., 2024a). Digital Twins with a virtual face of the physical systems intend to allow us to take data-driven decisions, a new height to mitigate societal challenges and enable balance between the technology and the human values. This study adds to the collective of knowledge by performing a detailed literature review and highlighting the main themes and tendencies of Digital Twins in regard to Industry 4.0, Industry 5.0 and Society 5.0. This research takes advantage of methodologies namely keyword analysis, co-occurrence mapping, as well as cluster analysis to systematically classify and understand the growing narrative on Digital Twins. The results shed light on the versatility of Digital Twins in various fields and offer the transformative power they contain, as well as guide the focus of future research. This detailed study reveals the cutting-edge research as well as provides insights into academic and industry practices that would enable exploitation of Digital Twins in advancing both industrial and societal paradigms.

3.2 Methodology

The searched academic databases include Scopus, Web of Science, and IEEE Xplore with certain keywords in the topic such as "digital twins," "Industry 4.0," "Industry 5.0," and "Society 5.0." However, the inclusion criteria were limited to peer-reviewed journal articles, conference papers and book chapters relevant to the field of study. Based on the relevant literature extracted, a co-occurrence analysis was conducted using VOSviewer software. It consisted of an extraction of keywords from the titles and abstracts of the selected papers in order to identify this most repeated terms and how they relate. The network was then processed to provide an overview on the predominant topics and patterns of the field of research. The underlying themes that emerged within the clusters were analysed in terms of associated relevance to digital twins in the contexts of Industry 4.0, Industry 5.0 and Society 5.0.

3.3 Results and discussions

Co-occurrence and cluster analysis of the keywords

The node of interest is “industry 4.0”, clearly indicated by the use of red shading (Fig. 3.1). Industry 4.0 signifies the current trend of automation and data exchange in manufacturing technology, which include cyber-physical systems, IoT, and cloud computing. The vast number of connections is a demonstration of its centrality and wide implication and application areas. The closely related nodes include “digital twin. Artificial intelligence,” “machine learning,” and “IoT.” The short distance from these other nodes means that the development and growth of industries require the technologies interpreted by the terminologies. Digital twins feature prominently in the expanded view of the node of interest, indicating its value and significance. The key reason for its importance is the ability to provide real-time data and analytical insight, which revolutionizes decision-making and operation efficiency. The surrounding terminologies “life cycle,” “optimization,” and “performance” send a signal of the integration of digital twins to every aspect of the product lifecycle, from design to decommissioning.

On the other side of the industry 4.0 cluster is a green cluster that focuses mostly on "cyber-physical systems" and "embedded systems". This cluster underlines the connection between computational algorithms and physical processes, which underlies the evolution of smart and interconnected industrial systems. Furthermore, the different terms used such as predictive maintenance, interoperability and network architecture indicate that communication, and maintenance of communication between the systems is critical to ensuring reliability and efficiency of the cyber-physical systems. In 'deep learning' and 'e-learning' also suggests a progression towards to increasingly more advanced learning algorithms and training systems to enhance the potential of such systems.

The blue cluster shows the importance of connectivity and data exchange in modern industrial environments especially Internet of Thing (IoT) and industrial internet of things (IIoT), This class includes terms like, cloud computing, big data, and blockchain, illustrating how these technologies are leveraged for robust, secure, and scalable IoT networks. Calling this cluster "cybersecurity" is highlighting how vulnerable these interrelated systems are to cyber threats, and how increasingly valuable it is to secure. On top of that, reference to the "5G mobile communication system" is pointing to the fact that modern communication networks are instrumental in making the high amount of data that IoT generates deliverable.

