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Transforming Industry using Digital Twin Technology

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Digital Twins in Industry: Real-World Applications and Innovations

Shamik Tiwari and Amar Shukla

Introduction

Digital twin (D-Twin) describes a virtual replica or simulation of a tangible entity, system, or process. It amalgamates data from numerous resources, such as sensors, simulations, and real-time analytics, to establish a digital counterpart mirroring the behavior and characteristics of its physical counterpart. A D-Twin is often made up of several parts that work together to produce a virtual copy of a real-world system or object. These elements consist of [1, 2]:

Physical Object: The entity or system that the D-Twin represents is known as the physical object. It could be a piece of machinery, infrastructure, a product, or even an entire factory. To gather data in real-time, the physical item is furnished with sensors, actuators, and other information gathering devices [3].

Data collection: To collect data from the actual object, sensors and other tools are employed. These sensors can measure a wide range of variables, including temperature, pressure, vibration, and others. Real-time measurements and archived data may both be present in the data gathered.

Data processing and integration: After data acquisition, the physical object is represented coherently by processing and integrating the collected data. Data from diverse sources must be cleaned, filtered, and aggregated to do this. Including extra data from outside sources, such as environmental or data about the supply chain, may also be a part of integration [4].

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Virtual model: Digital representation of the physical object is known as a virtual model. It is made with the use of simulation software, computer-aided design (CAD) software, or other modelling methods. The virtual model accurately depicts the physical object's form, structure, behavior, and functions.

Connectivity: The network architecture that permits interaction among the physical thing, sensors, data processing systems, and various other elements of the D-Twin ecosystem is referred to as connectivity. This connectivity can be cable or wireless and may make use of IoT, cloud computing, and edge computing technologies.

Analytics and AI: Data gathered from the physical object is processed using analytics and artificial intelligence techniques, then incorporated into the D-Twin. Predictive modelling, machine learning algorithms, and statistical analysis are some examples of these techniques. They aid in gaining insights, spotting patterns, spotting abnormalities, and making predictions about how the physical thing will behave and function.

Visualization and User Interface: Users may be able to interact with and view the virtual model and the accompanying data through the visualization component of the D-Twin. This can take the shape of augmented reality (AR) interfaces, dashboards, or 3D visualizations. The user interface gives people a way to keep an eye on and manage the actual item, evaluate data, and come to intelligent choices.

Feedback Loop: The D-Twin and the physical object interact in a feedback loop. The D-Twin is continuously updated with real-time data from the physical device, enabling continued monitoring, analysis, and adjusting. The D-Twin's views and forecasts can be employed to optimize the physical object's performance or to decide on upkeep, upgrades, or enhancements to the process.

Collectively, these elements form a dynamic and interactive D-Twin that offers a virtual version of a real-world system or item and facilitates observing, analysis, and decision-making. Figure 1 shows an example of D-Twin [5, 6].

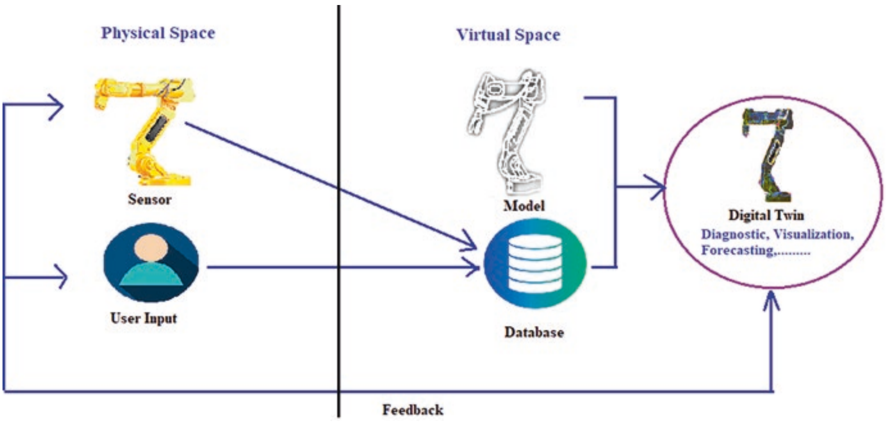

Fig. 1 Digital twin: An example

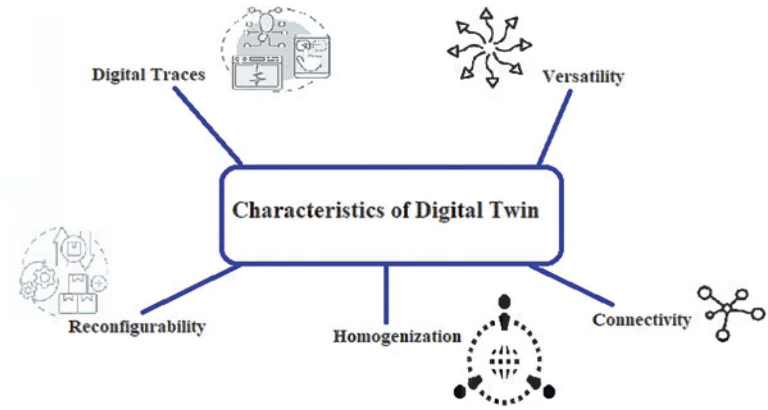

Fig. 2 Characteristics of digital twin

The main characteristics of D-Twins are connectivity, modularity, homogenization digital traces, and reconfigurability as provided in Fig. 2 [7, 8]. Connectivity: Connectivity is the foundation of a D-Twin. It makes it possible for the physical component and its digital counterpart to be connected. The sensors enable physical items to be connected so that data may be collected, processed, and shared via a variety of interconnection methods.

Homogenization: The homogeneity of data has consequences and is made possible by D-Twins. It makes it possible to separate information from its physical form.

Reconfigurability: Digital twins use sensors, AI methods, and statistical analysis to allow reconfigurability.

Digital Traces: Devices using D-Twins leave digital footprints. When a machine malfunctions, the traces can be used to identify the problem's underlying cause.

Versatility: The design and adaptation of products along with manufacturing units are examples of versatility. Manufacturers can modify machines and models because of the addition of flexibility to operational models.

Applications of Digital Twins

The adoption of D-Twin technologies is experiencing rapid growth, revolutionizing the operational landscape for businesses. Primarily applied in engineering and manufacturing, digital twins are instrumental in crafting accurate virtual representations and conducting simulations of operations. Here are a few examples of the diverse applications of D-Twins across various fields as shown in Fig. 3. Digital twins are flexible and adaptable. It enables them to be tailored to particular use cases and industry standards.

