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Review

From Reality to Virtuality: Revolutionizing Livestock Farming Through Digital Twins

Elanchezhian Arulmozhi [1], Nibas Chandra Deb [1], Niraj Tamrakar [1], Dae Yeong Kang [2], Myeong Yong Kang [2], Junghoo Kook [2], Jayanta Kumar Basak [3] and Hyeon Tae Kim [1,*]

[1] Department of Bio-Systems Engineering, Institute of Smart Farm, Gyeongsang National University, Jinju 52828, Republic of Korea; mohanachezhian@yahoo.com (E.A.)
[2] Department of Smart Farm, Institute of Smart Farm, Gyeongsang National University, Jinju 52828, Republic of Korea; dykang@gnu.ac.kr (D.Y.K.)
[3] Department of Environmental Science and Disaster Management, Noakhali Science and Technology University, Noakhali 3814, Bangladesh
* Correspondence: bioani@gnu.ac.kr; Tel.: +82-55-772-1896

Abstract: The impacts of climate change on agricultural production are becoming more severe, leading to increased food insecurity. Adopting more progressive methodologies, like smart farming instead of conventional methods, is essential for enhancing production. Consequently, livestock production is swiftly evolving towards smart farming systems, propelled by rapid advancements in technology such as cloud computing, the Internet of Things, big data, machine learning, augmented reality, and robotics. A Digital Twin (DT), an aspect of cutting-edge digital agriculture technology, represents a virtual replica or model of any physical entity (physical twin) linked through real-time data exchange. A DT conceptually mirrors the state of its physical counterpart in real time and vice versa. DT adoption in the livestock sector remains in its early stages, revealing a knowledge gap in fully implementing DTs within livestock systems. DTs in livestock hold considerable promise for improving animal health, welfare, and productivity. This research provides an overview of the current landscape of digital transformation in the livestock sector, emphasizing applications in animal monitoring, environmental management, precision agriculture, and supply chain optimization. Our findings highlight the need for high-quality data, comprehensive data privacy measures, and integration across varied data sources to ensure accurate and effective DT implementation. Similarly, the study outlines their possible applications and effects on livestock and the challenges and limitations, including concerns about data privacy, the necessity for high-quality data to ensure accurate simulations and predictions, and the intricacies involved in integrating various data sources. Finally, the paper delves into the possibilities of digital twins in livestock, emphasizing potential paths for future research and progress.

Keywords: digital twin; livestock management; animal health; precision agriculture; environmental monitoring; supply chain optimization

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1. Introduction

Food insecurity is a pervasive and pressing global issue with significant consequences for individuals, communities, and nations. As the global population approached nearly 8 billion in 2022 and is expected to exceed 10 billion by the latter half of the 21st century, the United Nations' Food and Agriculture Organization (FAO) predicts at least a 50% increase in food commodity production compared to 2012 [1,2]. Modern agricultural practices depend heavily on precise and up-to-date information about farm activities. Digital technologies, such as sensing and monitoring devices, advanced analytics, and intelligent equipment, are increasingly vital in agricultural operations [3]. The swift progress in technology, including cloud computing [4], the Internet of Things (IoT) [5], big data [6], machine learning [7], augmented reality [8], and robotics [9], is significantly transforming agricultural production towards smart farming systems. In developing countries, livestock production provides a steady food supply, employment opportunities, and the potential for higher income. Much of the demand for animal products will be met through local production. However, despite the increasing need for animal protein, consumers are more concerned about the environmental, public health, and animal welfare impacts of livestock farming [10]. Smart Farming represents the next phase of precision agriculture, where management activities depend on precise location data along with contextual information, situational awareness, and event triggers.