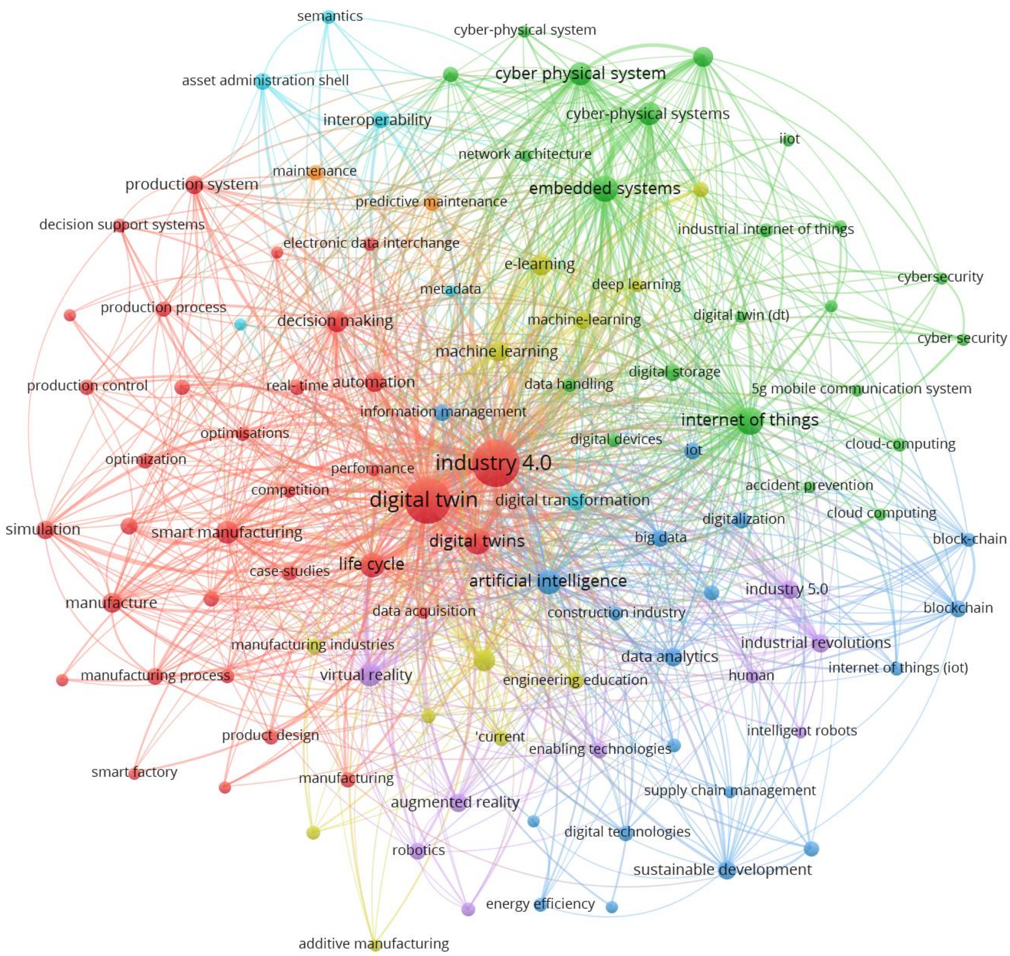

Fig. 3.1 Co-occurrence analysis of the keywords in literature

The amount of "artificial intelligence" and "machine learning" in the yellow cluster is likely to be a result of the industry cluster being where the emphasis in the importance of both terms also exists. Digital twin processes, along with the data producers such as IoT devices etc. are complex systems and require extensive use of these technologies to be functional. It is essentially data handling, data acquisition, and data analytics, showing how data-driven industries have become in the present era. The terms "virtual reality" and "augmented reality" might suggest that immersive technologies are used to enhance the visualization of and interaction with digital twin models, thus blurring the distinction between the virtual and the physical worlds. The concept of "Industry 5.0"-which is synonymous with human-centricity and sustainable development-is introduced within the purple cluster. This cluster connected to ideas of "supply chain management," "sustainable development," and "energy efficiency," that suggest a turn to greener and more socially responsible forms of industry. The between intelligent robots and robotics indicates a continued role of automation but with more focus on collaboration between humans and machines for enhanced efficiency and innovation.