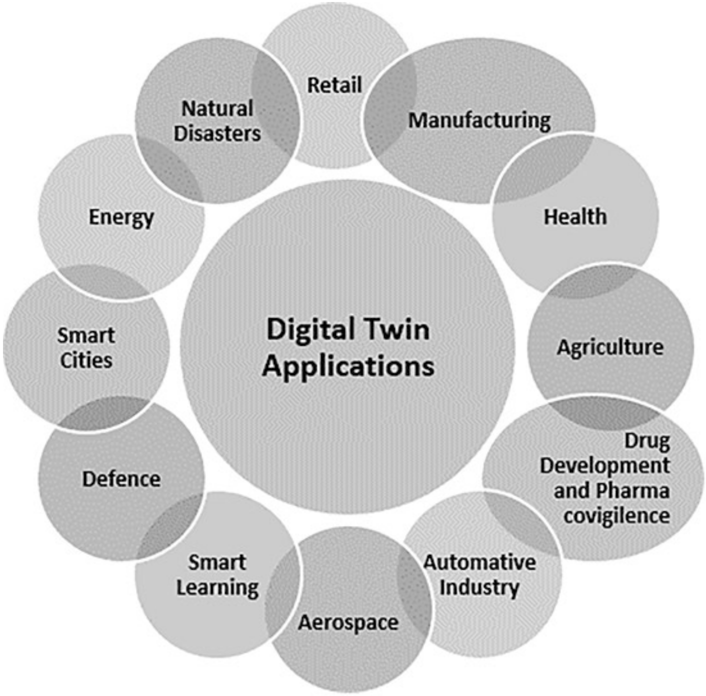

Fig. 3 Digital twin applications

Digital Twins in Manufacturing

In the manufacturing sector, digital twins find application in simulating diverse scenarios, enhancing production efficiency through the optimization of resources, and minimizing downtime. Crucial to the concept of smart manufacturing, data sourced from the plant, systems, supply chain, and equipment plays an integral role in leveraging the capabilities of digital twins. Manufacturers utilizing industry 4.0 apps employ the real-time data power of D-Twins to monitor and evaluate continuously shifting data in their manufacturing operations as shown in Fig. 4. Thanks to this technology [9], manufacturers now have the capability to test and validate a product even before it is introduced to the market. Digital twins aid engineers in identifying any potential process flaws before the product undergoes actual manufacturing by simulating the intended manufacturing procedure. The following few instances show how D-Twins can be used to meet various requirements for smart manufacturing [10, 11].

- Prototype testing and evaluation
- Shorten the time to market for products
- Enhance process and product performance
- Improve production efficiency

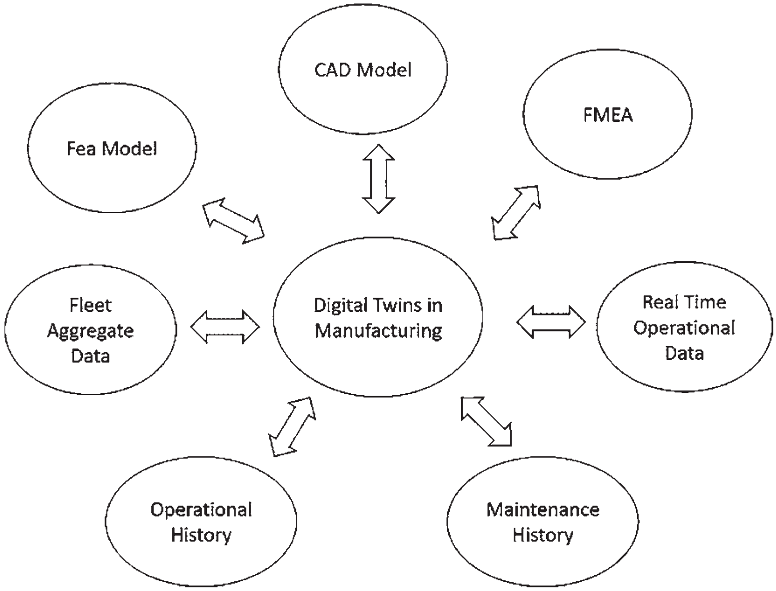

Fig. 4 Digital twins in manufacturing

- Equipment monitoring and preventive maintenance
- Turn on preventative maintenance
- Permit online commissioning
- For manufacturing organizations, D-Twins have several advantages, including:
- Reducing the duration of the manufacturing
- Predictive analysis results in little maintenance
- OEE (Overall Equipment Effectiveness) maximization
- Gaining fresh knowledge about the apparatus to improve performance
- The ability to conduct testing on a virtual duplicate without putting the real equipment at risk
- Evaluating a D-Twin with what-if questions
- Real-time asset management
- System optimization before deployment

Digital Twins in Automotive Industry

Digital twins can be used in the automotive industry to simulate complex systems like engines, transmissions, and suspensions. The D-Twin of the product encompasses the entire car, incorporating its software, engineering, electrical wiring, and physical behavior [12–14].

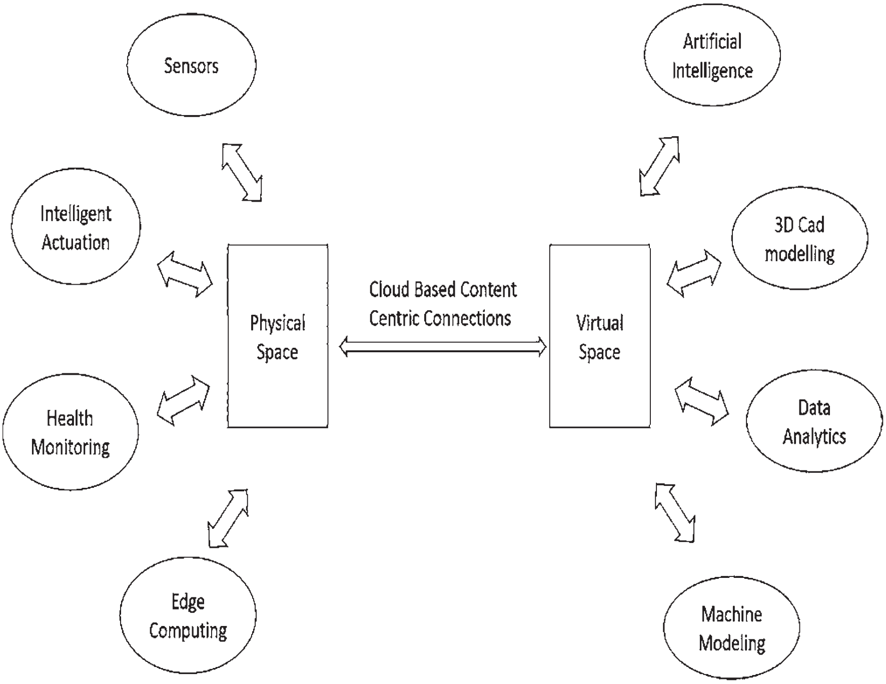

Fig. 5 Digital twins in automotive industry

This comprehensive representation enables the simulation and evaluation of each stage in the development process, facilitating the identification of issues and prediction of potential failures before the production of actual parts. Digital twins make it possible to observe some complex scenarios more effectively and can be used to determine specific circumstances that are needed for elaborate simulations as shown in Fig. 5. For instance, some situations are very challenging to replicate but can greatly improve sensors and programs [15].

