Revolutionizing Agriculture Through Digital Twins

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1. INTRODUCTION

The agriculture industry is essential to the functioning of any economy. The U.S. agricultural sector encompasses not only the farming industry but also a variety of related industries. This industry is an important source of food, raw materials, and a vital source of employment opportunities for the total population. In 2021, the agricultural sector employed nearly 10.5 percent of US employment—21.1 million full and part-time workers. The U.S. economy received an annual contribution of approximately $1.264 trillion in 2021 from crops, livestock, seafood, food service, and other agriculture-related industries. That accounted for a 5.4 percent contribution to the U.S. Gross Domestic Product (GDP). America's farms contributed $164.7 billion—about 0.7 percent of U.S. GDP (USDA, 2023). Agriculture's impact on GDP exceeds 0.7 percent, as various industries that depend on agricultural inputs add value to the economy. These industries include food and beverage manufacturing, food and beverage stores, food services and restaurants, textiles, apparel, leather products, forestry, and fishing (USDA, 2023). After the European Union, the United States is the world's second-largest agricultural trader. Agriculture is also a major source of US export earnings, accounting for approximately 25 percent of all US exports. Additionally, the US is one of the world's leading producers of food and agricultural products, which helps ensure a stable and secure food supply for the country's population. Finally, agriculture plays a critical role in ensuring food security in the US (USDA, 2022).

The global population has been steadily increasing over time, and this growth trend is projected to continue in the future. With more people to feed, there is a higher demand for agricultural products. Additionally, consumers today are increasingly concerned about the quality and safety of the food they consume and the environmental impact of food production. This has led to a growing need for sustainable and responsible agricultural practices that can meet these demands. As a result of these challenges, the agricultural sector is under significant economic pressure to increase productivity and efficiency while maintaining profitability. As a result, farmers must produce more with fewer resources and less land,

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which can be daunting. To meet these challenges, they need access to new technologies, techniques, and information to improve their yields and manage their resources more efficiently (FAO, 2017).

Moreover, environmental and climate change issues have become more critical for agriculture. The changing climate can affect the availability and quality of water, soil, and other resources necessary for agriculture, making it challenging to maintain consistent yields. Climate change can also lead to the emergence of new pests and diseases that can threaten crops and livestock, creating additional economic and environmental pressures (The World Bank, 2022).

In summary, food security, sustainability, productivity, and profitability have become more crucial for the agricultural sector, as the world population grows, market demand increases, and climate change and environmental issues become more pressing. The agriculture industry must adapt to these challenges by developing and implementing innovative and sustainable practices to remain productive, profitable, and environmentally responsible.

Amid the above challenges, the agriculture industry has been digitally transforming, but now it's happening at speed and scale (Verdouw et al., 2021). COVID-19 disruption is a significant motivator for many industries, including agriculture, for greater traceability and reduced waste. Technologies like Digital Twins are being developed in many industries, including agriculture, to improve the efficiency of supply chains. DT is an essential technology in agriculture because it enables users to make management decisions about things without being physically present. As a result, the technology allows systems to be managed more effectively– saving time, and costs, improving sustainability and attracting higher premiums for produce (Alves et al., 2019).

DT is attracting the attention of practitioners and scholars alike. Today, the technology is used across many industries to provide accurate virtual representations of objects and simulations of operational processes. Gartner estimates that by 2027, over 40 percent of large companies worldwide will use DT in their projects to increase revenue (Gartner, 2022). Moreover, Global Market Insight estimated that the DT market size estimated in 2022 at $8 billion is expected to grow at around 25 percent Compound Annual Growth Rate (CAGR) from 2023 to 2032 (Global Market Insight, 2022). In addition, according to a 2022 report, nearly 60 percent of executives across a broad spectrum of industry plan to incorporate DT within their operations by 2028 (Researchandmarkets, 2022).