The digital revolution has introduced a new era of innovation and efficiency across various industries. A significant advancement in agriculture is the advent of digital twin technology, a cutting-edge tool for monitoring and understanding systems and processes. Digital twins (DTs) are virtual replicas of physical assets or processes that enable real-time monitoring, predictive analytics, and enhanced decision-making [11,12]. They offer valuable insights and optimization opportunities. In the livestock sector, where the main priority is managing animal health, welfare, and productivity, the application of DT technology holds substantial promise for revolutionizing traditional farming practices and addressing emerging challenges [13]. The agricultural physical system, or the physical world in agriculture, is a complex and dynamic environment that includes essential information and characteristics of objects or devices, such as their shape, position, cooling mechanisms, material composition, and living organisms [14,15]. This physical system can pertain to a single component of an object or the entire object with its subcomponents in a physical setting. It encompasses living organisms, such as animals, and the structures and resources on a farm, including buildings [16], feeding systems [17], and animal populations [14,15,18–20]. Measurement technologies and sensors are essential to collect data from these physical objects. The physical system is fundamental, as a DT without a corresponding physical entity is merely a model. The scope of a DT is defined by the real-world physical system it represents.

DTs in smart livestock have various applications such as animal tracking and disease detection sensors, observing animal behavior, building sensors to monitor temperature, humidity, and ammonia levels, managing energy supply in livestock barns, and optimizing the food supply chain [14,15,18–23]. This review study examines the applications of DT technology in livestock farming, driven by its significant advancements and transformative potential. In addition, this study explores the potential benefits of using digital technology in livestock industries. In order to accomplish this objective, the present study aims to address the following research queries:

- What is the precise definition of "digital twins"? What are the architecture's essential characteristics and attributes that depend on digital twins? What are the leading technologies and fields where digital twins are used?
- What methods exist for integrating DT technology into the livestock industry? What is the impact of adopting DT on the livestock sector? In what scenarios can DT technology be employed in the livestock industry to attain notable benefits?
- What are the current opportunities and challenges in implementing artificial intelligence technology and DT technology in the livestock industry? What are the possible future paths and advancements in evolution and development?

Paper Outline

The remainder of the written material is structured as follows: Section 2 delineates the methodology for selecting research articles pertinent to the applications of digital technology in the livestock sector. The general overview of DTs, including the timeline, interpretations, and architecture, is presented in Section 3. Section 4 explores prospective domains for DT applications in livestock management and critically analyses existing published research articles. Section 5 delineates the significance of incorporating PLF in the implementation of DTs. Furthermore, it summarizes the concept, components, properties, and assumptions associated with implementing digital transformation in the livestock sector. Section 6 examines the benefits of implementing DTs in the livestock sector, while Section 7 addresses the immediate challenges and constraints. Section 8 concludes with a synthesis and analysis of the principal findings.

2. Materials and Methods

In this study, we identify and analyze the applications of the newly developed DT technology in livestock production systems to improve their outputs and enhance their sustainability. A systematic review was carried out using the methodology recommended by previous systematic and bibliometric reviews, following the PRISMA guidelines [15,19,24–27]. Furthermore, the methodology introduced in the study was chosen due to its high efficiency in identifying relevant research sources using strict quality criteria. Based on these criteria, the review was conducted.

Literature searching methodology: The literature search on DTs was conducted using the academic research databases Google Scholar, Scopus, and Web of Science (WoS). Works indexed in ScienceDirect, IEEE Xplore, and SpringerLink were indirectly included, as the previously mentioned databases cover these sources. The primary keyword used was ‘digital twin’, combined with terms such as ‘cattle’, ‘smart farming’, ‘swine’, ‘energy management’, ‘livestock production’, ‘pigsty’, ‘meat’, ‘animal’, ‘application’, ‘welfare’, ‘case study’, ‘environmental control’, ‘pig’, ‘dairy’, and ‘livestock.’ These keywords were combined using the Boolean operators ‘AND’ and ‘OR’ to yield the most precise results.

Eligibility Criteria: The selected contributions met the following criteria:

- Peer-reviewed journal articles and conference papers presenting DT technology applications in the livestock farming sector were included.
- Only contributions accepted and published in indexed journals and conference proceedings were considered.
- The literature search was restricted to works published in English.
- Contributions from around the world were included.