Digital Twins in Aerospace

Digital twins can simulate and monitor the performance of airplanes or spacecraft in real-time, including the functionality of individual components. Digital twins offer a virtual depiction of systems like an airplane, a spacecraft, or even a semiconductor part inside a bigger system in the aerospace industry. Similar technology to Digital twin has been employed by the aerospace sector for some time. However, it has primarily been used to create digital models of military planes and commercial aircraft in airports to figure out how to enhance the equipment and achieve peak performance. Additionally, they have been effective in using the tracking capability

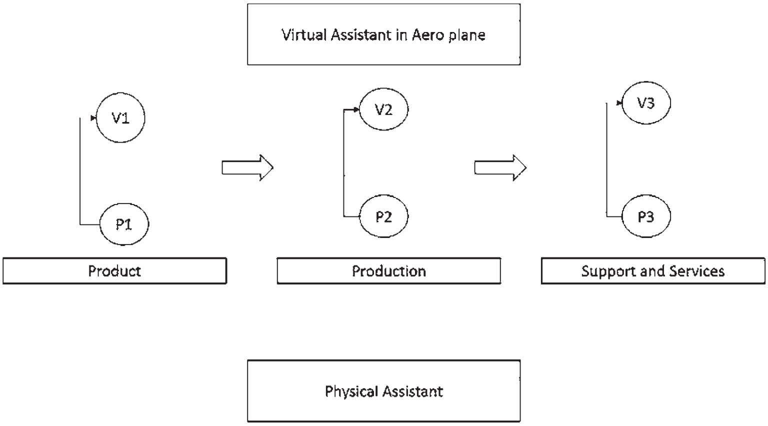

Fig. 6 Digital twins in health care

of D-Twins to follow airplanes around the globe to guarantee the effectiveness of their daily excursions. But as this technology advances and expands, more chances will start to emerge that will enable aircraft engineers to work more productively when it comes to carrying out new model tests, and when it applies to the business aspect of flying, passengers will ultimately have a more excellent and secure experience than ever earlier [16, 17].

To improve performance, the aviation sector still needs to fully implement D-Twin interfaces. When it pertains to a few of the most important components on which they must rely on such as aircraft monitoring, expansion, and examination, the air force and the armed forces, in contrast to the air force, are still unwilling to totally rely on digital twin as shown in Fig. 6. However, there has been a noticeable increase in the adoption of technology; as a result, it is going to be long before they build digital twin, and it will be ready for usage in the aviation sector [18].

Digital Twins in Healthcare

Digital twins can help doctors to test and diagnose medical conditions with greater accuracy, using real-time data from sensors and other devices. Futuristic precision healthcare is expected to include giving each patient an individualized diagnosis and course of medication, with simulation serving a growing part in healthcare. The development of D-Twin technology will make such customization feasible. The capacity to enhance the treatment of patients as well as study is one of the advantages of building a D-Twin in healthcare. For instance, by building a precise replica of a patient's brain, researchers can better understand diseases and how therapies affect human cells [19, 20].

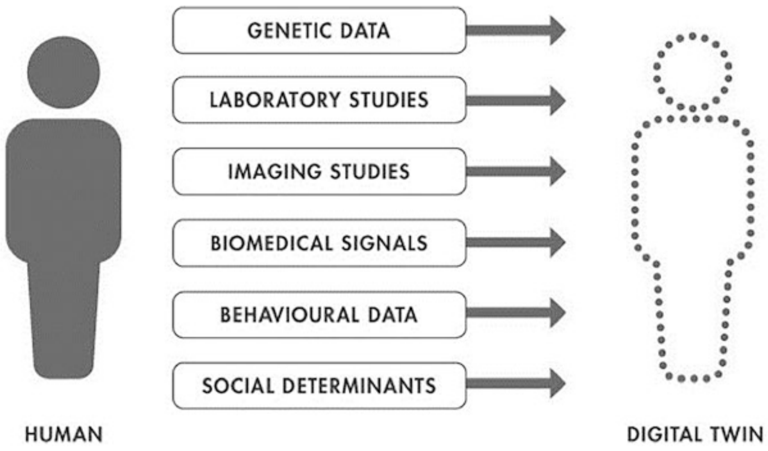

Fig. 7 Digital twin for healthcare [22]

A D-Twin is created when recreating a person or a patient employing recording of vital signs together with anatomical and physiological information. This data might originate from a variety of sources in the era of pervasive wearable technology and biological sensors. The virtual patient model can be updated with information from laboratory investigations and imaging scans performed during the patient's visit to a hospital as shown in Fig. 7. Additionally, a person's genetic, behavioral, and social variables could all be encoded in their D-Twin. A more comprehensive image of the medical condition of the individual is accessible to enhance decision-making when all these data are merged into one virtual depiction of the patient by D-Twin [21].

Digital Twins in Construction

Digital twins play a pivotal role in simulating construction projects, providing stakeholders with the ability to evaluate different outcomes and make well-informed decisions. Within the construction industry, a unified platform is utilized to generate digital twins by amalgamating various types of data. This integration includes 3D models, sensor data, and real-time performance data, enabling a comprehensive representation and analysis of construction projects as shown in Fig. 8. Through this platform, various scenarios, such as material selection, energy consumption, and service plans, can be simulated and optimized [23].

Furthermore, the use of digital twins can be instrumental in early detection of potential issues, resulting in decreased downtime and improved safety measures. An example of D-Twin application is modeling how extreme weather conditions might impact a structure or bridge. This allows engineers to anticipate potential issues and proactively implement protective measures to ensure the resilience and safety of the infrastructure [24].

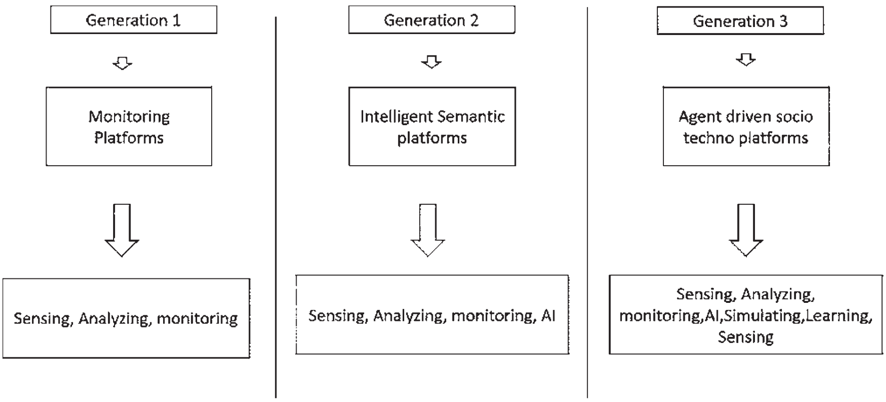

Fig. 8 Digital twin for construction

Digital Twins in Energy and Utilities

Digital twins can be used to predict energy consumption and optimize the use of resources, including renewable energy sources. The digitalization of the utilities sector creates potential for innovative, effective, and clever business practices, such as the application of D-Twin technologies. In fact, using a D-Twin for energy management is one of the finest ways to keep an eye on power usage and regulate energy sensors. The most important characteristics to search for in a D-Twin energy optimization solution are remote monitoring, automation capabilities, flexibility and scalability, and data and network security [25].

Planning and managing renewable energy infrastructure like solar farms or wind parks is made easier with the aid of D-Twins as shown in Fig. 9. They can model how many elements, including sunlight, wind patterns, and environmental variables, affect the efficiency of renewable energy resources. This data is useful for grid integration organizing, energy production prediction, and asset location [26].

Digital Twins in Smart Cities

Digital twins can be used to simulate how infrastructure and other systems work in smart cities, enabling city planners and administrators to optimize operations and increase efficiency. Urban planners as well as architects may visualize and simulate various urban development scenarios thanks to D-Twins. They can examine elements including building assignment, infrastructure needs, transit systems, and land usage as shown in Fig. 10. Decision-makers can make well-informed decisions on urban development, allocation of resources, and sustainability initiatives by modelling and analyzing these possible situations [27, 28].