Although the journey towards transforming the agriculture industry using DT technology has already begun, there have been very few reported examples of the business benefits realized by leading-edge farms and agricultural landscapes resulting from the applications of this new technology. Although still at a conceptual stage, DT is slowly penetrating and addressing the unmet needs in agriculture. Research about DT and agriculture is currently limited. As DT applications become more mainstream, examining the challenges, benefits, and drawbacks of using this technology in agriculture is essential. Section 2 provides the main perspectives and definitions of DT in literature. Section 3 reviews four enabling technologies of the DT. Section 4 studies trending DT applications and use cases in the agriculture industry. Section 5 highlights the challenges and opportunities of this technology. Section 6 provides a summary and conclusions. Section 7 suggests future research directions. Finally, section 8 lists references.

2. DT BACKGROUND AND DEFINITION

In 2003, the Digital Twins concept (a digital mirror and digital mapping) was first introduced by Professor Grieves in the Total Product Lifecycle Management course at the University of Michigan. Since then, its definition has evolved, and scholars have provided varied definitions of this technology and discussed various stages of DT development (Jones et al., 2020; Fuller et al., 2020; Rasheed et al., 2020; Stark and Damerau, 2019; Kritzinger et al., 2018; Tao et al., 2018). The Encyclopedia of Production Engineering states: "*The Digital Twin is a representation of an active unique 'product' which can be a real device, object, machine, service, intangible asset, or a system consisting of a product and its related services*" (Stark and Damerau, 2019). In general, the DT is defined as a "virtual representation of physical objects across life cycle that can be understood, learned, and reasoned with real-time data, or "a simulation model that acquires data from the field and triggers the operation of physical devices (Bolton et al., 2018; Negri et al., 2020). Furthermore, DT is defined as the convergence between physical and virtual products (Grieves, 2014; Tao et al., 2019). Fu et al., (2022) considered the DT a real-time digital representation of a physical object. They are remotely connected to real objects and provide rich representations of these objects. They go beyond static product designs, like CAD models, but comprise dynamic behavior (Boschert and Rosen, 2016; Grieves and Vickers, 2017).

It's important to note that DT differs from Digital Shadow (DS) and Digital Model (DM). These three technologies are differentiated based on their data flow architectures and intended uses. DM is useful for industrial design and concept development. DS is a powerful technology for tracking production, and a DT is a beneficial tool for evaluating real-time manufacturing (Sepasgozar, 2021).

A historic early application of DT technology is when NASA engineers used a simulator, a twin of the command module, and a separate twin of the module's electrical system to remedy and save Apollo 13 in 1970. NASA engineers completed the process in under two hours and saved the lives of the three astronauts on board. This technology was an extraordinary early application, which has only matured since then (Uri, 2020). Today, NASA uses DT to develop next-generation vehicles and aircraft.

DT is a cutting-edge technology that has revolutionized the industry by mirroring almost every facet of a product, process, or service. It has the potential to replicate everything in the physical world in the digital space and provide feedback from the virtual world to engineers (Fu et al., 2022). As a result, the technology enables companies to detect and solve physical problems faster, design and build better products, and ultimately realize the value and benefits more quickly than ever. Furthermore, technology enables businesses to improve business processes and performance (Qinglin et al., 2021).

The concept of DT is not new. However, DT has moved from idea to reality much faster in recent years. It is predicted that DT will be combined with more technologies such as speech capabilities, augmented reality, IoT, and AI. As a result, Gartner includes DT on its list of top 10 technology trends for 2017 (Panetta, 2016). Gartner also predicted that half of the large industrial firms would use DT in crucial business applications by 2021 (Panetta, 2016). Finally, MarketsandMarkets research predicted rapid growth for the DT technology within the next few years, thanks to rising interest in the manufacturing industry to reduce cost and improve supply chain operations. As a result, the market for DT technology was valued at $6.9 billion in 2022. However, it is expected to reach $73.5 billion by 2027– a CAGR of more than 60 percent (MarketsandNarkets, 2022).