The blue group represents the impact of digital technologies on the construction industry and engineering education. Digital twin technology and Industry 4.0 principles serve a wide spectrum of applications, much broader than traditional manufacturing - spanning construction and education - which are exemplified in this cluster. Making the cluster more engaging with words such as "engineering education" and "case studies", to educate individuals to make them future fit in the digital transformation age. The clusters are also present with a very smooth evolution from the core technologies of Industry 4.0 that are based on automation and data exchange, towards the industry 5.0 more interested about humans and the sustainable penetration. This validates the trend that has been gaining momentum, to consider technology advancements through a socio-environmental lens. It ensures that economic returns from digital transformation are more evenly shared in line with broader social objectives.

Methodologies for implementing digital twins

Technological Foundations

The Internet of Things (IoT) is instrumental in providing the mechanism to connect physical assets to their digital twins (Al-Ali et al., 2020; Jacoby, & Usländer, 2020; Baghalzadeh Shishehgarkhaneh et al., 2022). Physical systems are instrumented by IoT sensors and devices, collecting huge amounts of data sent to the digital twin (Steinmetz et al., 2018; Baghalzadeh Shishehgarkhaneh et al., 2022; Paramesha et al., 2024b; Rane et al., 2024b). This real-time data is critical to having a correct, current digital representation. Another pillar of Digital Twin technology; cloud computing whereas the cloud offers the infrastructure required to store and process all of the data delivered by countless IoT devices. In addition, it enables scalability, whereby digital twin applications can become more complex and cover different scales without the need for physical machines. In addition, edge computing is more often being added to digital twin designs to help perform data analysis closer to where it actually resides, which helps cut latency and gives the digital twin trail real-time decision-making authority. To deep dive and process the collected data from digital twins one of the Key things is Artificial Intelligence (AI) and Machine Learning (ML) (Alexopoulos et al., 2020; Kaur et al., 2020; Ritto, & Rochinha, 2021; Paramesha et al., 2024c). The system determine behaviours and patterns which may not resonate logically on their own and recommend maintenance and efficiencies in areas where they are needed once the system and all its moving components are properly up and running.

Table 3.1 Methodologies for implementing digital twins

References	Methodology	Description	Key Components	Applications	Benefits
Stojanovic, & Milenovic, (2018); Hui et al., (2022); Bariah, & Debbah, 2024); Shi, et al., (2024)	Data-Driven Modeling	Utilizes real-time and historical data to create and refine the digital twin model.	Sensors, IoT, Data Analytics	Predictive Maintenance, Process Optimization	Real-time insights, improved decision-making
Phanden et al., (2021); Ritto, & Rochinha, (2021); Somers et al., (2023); Rane et al., (2024c)	Simulation-Based	Uses physics-based models and simulations to replicate the behavior of physical systems.	CAD Models, Simulation Software, Physics Engines	Product Design, Performance Testing	Accurate predictions, risk mitigation
Kaur et al., (2020); Ritto, & Rochinha, (2021); Alexopoulos et al., (2020)	Machine Learning	Employs machine learning algorithms to analyze data and predict system behavior.	ML Algorithms, Training Data, Computational Resources	Anomaly Detection, Predictive Analytics	Automated insights, enhanced predictive power
Lin et al., (2021); Yang e al., 2022; Huang et al., (2023)	Hybrid Approach	Combines data-driven, simulation-based, and machine learning	Mixed components from other methodologies	Complex Systems, Multidisciplinary Applications	Comprehensive modeling, versatility