Research questions: This study aims to identify the most recent research on using DT technology in livestock production systems. The goal is to analyze the findings and determine the opportunities and challenges associated with this topic. Thus, the objectives of the research can be concisely summarized in the following research questions (RQs):

- RQ1—What is the definition of “digital twins”? What are the architecture’s fundamental features and qualities that rely on digital twins? What are the primary technologies and areas of application for digital twins?
- RQ2—How can digital twin technology be integrated into the livestock sector? What is the effect of implementing digital twins on the livestock industry? What are the specific situations in which digital twin technology can be utilized in the livestock industry to achieve significant advantages?
- RQ3—What are the current prospects and obstacles in utilizing artificial intelligence technology and digital twin technology in the livestock industry?
- RQ4—What are the potential future trajectories and advancements in evolution and development?

3. Digital Twin Technology

3.1. Timeline of Digital Twins

Despite the recent surge in the popularity of DT technology, the concept is only partially novel. An advanced technique for evaluating and overseeing embedded systems was employed in space missions, originating from the early Apollo missions by the National Aeronautics and Space Administration (NASA). The “Twin” concept was first utilized as a safety measure during the Apollo missions in the late 1970s. As shown in Figure 1, the timeline of DT evolution is described.

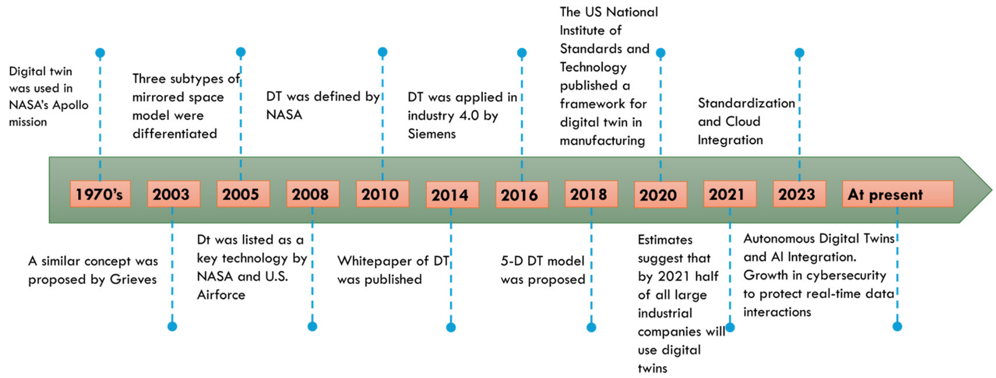

Figure 1. The timeline of Digital Twins.

The DT concept is credited to Michael Grieves, who collaborated with John Vickers from NASA. Grieves first introduced the idea during a lecture on product life-cycle management (PLM) in 2003, where he referred to it as the "Conceptual Ideal for PLM". Even in its early development, Grieves highlighted several core aspects of DTs [12,15,28]. Grieves emphasized the need for data and information exchange between real and virtual entities to ensure they mirror each other while discussing the distinction between real and virtual spaces. The next decade, the 2010s, proved to be a watershed moment in the growth of DTs as a concept supported by swift development of IoT and data analytic tools. The capacity to gather, preserve, and evaluate information allowed the production, aviation, or automotive industries, for example, to begin implementing DT technology for optimizing the systems and performing predictive maintenance. The decade saw the incorporation of DTs within operational workflow processes for improved efficiency and better decision making. In 2016, Siemens introduced DT technology as part of Industry 4.0. Since then, interest from researchers has surged, leading to a significant increase in related research activities [29–31]. At present, the three-dimensional DT model established by Grieves is the most implemented. However, with the ongoing evolution of application requirements, new trends and needs in DT development and application are emerging. To meet these demands, previous study [31] introduced a five-dimensional DT model that expands on Grieves' original concept, aiming to facilitate broader applications of DTs across diverse sectors. The five-dimensional DT model can be expressed through the following formula [29]:

$$M_{DT} = (PE, VE, SS, DD, CN) \tag{1}$$

where M_{DT} refers to the DT, PE represents the physical entity, VE is the virtual equipment, SS stands for services for PE and VE, DD refers to DT data, and CN is the connection among PE, VE, SS and DD.

This formulation encapsulates the key dimensions contributing to a comprehensive DT system.

3.2. Overview and Interpretations of Digital Twins

DTs have been delineated by diverse organizations and scholars. Two widely recognized definitions are those provided by NASA and Grieves. NASA characterized a DT for a space vehicle as "*A Digital Twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*" [32]. Grieves described DT as follows: "*Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level*" [32].