3. DT TECHNOLOGIES

The three main aspects of DT are data acquisition, data modeling, and data application (Lv and Xie, 2021). DT uses a particular technology, depending on the application type, to a greater or lesser extent, to collect and store real-time data, obtain information to provide valuable insights and create a digital representation of a physical object. These technologies include the Internet of Things (IoT), Artificial Intelligence (AI), Extended Reality (XR), and Cloud (Figure 1).

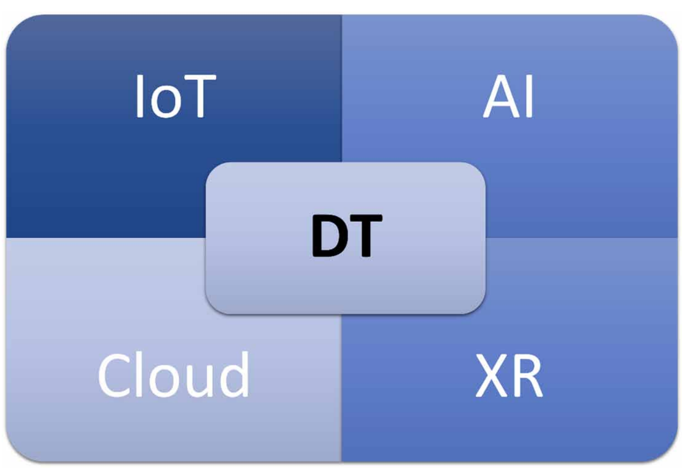
3.1 Internet of Things (IoT)

IoT refers to a giant network of connected "things." The connection is between things-things, people-things, or people-people (Attaran, 2017). DT use IoT as its primary technology in every application. By 2027, more than 90 percent of all IoT Platforms will have Digital Twinning capability (Researchandmarkets, 2022). IoT uses sensors to collect real-time data on physical systems, processes, and environments, which can be used to build and update DTs. IoT devices can transmit data to the DT in real-time, ensuring that the DT accurately reflects the current state of the physical system and allowing for immediate analysis and response to changing conditions. This data can include information on temperature, humidity, pressure, vibration, and other key variables (Sasikumar et al., 2013). The digital version then can then be analyzed, manipulated, and optimized. This can include adjusting settings and parameters, detecting and responding to faults, and optimizing performance. Finally, IoT data can be used to simulate and test different scenarios and conditions within the DT, before implementing them in the real world and without affecting the physical system (Gopal, et al., 2023).

3.2 Cloud Computing

Cloud computing refers to delivering hosted services over the Internet. The technology efficiently stores and accesses data over the Internet (Attaran, 2017). Cloud computing is essential for creating and operating DTs, as it provides a secure and scalable environment for storing and managing the vast amounts of data generated by DTs. This data can include real-time sensor data, historical data, complex and resource-intensive simulations data, and analytics, among others, and can be easily accessed from any location. Cloud computing enables DT to effectively reduce the computation time of complex systems and overcome the difficulties of storing large amounts of data (Shu, 2016). Cloud computing allows teams, regardless of their physical location, collaborate on the development and operation of DTs, work together on complex projects and share resources. Cloud computing also provides robust security and privacy controls to protect critical infrastructure and sensitive data of DTs. Finally, Cloud computing provides a cost-effective way to deploy and scale DT- organizations pay for only the resources they need and can easily adjust their usage as requirements change (Barricelli et al., 2019).