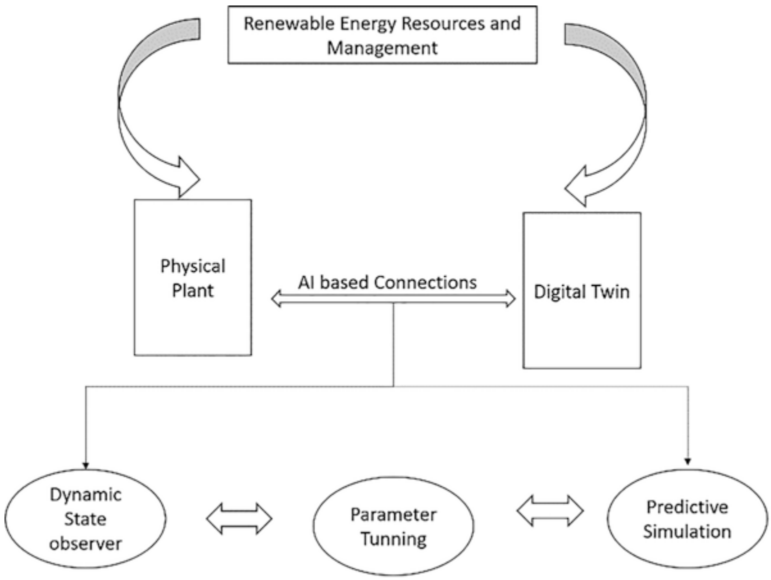

Fig. 9 Digital twins in energy resources and utilities

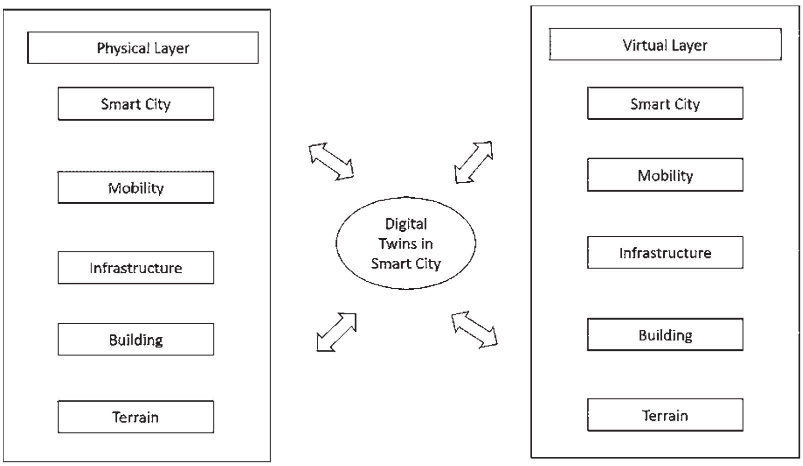

Fig. 10 Digital twins in smart cities

Cities' infrastructure, including roadways, connections, energy companies, and transportation networks, can be managed and maintained with the aid of D-Twins. Digital twins may track the health of infrastructure assets, forecast maintenance requirements, and optimize repairs by combining data from numerous sensors and internet of things (IoT) devices. This assures effective operations, reduces disruptions, and lengthens the infrastructure's entire lifecycle.

Digital Twins in Defense

Digital twins are employed in the defense sector to simulate and test a variety of technologies, including weapon systems, vehicles, and other defense-related equipment. This application helps mitigate the risk of human error and enhances overall performance by providing a virtual environment for rigorous testing and analysis. The efficiency and maintenance of military devices, such as automobiles, planes, or maritime vessels, can be tracked via D-Twins. The D-Twin can analyze the equipment's performance parameters, spot irregularities, and foretell required repairs by gathering data from sensors and other sources. This proactive strategy improves readiness for operation in general, decreases downtime, and optimizes maintenance plans [29, 30].

By recreating and visualizing the operational context, D-Twins can help with mission execution and evaluation. They can include information about the topography, the weather, and other pertinent variables to give commanders information and enhance their ability to make strategic choices. This makes it possible to more effectively allocate resources, evaluate risks, and carry out missions.

Digital Twins in Agriculture

Digital twins can facilitate farmers to improve crop yield and decrease waste by simulating different climate scenarios and optimizing resource use. In the world of agriculture, D-Twins are having a big impact on farming techniques and increasing total yields in agriculture. When referring to virtual reproductions or simulations of actual farming systems, such as crops, animals, and complete agricultural ecosystems, we employ the D-Twins in agriculture. Digital twins offer real-time monitoring, analysis, and forecasting capabilities for optimizing many parts of agricultural operations by utilizing data, sensors, and sophisticated analytics [31].

Digital twins can replicate agricultural development and growth while accounting for elements such as soil characteristics, weather patterns, and irrigation techniques.

Farmers may track the health, behavior, and well-being of livestock by using D-Twins to construct virtual duplicates of the animals. Body temperature, levels of activity, and feeding habits are just a few of the elements that sensors on animals may gather information on, which can then be included into the D-Twin as shown in Fig. 11.

By replicating the full agricultural activity, D-Twins assist precision farming practices. Based on soil and weather conditions, they can offer insights on the best planting strategies, seed choices, and fertilizer applications.

Digital twins can aid in the optimization of planting schedules, determination of the best time for harvesting, and management of potential hazards like outbreaks of

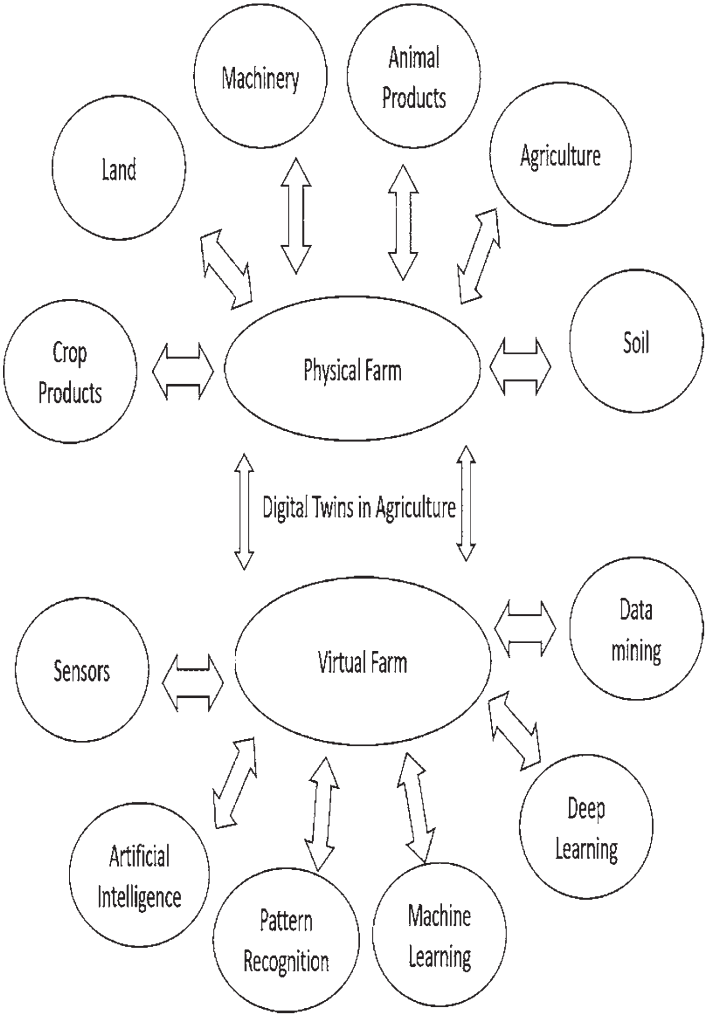

Fig. 11 Digital twins in agriculture

diseases or unfavorable weather occurrences by integrating data from numerous sources, like as weather forecasts, market pricing, and historical trends [32].