However, Greaves pioneered the technological realm by formalizing the prototype components of DTs currently in use. According to his assumptions, DTs are virtual representations of physical assets, as previously discussed. In addition, he stated that a fundamental

DT model is composed of three primary components: (a) physical products in their real representation, (b) virtual products in their virtual representation, and (c) the bidirectional data connections that transmit data from the physical to the virtual representation, as well as information and processes from the virtual representation back to the physical. This flow was illustrated by Grieves as a cyclical interaction between physical and virtual states (mirroring or twinning), where data is transferred from the physical realm to the virtual, and information and processes are conveyed from the virtual realm back to the physical. Figure 2A elucidates the theoretical framework governing the relationship between the physical environment and the virtual environment. Similarly, Figure 2B depicts the transfer of states between the physical asset and its DT.

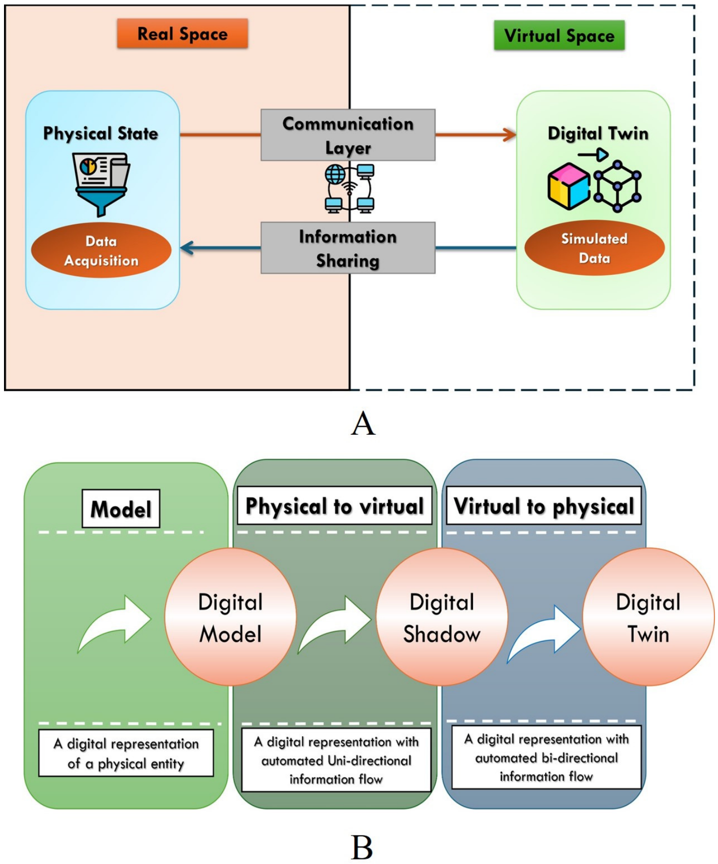

Figure 2. (**A**) elucidates the theoretical framework governing the relationship between the physical environment and the virtual environment; (**B**) the transfer of states between the physical asset and its digital twin.

3.3. Technologies That Facilitate Digital Twins

Recent technological advancements have eliminated the technical obstacles to implementing DTs. The DT framework integrates various techniques, including cloud computing, machine learning, augmented reality and virtual reality, IoT, and application programming interfaces to achieve DT implementation. Each technology not only provides essential functionalities but also enhances the synchronization, intelligence, and user interactivity within the DT framework. The following points will be discussed below.

- Internet of Things (IoT): IoT forms the backbone of DTs by connecting physical devices and sensors that continuously collect and transmit data. This flow of real-time data enables a highly responsive DT, allowing the virtual model to reflect changes in the physical object in an accurate and timely manner. They also collect data on biological parameters such as animal body temperature, weight, movement, and relative information [4,33,34]. Additionally, they monitor animal health indicators such as activity monitoring, stress, respiration, and potential issues [35]. The transmission of this data through communication protocols and gateways allows the DT to perform intelligent optimization of the environment, predictive health scenarios, and real-time monitoring by ensuring that the virtual model remains synchronized with the physical asset [36,37].