Figure 1. Technologies of DT



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3.3 Artificial Intelligence (AI)

AI, as a discipline of computer science, seeks to mimic the basis of intelligence to create a new intelligent machine capable of responding like human-to-human intelligence. Areas of AI study include Robotics, image recognition, and language recognition. Neural Networks, Machine Learning, Deep Learning, and expert systems (Wu and Lu (2019), AI can assist DT by providing an advanced analytical tool capable of automatically analyzing obtained data collected from sensors placed on the physical asset or process. This enables real-time monitoring of the physical asset or process, provides valuable insights, enhances the ability to detect anomalies or potential issues, makes predictions about outcomes, and gives suggestions as to how to avoid potential problems (Lv and Xie, 2021). Moreover, AI can be used to provide recommendations and insights to decision-makers based on the data collected from the DT. This enables data-driven decision-making and can help improve overall performance and reduce costs. Finally, AI can be used to optimize the performance of the physical asset or process. This includes optimizing energy consumption, reducing waste, and improving efficiency.

3.4 Extended Reality (XR)

XR is an umbrella term used to describe immersive technologies like Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). These technologies can merge the physical and virtual worlds and extend the reality we experience (Marr, 2019). XR creates digital representations of objects where digital and real-world objects co-exist and interact in real-time. XR aims to create an immersive leading to enhanced perception, learning, and entertainment. XR technologies enable users to interact with digital objects and environments naturally and intuitively through various sensory inputs such as sight, sound, and touch. Therefore, XR can enhance the value of DTs by providing more immersive and interactive experiences that enable users to understand better and optimize the behavior of the real-world object or process.

Overall, XR can help DTs in several ways, including training, collaboration, maintenance, and repair. XR can simulate scenarios and train users to interact with the DT. This can be particularly useful for complex systems or processes that are difficult to replicate in the real world. Additionally, XR can enable multiple users to interact with the DT simultaneously, regardless of their physical location. This can facilitate collaboration and knowledge sharing among stakeholders. Finally, XR can overlay information about the DT onto the physical object or process, making it easier to diagnose and repair issues in real time.

4. DT USE CASES AND APPLICATIONS

Today, engineering and manufacturing predominantly use DT to provide accurate virtual representations of objects and simulations of operational processes. DT applications in operations and supply chain management, especially the role of DT in terms of operations traceability, transport maintenance, remote assistance, asset visualization, and design customization, are reviewed in related publications (Chiara et al. 2019; Geng et al. 2022; Kritzinger et al., 2018; Havard et al., 2019; Redelinghuys et al. 2019; Qiao et al. 2019; Warke et al., 2021; Bilberg and Malik, 2019; Qi and Tao, 2018). The technology is poised to deliver upon its many promises in other industries, including automotive, aerospace, construction, agriculture, mining, utilities, retail, healthcare, military, natural resources, and public safety sectors

(Verdouw et al., 2021; Boschert, S., 2016; Redelinghuys, 2019; Dinter, 2022; Bhatti et al. 2021; Stark and Damerau, 2019; Alves et al. 2019; Erdélyi and Jánosi, 2019; Fuller et al. 2020; Qi and Tao, 2018).

DT is becoming more popular in different industries, and agriculture and farming are no exception. However, the volume of research on agricultural DT remains limited. Recent agricultural research articles focus on investigating and demonstrating the feasibility of applications and use cases (Verdouw et al., 2021; Laryukhin et al. 2019; Laryukhin et al. 2019; Purcell and Neubauer, 2022; Ahmed et al., 2019; Alves et al., 2019). For example, livestock sensors enable remote monitoring and modeling of aspects of animal health (Erdélyi and Jánosi, 2019; Seng-Kyoun Jo, et al., 2018). Field information systems report on the status of fields, on the current soil, water, crop, and other properties, to improve management decisions (Alves et al., 2019; Laryukhin et al. 2019). DTs would also support future projections of those properties. They can be used to inform management actions such as crop rotation plans, anticipated over or under-production and address shortfalls in production. In addition, remote tracking of farming machinery enables the detection, repair, or pre-emption of problems (Purcell and Neubauer, 2022). DT can also be used in controlled indoor farming and aquaculture growing environments to keep track of production and problem interventions and create an efficient management schedule.