Digital twins can suggest exact irrigation plans, cut chemical inputs, and minimize environmental effect while preserving crop output by analyzing data on soil moisture levels, nutrients, and weather trends.

By simulating various layouts, infrastructural setups, and crop rotation techniques, D-Twins can help with the design and planning of agricultural operations. This aids farmers in making the most use of their land, evaluating the viability of new initiatives, and locating any possible obstacles or inconsistencies [33].

Digital Twins in Retail

Digital twins can provide retailers with an accurate insight into their supply chains, allowing them to optimize inventory management and logistics. Retailers can use these D-Twins as a potent tool to improve several aspects of their business, such as product design, managing inventory, consumer experience, as well as supply chain management.

During the design phase, retailers can make D-Twins of their products. Before producing the actual product, they can test and improve various features, materials, and combinations using these virtual models. It aids in lowering expenses, enhancing excellence, and speeding time to trade [34, 35].

Businesses can see their inventory quantities, locations, and circumstances in real time thanks to D-Twins. They may watch things as they move through the supply chain, keep an eye on stock levels, and improve replenishment procedures by combining data from sensors, RFID tags, and other sources. By doing this, you can manage your inventory effectively and avoid shortages and overstocking.

Digital Twins in Drug Development and Pharmacovigilance

In the context of drug development and pharmacovigilance, digital twins can be applied to various stages of the drug lifecycle, from preclinical studies to post-market surveillance.

In drug development, digital twins can help accelerate the discovery process by simulating the effects of potential drugs on virtual models of biological systems. By creating a virtual representation of a biological target, researchers can use computational methods to design drugs that are more likely to be effective and safe. Digital twins can also be used to optimize clinical trial design and predict drug efficacy and toxicity [36].

In the field of pharmacovigilance, digital twins play a crucial role in real-time drug safety monitoring. Through the creation of a virtual representation of a patient population, digital twins are instrumental in identifying potential adverse events and drug interactions before they manifest. Moreover, digital twins contribute to the identification of patient subpopulations at a heightened risk of adverse events, facilitating targeted monitoring and timely intervention measures [37].

Overall, digital twins have the potential to revolutionize drug development and pharmacovigilance by providing a more efficient and accurate way to predict drug behavior and optimize patient outcomes. However, there are still challenges to be addressed, such as data quality and privacy concerns before digital twins can be fully integrated into drug development and pharmacovigilance processes.

Simulate and Prepare for Natural Disasters Using Digital Twins

Digital twins are useful resources for planning and modelling natural disasters. Digital twins give organizations the ability to assess the possible effects of disasters, establish response strategies, and improve emergency preparedness by building digital copies of physical settings and infrastructure. Different kinds of natural disasters, including hurricanes, earthquakes, floods, and wildfires, can be simulated using D-Twins. Organizations can perform simulations to learn how the disaster might develop and impact their property, facilities, and neighborhoods by including pertinent data, such as historical climate trends, topographical data, and building designs. These simulations can be used to find weak points, assess evacuation options, and gauge the efficiency of different response tactics [38].

With the help of D-Twins, stakeholders can be trained and educated on catastrophe preparation and action. They can be utilized in scenario-based training sessions, giving staff members the chance to practice the duties they have in a lifelike virtual setting. This enhances planning, decision-making, and the efficiency of emergency responses. The rehabilitation and reconstruction process after a tragedy can be aided by D-Twins. Organizations can utilize D-Twins to assess destruction, plan rebuilding activities, and simulate the efficacy of various recovery techniques by preserving the as-is state of the affected regions prior to a disaster [39].

Digital Twins Enabled Smart Learning in Education

By providing intelligent learning experiences, D-Twins have the potential to revolutionize the education industry. Digital twins can improve teaching strategies and individualized training and offer immersive and engaging educational experiences by building virtual reproductions of actual learning environments [40].

The learning preferences, strengths, and shortcomings of pupils can be captured in virtual profiles made using D-Twins. Digital twins can offer personalized paths to learning and customizable material that cater to the needs of each student by analyzing data from numerous sources, including assessments, learning analytics, and educational assets. This individualized approach boosts involvement, allows students to learn at their own speed, and improves learning results. Students may perform virtual experiments as well as simulations in D-Twins that can mimic actual laboratories. This makes learning opportunities accessible that might not otherwise be possible due to limitations on time, money, or security. Students can investigate intricate scientific ideas, carry out investigations in a safe virtual setting, and track results in real-time, encouraging practical learning and analytical thinking [41].

Future of Digital Twins

Here are some potential trends and developments in the future of digital twins:

- Integration with IoT and Sensor Technologies: The synergy between digital twins and the Internet of Things continues to grow. As more devices and sensors are connected, digital twins can provide richer and more accurate representations of physical assets.
- Advancements in AI and Machine Learning: As artificial intelligence and machine learning technologies evolve; digital twins will likely benefit from more sophisticated analytics and predictive capabilities. This could enhance their ability to simulate and forecast the behavior of physical assets.
- Extended Use Cases: The application of digital twins is likely to expand into new industries and use cases. Beyond manufacturing and industrial settings, digital twins may find applications in healthcare, smart cities, logistics, and more.
- Blockchain for Security and Trust: Blockchain technology could be integrated to enhance the security and trustworthiness of digital twin data. This is especially crucial in industries where data integrity is paramount, such as healthcare and critical infrastructure.
- Decentralized Digital Twins: Decentralized and distributed architectures, such as blockchain, could be used to create decentralized digital twins. This approach may provide greater resilience, security, and scalability.
- Standardization and Interoperability: The development of industry standards and interoperability protocols will be essential for the widespread adoption of digital twins. This ensures that different systems and platforms can seamlessly work together.
- Human Digital Twins: The concept of creating digital twins for individuals (human digital twins) could gain traction, especially in healthcare and personalized medicine. This could aid in better understanding individual health and predicting potential health issues.
- Ethical and Privacy Considerations: As the use of digital twins becomes more prevalent, there will likely be increased attention to ethical and privacy considerations. Striking a balance between collecting valuable data and protecting individuals' privacy will be crucial.
- Edge Computing for Real-Time Processing: With the rise of edge computing, the processing and analysis of data from digital twins may move closer to the source, enabling real-time insights and reducing latency.
- Lifecycle Management: Digital twins may play a more significant role throughout the entire lifecycle of a product or asset, from design and manufacturing to operation, maintenance, and decommissioning.