		methodologies for comprehensive models.			
Orozco-Romero et al., (2020); Qiu, et al., (2023); Marah, & Challenger, (2023)	Agent-Based Modeling	Uses autonomous agents to simulate interactions and behaviors within a system.	Agent Software, Behavioral Rules	Urban Planning, Supply Chain Management	Dynamic interaction modeling, scenario testing
Bondarenko, & Fukuda, (2020); Gejo-García et al., (2022)	System Dynamics	Focuses on understanding and modeling the feedback loops and time delays in complex systems.	Feedback Loops, Dynamic Models	Policy Making, Strategic Planning	Holistic view, long-term analysis
Liu et al., (2021); Zhang et al., (2023)	Process-Oriented	Models the workflow and processes of a system to optimize and simulate operations.	BPM Tools, Workflow Software	Manufacturing, Business Processes	Efficiency improvement, process optimization
Wang et al., (2020); Wen et al., (2022); Almasan et al., (2022)	Network-Based	Models the interconnections and dependencies within a network of components.	Network Analysis Tools, Graph Theory	Telecommunication, Transportation Systems	Improved network reliability, optimization
Karakra et al., (2018); Flores-García	Discrete Event Simulation	Models systems where state changes occur at	Discrete Event Simulation Software	Logistics, Operations Management	Detailed process analysis, resource optimization

(2020); Qiu et al., (2023)		discrete points in time.			
Ugarte et al., (2022); Ugarte Querejeta et al., (2022); Wang et al., (2023)	Virtual Commissioning	Simulates the commissioning of systems to ensure they function correctly before physical deployment.	Virtual Commissioning Software, Simulators	Industrial Automation, Robotics	Reduced commissioning time, early error detection

Modeling techniques

Physics-based modeling:

Physic based models describe systems behaviour in terms of a set of physical laws and they use mathematical rule that define a system to predict the physical behaviour of system. These models are often accurate and can be useful in predicting how systems will respond to different conditions (Sun, & Shi, 2022; Rios, & Bolander, 2023; Paramesha et al., 2024d). For example, physics-based models for aerodynamics of an aircraft to help engineers finally carry out tests on various configuration design in a virtual world in aerospace engineering. Table 3.1 shows methodologies for implementing digital twins.

Data-driven modeling:

This type of model is data-driven which uses historical as well as real-time data to provide a predictive representation of the system (Bariah, & Debbah, 2024; Shi, et al., 2024). This data analysis work is frequently done with machine learning algorithms (Stojanovic, & Milenovic, 2018; Hui et al., 2022). It could be a powerful tool in scenarios where getting a comprehensive physical model is difficult or unfeasible. Data-driven models may optimize traffic flow in smart cities by making use of patterns derived from all sorts of sensors across city boundaries for instance.

Hybrid modeling:

As the name suggests, hybrid modeling is a combination of physics-based and data-driven modeling methods and takes advantage of benefits of both. This method can produce more general and accurate models, particularly in complex systems where either physics-based models or data-driven models (Lin et al., 2021; Yang e al., 2022; Huang et al., 2023;

Paramesha et al., 2024e). Personalized digital twins combining physiological models with patient-specific data are also being used to tailor treatments and predict health outcomes in the healthcare domain using hybrid models.

Integration strategies

Interoperability:

Interoperability is important for the integration of digital twins with other systems and platforms (Jacoby, & Usländer, 2020; Schmidt et al., 2023). Standardized protocols and data formats make sure that digital twins communicate with IoT devices, cloud platforms, and enterprise systems.

Application Programming Interfaces (API) -driven integration:

Digital twins should interact and integrate all the other software applications and service hence it should be API based (Redeker et al., 2021; Redeker et al., 2022). APIs make the connection between the digital twin data from a third-party tool and actions to be triggered; standardizing the way for digital twins to consume and act on data. In the auto space, APIs permit digital twins of vehicles to speak to fleet management systems, relaying live statuses on performance and need for maintenance.

Cybersecurity:

With digital twins managing sensitive data and having the ability to impact physical systems, security is one of the priority areas and must be approached very carefully. It is and will be necessary to adopt strong cyber security measures such as encryption, authentication, and access control to protect digital twins from cyber threats. Regular security assessments and continuous monitoring also must be in place to recognize and solve vulnerabilities as they may arise.

Scalability:

For larger and more complex digital twins, scalability is of utmost concern (Monteiro et al., 2023; Jia et al., 2022). Historically, expanding digital twin applications required large hardware investments, but with cloud computing, a scalable infrastructure is available. On top of that, modular architectures allow for scalable change of a system piece-by-piece, where new functionality, new components can be grafted in line without disrupting the older components.