Furthermore, the DT of a farm enables effective management of the farm– saving time, and costs, improving sustainability, and attracting higher premiums for produce. Furthermore, it allows remote management decisions for short-term responsive actions and longer-term planning. Finally, DT enables the modeling, simulation, and automation of dynamic agriculture systems and helps to achieve true digitization in a complex area such as agriculture (Purcell and Neubauer, 2022).

The benefits of creating a DT in agriculture and farming are many and still not fully explored. DT technology benefits in the agriculture industry are illustrated through several use cases in Table 1. The remaining part of this section lists some trending agriculture applications of DT to increase awareness and understanding of the DT and its possibilities.

4.1 Farm Management, Resource Optimization

Although DT concepts in smart farming are in their infancy and early demonstration stages, many farmers are considering integrating intelligent technologies and techniques that enhance the efficiency of the farming process (Verdouw et al., 2021). Farming processes are highly complex and dynamic because they depend on natural conditions, such as weather, diseases, soil conditions, seasonality, and climate (Trienekens et al., 2014). DT technology can significantly enhance the needed control capabilities of the agricultural industry by enabling the decoupling of physical and information aspects of farm management. The technology can give a virtual representation of a farm with great potential for enhancing efficiency and productivity while reducing energy usage and costs. Farm managers can use DT to routinely view reports on the current soil, water, crop, and other properties and gain future projections of those properties. For example, DT enables farmers to create a replica of farm machinery and monitor equipment performance and predict when maintenance is needed, reducing downtime and repair costs (Deshmukh et al. 2021). Farmers can use the information to mitigate shortfalls in production, anticipate output, and make crop rotation plans. This can help farmers optimize their crop management strategies and reduce the risk of crop failures. DT can be used to monitor crop growth, health, and productivity by simulating the effects of different environmental conditions, such as temperature, humidity, and light, allowing farmers to optimize planting strategies, irrigation, and fertilization (Al-Saggaf et al., 2021). DT can also be used for resource optimization, such as crop irrigation optimization for yield improvement (Alves et al., 2019).

Another promising application of DT is in indoor farming with its controlled environment. DT can provide a digital replica of an indoor farm enabling farmers to keep track of production, issue interventions, and create a future management schedule.

4.2 Weather Modeling

An agricultural DT can also help in weather modeling and prediction of the long-term effects of climate change. Furthermore, DT allows farmers to identify where and how the agricultural system's resources are stressed by factors such as soil quality, pollution, invasive plants, animals, or other factors (Laryukhin et al. 2019).

4.3 Soil Management

DT can assist in measuring and understanding everything we can about the content and capacity of the soil in which crops grow and the seeds and crops that require that soil (Laryukhin et al. 2019). Using DT, the simulated outcomes through a growing season can answer questions about expected yield, the required fertilizer, sunlight, and water (Purcell and Neubauer, 2022; Ahmed et al., 2019; Alves et al., 2019). Farmers can use DT to model soil properties, monitor changes in soil health over time and make more informed decisions about crop rotations and soil management practices. (Zhu et al., 2021).

Table 1. Potential Use Case and Benefits

Potential Use Cases	Benefits Gained
Farm Management	• Improve efficiency and productivity of a farming process • Enhance Plant monitoring • Help review operational strategies • Allows remote management decisions for short-term responsive actions and longer-term planning • Share designs, information, and insights easily across ecosystems
Supply Chain Management	• Improve visibility into the farm supply chain management • Provides greater traceability and transparency • Improves the community of the various stakeholders
Soil Management	• Can assist in measuring and understanding the content and capacity of the soil • Can answer questions about expected yield. • Test limitless "what-if" scenarios required fertilizer, Sunlight, Water
Resource Optimization	• Help enhance the efficiency of the farming process • Help answer questions about expected yield • Help optimize energy usage and costs • Play a key role in developing and farming new crops
Livestock Monitoring	• Enable remote monitoring and modeling of aspects of animal health • Help intelligently model the best barn systems to maintain air quality and temperature • Can create simulations of new livestock treatments leading to better-informed decisions
Weather Modeling	• Help in weather modeling • Help prediction of the long-term effects of climate change • Identify where and how the agricultural system's resources are stressed • Help strategize for many possible futures
Indoor Production	• Provide real-time visibility into indoor farming and aquaculture • Keep track of production and problem interventions • Help create an efficient management and maintenance schedule