Conclusion

The numerous ways that D-Twin technology is applied across various businesses and sectors are referred to as D-Twin applications. A D-Twin is a virtual version of a real-world system, process, or item that allows for surveillance, assessment, and modelling in real-time. Some important D-Twin applications are presented in this chapter. These are only a few instances of D-Twin applications. Technology has the power to transform several industries by delivering real-time insights, allowing predictive capabilities, and streamlining processes based on simulations of data. The use of D-Twins in the future has an opportunity to significantly progress numerous fields. With improvements in AI, IoT, simulation capabilities, and collaborative tools driving their wider use and providing significant advantages in terms of productivity, effectiveness, and development across sectors, the future of D-Twins appears bright.

References

1. Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE Access, 28*(8), 108952–108971.
2. Zheng, Y., Yang, S., & Cheng, H. (2019). An application framework of digital twin and its case study. *Journal of Ambient Intelligence and Humanized Computing, 13*(10), 1141–1153.
3. Liu, M., Fang, S., Dong, H., & Xu, C. (2021). Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems, 1*(58), 346–361.
4. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. (2018). Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics, 15*(4), 2405–2415.
5. Haag, S., & Anderl, R. (2018). Digital twin–Proof of concept. *Manufacturing Letters, 1*(15), 64–66.
6. Wright, L., & Davidson, S. (2020). How to tell the difference between a model and a digital twin. *Advanced Modeling and Simulation in Engineering Sciences, 7*(1), 1–3.
7. Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology, 1*(29), 36–52.
8. VanDerHorn, E., & Mahadevan, S. (2021). Digital Twin: Generalization, characterization and implementation. *Decision Support Systems, 1*(145), 113524.
9. Kholopov, V. A., Antonov, S. V., Kurnasov, E. V., & Kashirskaya, E. N. (2019). Digital twins in manufacturing. *Russian Engineering Research, 39*, 1014–1020.
10. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *Ifac-PapersOnline, 51*(11), 1016–1022.
11. Onaji, I., Tiwari, D., Soulatiantork, P., Song, B., & Tiwari, A. (2022). Digital twin in manufacturing: Conceptual framework and case studies. *International Journal of Computer Integrated Manufacturing, 35*(8), 831–858.
12. Piromalis, D., & Kantaros, A. (2022). Digital twins in the automotive industry: The road toward physical-digital convergence. *Applied System Innovation, 5*(4), 65.
13. Damjanovic-Behrendt, V. (2018). A digital twin-based privacy enhancement mechanism for the automotive industry. In *2018 International conference on intelligent systems (IS)* (pp. 272–279). IEEE.

14. Veledar, O., Damjanovic-Behrendt, V., & Macher, G. (2019, September 18–20). Digital twins for dependability improvement of autonomous driving. In *Systems, software and services process improvement: 26th European conference, EuroSPI 2019*, Edinburgh, UK, Proceedings 26 2019 (pp. 415–426). Springer International Publishing.
15. Biesinger, F., Kraß, B., & Weyrich, M. (2019). A survey on the necessity for a digital twin of production in the automotive industry. In *2019 23rd International conference on mechatronics technology (ICMT)* (pp. 1–8). IEEE.
16. Phanden, R. K., Sharma, P., & Dubey, A. (2021). A review on simulation in digital twin for aerospace, manufacturing and robotics. *Materials Today: Proceedings, 38*, 174–178.
17. Li, L., Aslam, S., Wileman, A., & Perinpanayagam, S. (2021). Digital twin in aerospace industry: A gentle introduction. *IEEE Access, 10*, 9543–9562.
18. Liu, S., Bao, J., Lu, Y., Li, J., Lu, S., & Sun, X. (2021). Digital twin modeling method based on biomimicry for machining aerospace components. *Journal of Manufacturing Systems, 58*, 180–195.
19. Ahmadi-Assalemi, G., Al-Khateeb, H., Maple, C., Epiphaniou, G., Alhaboby, Z. A., Alkaabi, S., & Alhaboby, D. (2020). Digital twins for precision healthcare. In *Cyber defence in the age of AI, smart societies and augmented humanity* (pp. 133–158). Springer.
20. Kaul, R., Ossai, C., Forkan, A. R., Jayaraman, P. P., Zelcer, J., Vaughan, S., & Wickramasinghe, N. (2023). The role of AI for developing digital twins in healthcare: The case of cancer care. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 13*(1), e1480.
21. Angulo, C., Gonzalez-Abril, L., Raya, C., & Ortega, J. A. (2020). A proposal to evolving towards digital twins in healthcare. In *Bioinformatics and biomedical engineering: 8th international work-conference, IWBBIO 2020*, Granada, Spain, May 6–8, 2020, Proceedings (pp. 418–426). Springer International Publishing.
22. Suomi, V. *Next-generation digital twins in healthcare*. https://www.medtechintelligence.com/column/next-generation-digital-twins-in-healthcare/
23. Kor, M., Yitmen, I., & Alizadehsalehi, S. (2023). An investigation for integration of deep learning and digital twins towards Construction 4.0. *Smart and Sustainable Built Environment, 12*(3), 461–487.
24. Akanmu, A. A., Anumba, C. J., & Ogunseiju, O. O. (2021). Towards next generation cyber-physical systems and digital twins for construction. *Journal of Information Technology in Construction, 26*, 505–525.
25. Teng, S. Y., Touš, M., Leong, W. D., How, B. S., Lam, H. L., & Máša, V. (2021). Recent advances on industrial data-driven energy savings: Digital twins and infrastructures. *Renewable and Sustainable Energy Reviews, 135*, 110208.
26. Onile, A. E., Machlev, R., Petlenkov, E., Levron, Y., & Belikov, J. (2021). Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Reports, 7*, 997–1015.
27. Dembski, F., Wössner, U., Letzgus, M., Ruddat, M., & Yamu, C. (2020). Urban digital twins for smart cities and citizens: The case study of Herrenberg, Germany. *Sustainability, 12*(6), 2307.
28. Zheng, T., Liu, M., Puthal, D., Yi, P., Wu, Y., & He, X. (2022, May 24). Smart grid: Cyber attacks, critical defense approaches, and digital twin. arXiv preprint arXiv:2205.11783.
29. Wu, J., Yang, Y., Cheng, X. U., Zuo, H., & Cheng, Z. (2020). The development of digital twin technology review. In *2020 Chinese Automation Congress (CAC)* (pp. 4901–4906). IEEE.
30. Kraft, E. M. (2016). The air force digital thread/digital twin-life cycle integration and use of computational and experimental knowledge. In *54th AIAA aerospace sciences meeting* (p. 0897).
31. Pylianidis, C., Osinga, S., & Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. *Computers and Electronics in Agriculture, 184*, 105942.
32. Purcell, W., & Neubauer, T. (2022). Digital twins in agriculture: A state-of-the-art review. *Smart Agricultural Technology, 3*, 100094.