Real-time data integration:

Value realization from digital twins is rooted in real-time and predictive analytics. Real-time data from sensors in IoT and other sources is integrated to ensure digital twins remain updated and accurately reflect the physical asset. Edge computing and real-time data streaming platforms make it easier to handle all fast moving real-time data streams.

Digital twin platform for smart cities

The framework of the digital twin platform (Table 3.2) provides an aggregated approach to management and optimization in urban environments. By integrating divergent data sources and applications, cities can improve their planning, sustainability, and operational efficiency. Combining technologies such as AI, machine learning, and real-time data visualization will give life to an interactive model of the city so that decisions are better made and urban services improved.

Table 3.2 Digital twin platform for smart cities

Category	Components	Description
Applications	Energy and Building Monitoring	Real-time monitoring and management of energy use and building performance.
	Urban Planning	Models and tools for effective urban development and land-use planning.
	Circular Economy and Sustainability	Systems that assist or encourage recycling, resource efficiency, and sustainable practices.
	Traffic, Mobility, Fleet Management	It consists of the management of transportation networks, the flow of traffic, and fleets of vehicles.
	Risk Mitigation and Water Management	In disaster risk reduction and efficient water resource management.
	Pollution Monitoring	Real-time monitoring of the extent of pollution and the level of environmental quality.
	Healthcare	Service integration and monitoring for improved public health outcome.
Digital Twin Platform	Visualization	It provides tools for data and model visualization, including 3D models, maps, and augmented reality.

	Simulation	Creation of digital simulations of physical processes and systems.
	ML/AI	Machine learning and artificial intelligence for predictive analytics in decision support.
	Analytics	Advanced analytics data in insights and decision making.
	DT Model Repository	Centralized repository for digital twin models.
	Federation	Integration of multiple digital twin systems and models.
	DT Edge Instance	Edge computing for real-time data analysis and processing.
	Device Management	IoT device and sensor management tools
	Data Storage	Secure and scalable solutions for large data storage.
	Data Synchronization	Ensuring consistency and real-time updates across data sources.
Data Acquisition	Buildings	Building management systems, sensors, and IoT devices provide this data.
	Citizens	Information that is collected from citizen interactions, surveys, and mobile applications.
	Open Data	Publicly available datasets from governments and other sources.
	Infrastructure	Infrastructural data from urban structures, roads, bridges, and utilities.
	Urban Services	Data from services like public transportation, waste management, and emergency services.
Physical World	-	It represents every real-world entity and data source that feed into a digital twin platform.
Security	-	Ensuring data privacy, integrity, and protection across all components of the platform.

The creation and management of digital models of buildings' physical and functional characteristics are issues that Building Information Modeling (BIM) mainly deals with.

In that respect, it holds hands with Industry 4.0, which insists on digitization for more efficiency and accuracy within manufacturing and construction processes. For instance, it optimizes the design and construction phases using 3D models with detailed data management and proper documentation. This makes Digital Twin technology much more than BIM, as it has combined real-time data and analytics in a digital platform that closes the gap between the digital and the physical world. This is important for Industry 5.0. Digital Twin enables real-time monitoring, predicts maintenance, and advances analytics in fostering operation optimization and innovation decision-making. And enhanced by machine learning and real-time data, it increases the adaptability and responsiveness of systems—entirely aligned to the goals set out by Industry 5.0 and Society 5.0. Digital Twin technology builds from the groundwork that BIM has laid with structured, interoperable data supporting the whole life cycle of assets from concept design through operation and maintenance to end-of-life. Inherent in this integrated concept is an increased gain of efficiency and sustainability while promoting a more connected and intelligent industrial and societal framework.