4.4 Supply Chain Management

In agriculture food supply chains, customers prioritize the safety of agriculturally produced foods while farmers seek revenue increases. However, the complexities and dynamism of food supply chains put many obstacles to the effectiveness of traceability and management of food products (Hasan and Habib, 2022). Therefore, it is critical to have complete visibility into the farm supply chain management to guarantee the food's quality. DT technology provides the agriculture supply chain with greater traceability and transparency. Furthermore, utilizing this technology improves the community of the various stakeholders that can support farmers by continuously monitoring physical farms and updating the state of the virtual world (Verdouw et al., 2021).

4.5 Logistics Management and Sustainability

Farmers and producers can routinely consult DT and improve the accuracy and efficiency of logistics and supply chain management, from inventory, material handling, transportation and shipping, fleet management, and route efficiency. DT can help farmers anticipate disruptions, create contingency plans, determine the optimum safety stock, identify optimum transportation/logistics routes, and help the organization build a more resilient supply chain. Another important application of DT is tracking carbon, biodiversity, and water catchment services. It would tell us whether they are changing and whether we cause those changes.

4.6 Livestock Monitoring

Herd management is a classic use case for DT technology where sensors on the herd, at feeding and milking stations, collect continuous data. DT processes and uses this data to provide information regarding milk or meat production efficiency and animal health. This enables more effective intervention, offering the potential to improve animal outcomes. DTs can be used for precision livestock farming to monitor the health and behavior of livestock, allowing farmers to identify potential problems and adjust management practices accordingly (Georgiev et al., 2021). Erdélyi and Jánosi (2019) explored the application of DT for monitoring, managing, and optimizing livestock. Jo et al., proposed DT technology for simulating the energy consumption of a pigsty to provide decision support for optimal pigsty design. In addition, the same researcher investigated the feasibility of an agricultural DT for the optimal growth of agricultural livestock, achieved through the regulation of barn systems to maintain air quality and temperature (Jo et al., 2019).

5. DT DRIVERS, CHALLENGES AND THREATS

5.1 DT Drivers and Opportunities

The COVID-19 pandemic fueled the growth of the DT market size across various applications, including real estate, healthcare, energy, and retail, driving the market's growth prospects. Furthermore, to recover from economic disruptions caused by the pandemic, several organizations are also adopting DT technology to optimize their supply chains and operational processes (Technavio, 2022). Furthermore, the current acceleration is mainly made possible by the decreasing costs of technologies that enhance both IoT and the DT. Finally, in the past few years, DT leveraged vital business applications, and it is predicted that the technology will expand to more use cases, applications, and industries. As a result, applications of DT's technology have been growing exponentially (Verdouw et al., 2021).

5.2 DT Challenges and Threats

As discussed in this article, DT technology has many advantages; however, the technology currently faces shared challenges in parallel with AI and IoT technology. Those include data standardization, data management, and data security, as well as barriers to its implementation and legacy system transformation (Technovio, 2022). Other challenges listed in the literature includes the need for updating old IT infrastructure, the challenges of connectivity, privacy and security of sensitive data, and lack of standardized approaches to modeling (Fuller et al., 2020).

DT solutions require a massive amount of data to be stored and processed regularly for creating and updating digital models, making it time-consuming. However, that requires farmers and livestock owners to improve the data handling capacity to be updated to handle such large data sets. In addition, extensive training is required to ensure workers understand the complex technology and ensure proper application. Finally, privacy and security are some concerns to avoid data breaches.