33. Purcell, W., Neubauer, T., & Mallinger, K. (2023). Digital Twins in agriculture: Challenges and opportunities for environmental sustainability. *Current Opinion in Environmental Sustainability, 61*, 101252.
34. Kümpel, M., Mueller, C. A., & Beetz, M. (2021). Semantic digital twins for retail logistics. In *Dynamics in logistics: Twenty-five years of interdisciplinary logistics research in Bremen, Germany* (pp. 129–153). Springer International Publishing.
35. Maïzi, Y., & Bendavid, Y. (2021). Building a digital twin for IoT smart stores: A case in retail and apparel industry. *International Journal of Simulation and Process Modelling, 16*(2), 147–160.
36. Kumar, S. H., Talasila, D., Gowrav, M. P., & Gangadharappa, H. V. (2020). Adaptations of Pharma 4.0 from Industry 4.0. *Drug Invention Today, 14*(3), 405.
37. Paulick, K., Seidel, S., Lange, C., Kemmer, A., Cruz-Bournazou, M. N., Baier, A., & Haehn, D. (2022). Promoting sustainability through next-generation biologics drug development. *Sustainability, 14*(8), 4401.
38. Kaewunruen, S., Peng, S., & Phil-Ebosie, O. (2020). Digital twin aided sustainability and vulnerability audit for subway stations. *Sustainability, 12*(19), 7873.
39. Ham, Y., & Kim, J. (2020). Participatory sensing and digital twin city: Updating virtual city models for enhanced risk-informed decision-making. *Journal of Management in Engineering, 36*(3), 04020005.
40. Mashaly, M. (2021). Connecting the twins: A review on digital twin technology & its networking requirements. *Procedia Computer Science, 184*, 299–305.
41. Guc, F., Viola, J., & Chen, Y. (2021). Digital twins enabled remote laboratory learning experience for mechatronics education. In *2021 IEEE 1st international conference on digital twins and parallel intelligence (DTPI)* (pp. 242–245). IEEE.

Artificial Intelligence in Digital Twins for Sustainable Future

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Introduction

Artificial intelligence, often abbreviated as AI, represents a domain within computer science dedicated to constructing intelligent machines capable of emulating human-like cognitive functions. Its primary objective revolves around the development of algorithms and systems that empower computers to engage in reasoning, decision-making, and data-driven learning processes. This multifaceted field spans various subfields such as machine learning, natural language processing, computer vision, and robotics, each contributing to the overarching goal of creating intelligent systems. By harnessing AI technologies, researchers aim to bridge the gap between human intellect and machine computation, thereby revolutionizing industries, advancing scientific discovery, and augmenting human capabilities in diverse domains.

Deep learning, which uses neural networks with numerous layers to learn complicated patterns, machine learning, which allows computers to learn from data without explicit programming, and natural language processing, which enables computers to comprehend and produce human language, are some of the AI techniques. Robotics, computer vision, data mining, and pattern recognition are just a few of the industries where AI is used. With the potential to revolutionize technology and enhance our daily lives, it is changing sectors.

The concept of a digital twin revolves around crafting a virtual representation of a physical entity, enabling the display, analysis, and optimization of its performance in real-time. Through the integration of sensors and IoT devices, data is collected from the physical entity and transmitted to its digital counterpart, facilitating an accurate emulation of its behavior. This digital model serves as a dynamic reflection

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of the physical entity, providing insights into its operation, facilitating predictive maintenance, and supporting decision-making processes across various industries.

To qualify as a digital twin (DT), synchronization between the virtual and physical attributes is essential at all times. In the context of a patient-centric Healthcare DT, this entails the creation of a virtual patient within a digital environment, requiring a significant dataset that accurately mirrors the patient's physical condition. This data convergence enables real-time monitoring, analysis, and simulation of the patient's health status, facilitating personalized healthcare interventions and improving overall patient outcomes. Merely possessing one aspect of patient data is insufficient for the Healthcare DT to form a comprehensive understanding of a patient who may encounter unpredictable health incidents. It necessitates access to all relevant information concerning the patient's medication, hospital records, and overall healthcare management [1–4]. Furthermore, it is important to acknowledge that the human body is intricate, influenced by various external factors such as environmental conditions, age, social activities, and more. Moreover, when delving into the causal factors of a disease or co-morbidity, individual variability becomes a critical consideration, as different factors can exert varying effects on different individuals [5]. Hence, the accumulation of comprehensive patient data from birth to death becomes paramount. This wealth of data enables the digital twin (DT) to analyze and accurately deduce the current state of the patient, as well as predict future threats based on real-time data insights [6]. This fundamental principle underpins the development of patient-centric healthcare DTs, offering invaluable benefits in scenarios such as remote patient monitoring. In such instances, the DT can provide all requisite data, enabling effective inquiry resolution.

Blockchain operates as a decentralized ledger system, where the ledger comprising data from all blocks is distributed across multiple peer nodes within the network. The replication process across a distributed network readily facilitates the attainment of immutability and non-repudiation [7]. Data stored within a blockchain, along with additional blocks, are exclusively appendable at the blockchain's terminus. These blocks are intricately connected to their antecedent blocks through the utilization of Cryptographic Hash Functions [8]. Once a block becomes part of the chain, it is inherently shielded from alteration or removal [9].

Therefore, blockchain incorporates a consensus mechanism that relies on prior consensus on rules and adheres to the principle of majority dominance [10]. This is why the blockchain system relies primarily on consensus algorithms, which guarantee consistency across distributed nodes [11].

Blockchain can be generally categorized into two types:

The concept of a Public Blockchain involves enabling unrestricted participation for creating, validating blocks, and recording data onto the blockchain ledger. This type of blockchain is often referred to as a permissionless blockchain due to its open access nature [12]. Within this blockchain framework, participants remain anonymous, and all transaction records are accessible to the public. While it has demonstrated notable strength in terms of security, it also exhibits limitations in propagation speed, leading to restricted transaction throughput and comparatively higher latency [13]. Prominent instances of public blockchain systems include Bitcoin [14] and Ethereum [15]. In the healthcare domain, notable examples of public blockchain systems encompass MedRec [16] and FHIRChain [17]. Conversely, a Private Blockchain functions as a permissioned system, permitting only a predefined set of entities to participate in the validation process. This strategy addresses concerns regarding energy consumption while upholding stringent security protocols [18]. The synchronization of blocks across the distributed network in a private blockchain is expedited due to the smaller participant pool engaged in block validation [19]. Private blockchain solutions are particularly crucial in scenarios where data privacy is imperative, such as in financial reports and health data management. Prominent private blockchain platforms include Hyperledger Fabric, Hyperledger Sawtooth, and Corda [20]. In the healthcare sector, various private blockchain-based systems have been developed [21–24]. Due to its remarkable versatility and practicality, it has captured the interest of the researchers. In this overview, we present a summary of several noteworthy recent research findings [25]. The article offers a construction case study on a hospital DT in China, which had already undergone the construction phase. The hospital twin had already been constructed prior to the authors' delineation of its development using the Continuous Lifecycle Integration method. During the construction process, numerous sensors were strategically installed to capture real-time data from the hospital, enabling centralized control of the entire system through the use of DT.

Alternatively, Liu and colleagues introduced a cloud-centric framework integrating healthcare Distributed Technologies (DT) [26]. The main motive of this project is to provide the medical services to the elders who are not able to take medical facilities due to their disease. The authors have designed a system that consists of four components: The chapter discusses various elements such as physical objects, virtual objects, cloud healthcare service platforms, and healthcare data. While the authors have covered significant aspects, they have not explicitly included any algorithms for predictive measures.