Implementing digital twins in industry

In Fig. 3.2, the stages of introducing digital twins into an industrial environment follow a sequence in a systematic manner moving from setting the goals to tracking and maintaining the digital twin. It starts with defining objectives which highlights the key parameters for why a company wants to use digital-twins and what is it going to be able to provide. The underlying conceptual setup guarantees that the implementations are in contribution with the organization's wider strategic objectives providing a clear sight of direction for the upcoming steps. Data collection includes collecting data from sensors, IoT devices, etc. This data provides the material for building reliable digital twins of real-world objects. After data collection the data integration is responsible for making data from different sources together, as a one system.

An important aspect of this integration is the creation of a trustworthy digital twin by integrating all necessary information into one complete model. This is followed by modeling, where models of physical assets and processes are digitalized. These models act as the digital twin, offering users a virtual representation to interact with and study. With the models in place, the next phase is simulation, using the digital twins to indicate the anticipated performance and outcomes in different conditions. These simulations facilities offer an invaluable way for testing and validation, without the need to interfere with real-world operations. Finally, optimization follows the simulation to use the knowledge that was obtained to improve processes and facilities. This step gears toward optimizing operations with the use of data to accelerate the business process, cut down costs, and elevate total output. During the implementation phase the solutions identified during optimisation must now be deployed to real-world operations in such a manner that the benefits of the digital twin are successfully realized. The last stage is monitoring and maintenance, which simply tells us the fact of keeping track of digital twins and keeping them alive and useful. We continuously updating the digital twins to keep them relevant and effective - allowing for the continuous improvement and adaptation of the twins in a changing world, governed in part by the desire of the digital world itself.

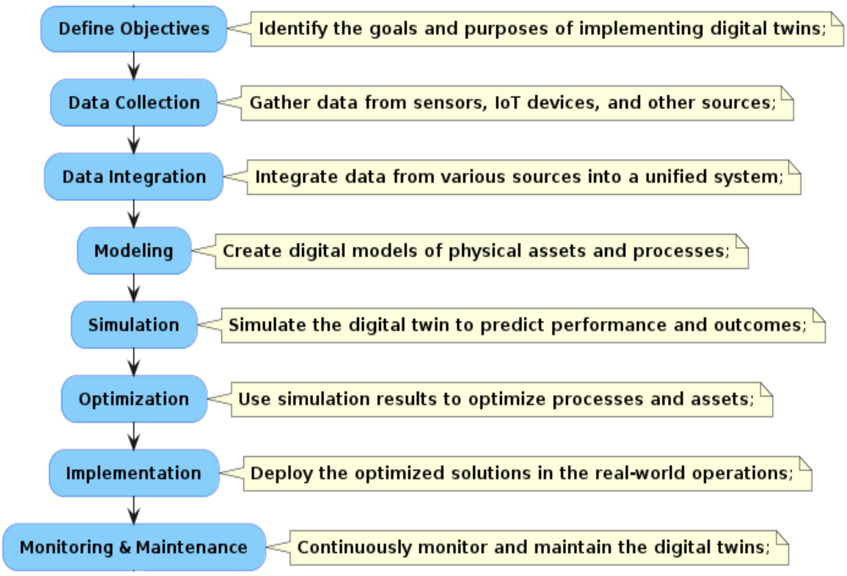

Fig. 3.2 implementing digital twins in industry

3.4 Conclusions

Digital twins are critical for Industry 4.0 advancements, which involve the creation of virtual replicas of physical assets, processes, and systems. By enabling predictive maintenance, optimising the manufacturing processes and monitoring the real-time, they have increased efficiency as well as reduced their operational costs. Industry 5.0 is making digital twins smarter to enable human-machine interaction and enable tailored and ecological manufacturing solutions. The combination of human-cantered methods alongside AI and Robotics enables a more pliable and resilient industrial biosphere. Digital twins are important elements for solving social challenges and building smart cities and public services in Society 5.0. This means, they make it possible to simulate urban scenarios, enhancing disaster prevention, transportation systems and energy distribution. Combining digital twins with IoT, AI and big data analytics is a much broader way to address societal development, finding a well-respected equilibrium between economic progress, personal and community well-being. The advancement in digital twin evolution will continue to power innovation and scale resulting in a more intelligent, intuitive, and sustainable world.

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