The significant challenges likely to hamper the DT market's growth include the high deployment cost and complex architecture. Implementing DT solutions requires substantial investment in technology platforms (sensors, software), infrastructure development, maintenance, and security solutions. Furthermore, DT infrastructure maintenance is costly, requires significant investment in operations, and will require sufficient financial justification. In addition, the DT's high fixed cost and complex infrastructure are expected to slow down the deployment of DT technology (Technavio, 2022). Finally, several risks and threats could target the DT's physical and digital components. These threats include data integrity and confidentiality, unauthorized access to the digital twin software or source code, data communications between IoT and the cloud, and the physical security of the IoT and DT devices (Alcaraz and Lopez, 2022; Hearn and Rix, 2019).

6. SUMMARY AND CONCLUSION

DT technology has recently become the center of attention for industry and academia. As discussed in this paper, most articles published in academic journals discuss the application of DT solutions in manufacturing, especially in industry 4.0. Research concerning DT solutions in manufacturing deals with production planning and control, the primary data sink within a production system that ties everything together. Supply chain management is another area where use cases of DT are reviewed in the literature. Use cases in the agriculture and farming industry are also growing.

In agriculture, DT solutions have a wide range of applications, including farming, indoor production, and high-value livestock management. With DT solutions, farmers can leverage advanced technologies such as drones and sensors to collect data on soil moisture, temperature, and other parameters. These data points can then be analyzed using AI algorithms to provide valuable insights and analytics that can help optimize crop yields, reduce waste, and improve profitability. DT solutions also enable farmers to automate many of the manual tasks traditionally associated with farming, reducing labor costs, and increasing efficiency. For instance, automated irrigation systems can be used to water crops at optimal times, and autonomous machinery can be employed to sow seeds and harvest crops. Furthermore, DT solutions offer an opportunity to improve the quality and safety of agricultural products. By leveraging data analytics, farmers can ensure that their crops are grown in optimal conditions, free from harmful pests and diseases. This, in turn, results in high-value production systems, as consumers are willing to pay a premium for quality, safe, and sustainably produced food products.

Digital Twin solutions have emerged as a promising technology for various industries, including agriculture, especially in the post-pandemic era, where remote monitoring and control of agricultural processes have become necessary. In the agriculture industry, Digital Twins can help farmers monitor and optimize crop growth, track soil conditions, predict weather patterns, manage irrigation, and improve yield and resource efficiency. Furthermore, using Digital Twins can lead to reduced costs and increased productivity for farmers, contributing to the industry's overall sustainability.

Furthermore, DT solutions offer an opportunity to improve the quality and safety of agricultural products. By leveraging data analytics, farmers can ensure that their crops are grown in optimal conditions, free from harmful pests and diseases. This, in turn, results in high-value production systems, as consumers are willing to pay a premium for quality, safe, and sustainably produced food products.

In conclusion, DT solutions are vital to achieving highly advanced digital transformation in agriculture. By embracing these solutions, farmers can gain unprecedented efficiencies and insights, leading to more profitable and sustainable farming practices.

7. FUTURE RESEARCH DIRECTIONS

Technical challenges still need to be addressed to realize Digital Twins' potential in agriculture fully. These challenges include the integration of different data sources, the development of accurate and reliable models, and the need for real-time data analysis and decision-making. In addition, the cost of developing and deploying Digital Twin solutions can be high, which may limit their adoption by smaller farms or growers. Therefore, more research is needed to address these challenges and identify new use cases for Digital Twins in agriculture. Researchers can experiment with new approaches to current applications, such as using machine learning algorithms to improve the accuracy of crop growth predictions or combining IoT and Digital Twins to enable remote monitoring and control of irrigation systems. Overall, Digital Twins have the potential to revolutionize the agriculture industry, but continued research and development are necessary to fully explore their benefits and overcome technical and economic barriers to their adoption.

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