In this particular chapter [27], the authors utilize edge computing to create a healthcare Twin aimed at mitigating heart diseases by leveraging real-time data collected through IoT devices, primarily smartphones. The collected data undergoes data fusion transformation before being stored in a central data storage system. The twin comprises three main structures: data source, AI-inference engine, and multimodal interaction and smart service. The authors' primary focus is on training a Convolutional Neural Network (CNN), although challenges related to data storage and security remain unaddressed. Shamanna et al. [28] have presented a related study on Precision Nutrition applied to DT, introducing Twin Precision Nutrition (TPN). The research focuses on monitoring a specific group of type 2 diabetic patients aged 64 years, aiming to reduce HbA1c levels in their blood. The TPN platform utilizes data collected from body sensors and a mobile app to track and analyze various health signals, enabling personalized treatment for the patients. However, the authors have not detailed the specific mechanism through which they conducted the analysis despite utilizing real-time data.

In their publication, Barbiero and co-authors [29] introduced an innovative architecture that combines the functionalities of a generative model with a graph-based depiction of pathophysiological circumstances. Through the utilization of synthetic data and the enrichment of navigable states within the biological system, their framework facilitates the emulation of intricate clinical scenarios that would have otherwise presented difficulties for thorough examination.

The authors have adopted multiple data models to systematically gather information and have leveraged graph neural networks for deep learning to generate predictions regarding the patient's physiological state evolution.

Petrova et al. [30] have introduced a digital twin (DT) platform tailored for studying behavioral changes in patients suffering from cognitive disorders, with a specific emphasis on multiple sclerosis. The platform encompasses several key components, including data collection functionality specifically tailored for DT purposes. Additionally, an advanced analytical application is integrated within the platform, enabling data aggregation, enrichment, analysis, and visualization, facilitating the generation of novel insights and decision support. The authors have indicated that patient data will be sourced from Electronic Health Records (EHRs), open clinical datasets, social networks, and external applications. However, they have not outlined the necessary measures to ensure data integrity and confidentiality, which may present potential vulnerabilities.

In their publication [31], the authors have introduced a digital twin system for risk diagnosis, aiming to improve decision-making processes for liver diseases by incorporating explainable artificial intelligence. The authors have utilized their developed Random Forest (RDF) model along with the Local Interpretable Model-Agnostic Explanations (LIME) library, which is a state-of-the-art tool for explainable AI. Recognizing the sensitivity of healthcare matters, the authors have emphasized the importance of using explainable AI techniques. While the authors have provided comprehensive details about the algorithms employed, they have not addressed aspects related to storage facilities and security measures, which are crucial in healthcare systems.

In the realm of Healthcare DT, a noteworthy and recent contribution can be found in [32]. The authors present a framework that offers significant benefits for digital healthcare and healthcare operations. The framework revolves around an intelligent context-aware healthcare system primarily focused on diagnosing heart problems and detecting heart disease through the classification of ECG heart rhythms using DT. This system seamlessly integrates artificial intelligence (AI), data analytics, IoT, virtual and augmented reality, as well as digital and physical objects. By combining these technologies, the framework enables real-time data analysis and proactive problem resolution through continuous status monitoring and provides valuable insights for risk management, cost reduction, and predicting future opportunities. However, similar to the aforementioned works, the authors have not addressed the issue of safeguarding the stored data.

The authors have presented a visionary concept that explores the integration of multi-agent systems with DT in the healthcare field [33]. In this context, multi-agent systems refer to software agents capable of providing responses prior to taking actions. From a DT perspective, these agents serve as a framework for developing intelligent systems that combine AI and Distributed AI techniques, incorporating a certain level of autonomy on top of DTs to leverage their inherent features. However, the authors have not included any empirical process or analysis to substantiate their proposal.

The healthcare sector is witnessing significant advancements in DT, indicating substantial progress. However, a critical challenge lies in the gathering of detailed and complex data from the physical environment. Additionally, ensuring the secure storage of this vast amount of data and preserving its integrity and confidentiality remain a paramount concern for DT in the healthcare sector.

Digital Twin (DT)

A digital twin (DT) refers to the representation of a digital asset's anatomy in a digital environment, mirroring a physical phenomenon extracted from the real world. Serving as a complex system, it ensures consistency between the digital and physical realms while also acquiring cognitive insights about the physical environment. The primary role of a DT is to facilitate interaction between the physical and digital domains, making it a crucial component of its functionality. The rapid advancement of cutting-edge technologies such as Radio-Frequency Identification (RFID) and the Internet of Things (IoT) facilitates the convenient collection of data from various aspects of a physical phenomenon. Figure 1 illustrates the structural model and technical composition of a digital twin.

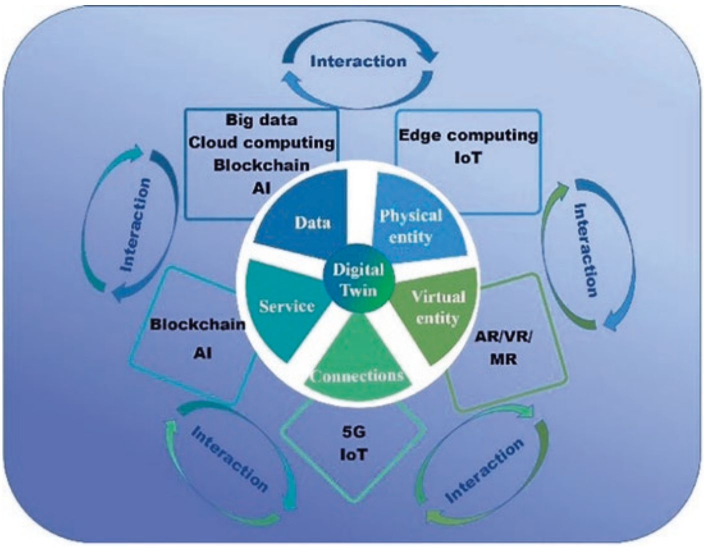

Fig. 1 Structural model and technical composition of digital twin [34]

Categorization

DT can be categorized into two types based on its intended purpose of utilization:

(a) Digital Twin for Developing a Product

The representative DT possesses all the information required to develop the physical product, even though the product itself is yet to be created. By leveraging prior knowledge, the representative DT can anticipate the workflow and behavior of the product through factors such as the current development status, work allocation, and product description. As an illustration, a DT can be introduced during the manufacturing stage of a hospital facility. This is categorized as part of Product Lifecycle Management within the healthcare industry.

(b) Digital Twin for an Individual Instance

This particular form of DT possesses knowledge regarding either a tangible product or a non-spatial phenomenon, and it has the capability to continuously synchronize the virtual representation with real-time data sourced from IoT devices within the physical environment [2]. Suppose an automobile has been constructed with sensors integrated into every crucial component. In such a scenario, the DT would continuously receive data from the vehicle, enabling it to evaluate the current condition of the car through vehicle health management [3]. Remote analysis can facilitate the determination of maintenance intervals for parts, product longevity, and other related factors, thus enabling the extraction of valuable insights regarding the specific instance.

Characteristics of Digital Twin

- *Connectivity*
- In virtual twin technology, we connect physical property and their virtual opposite numbers. We attach sensors to physical objects to decorate their connectivity with their digital representations.
- Data from the physical components are acquired and incorporated through these sensors. This integration allows the sensors to speak the accumulated information to a consumer.
- *Homogenization*
- Digital technology is also characterized by the homogenization of records from bodily components. This approach that a virtual representation just like the physical object may be created for the usage of the accrued statistics. This era can also enable statistics to be decoupled from physical artifacts [35].
- *Reprogrammable*