- Machine learning (ML): ML, a form of artificial intelligence, allows computers to acquire knowledge from data and make inferences or judgments without explicit programming [38,39]. ML facilitates sophisticated simulations and scenario planning, offering profound insights for strategic decision-making. ML enhances DT by allowing more adaptive and data-driven decision-making processes, optimizing supply chains, and simulating environmental impacts, thereby increasing operational responsiveness across industries [3,11,27,36].
- Cloud computing provides the scalable infrastructure needed to handle large volumes of data generated by DT systems [40]. By offering remote access to storage and processing resources, cloud computing supports real-time monitoring and enables predictive analytics at a global scale. This technology reduces the need for local infrastructure, making DT implementation more flexible and cost-effective [41–43].
- Augmented reality (AR) and Virtual reality (VR): AR and VR introduce immersive visualization in DTs through letting users interact with virtual models in three-dimensional space. While AR overlays data, in real time, on actual equipment for going through maintenance or operational tasks, VR uses completely virtual simulations to train or test designs. The use of such technologies makes the normally complex DT data easily accessible and intuitively understandable to better inform engineers and operators in decision-making [8,21,44].

Together, these technologies enable a DT to capture real-time data from physical systems, analyze it, and simulate scenarios that inform actionable insights. Figure 3 illustrates a simplified sequence chart that represents the interactions and components associated with these technologies that enable digital transformation, where the physical object signifies the actual object or system being monitored and controlled. The DT is the virtual representation of the Physical Object (PO), wherein data is processed and analyzed. The PO provides sensor-aggregated data to the DT, which subsequently transmits the data to the Analytics component for processing. The Analytics component delivers analytical results to the DT. The DT transmits these analytical results to the decision maker, who bases decisions on the information received. The DT subsequently transmits optimized actions to the Actions component. The Actions component executes the optimized actions in the PO [19,30,45].

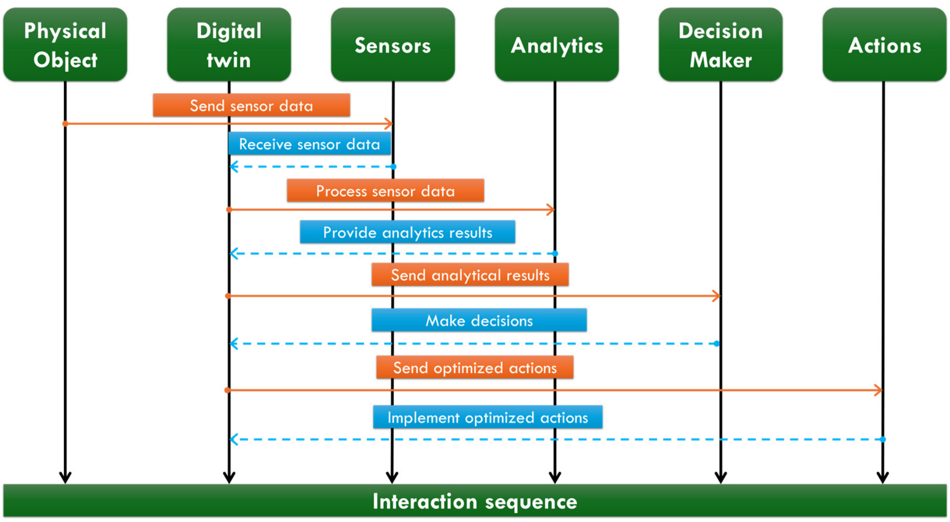

Figure 3. The basic configuration of digital twin components.

3.4. Architecture of Digital Twins

To effectively integrate devices with their virtual counterparts and enable smooth information exchange among DTs, physical twins, and external systems, a previous study [46] proposed a six-layer DT architecture, shown in Figure 4. This architecture includes various physical devices, sensors, and data collection systems that manage data transfer and processing in the virtual environment. Layers 1 and 2 represent the physical entity: Layer 1 includes devices like actuators and sensors, while Layer 2 specifies the data sources. Layer 3 contains a local data vault that gathers controller values from Layer 2 and facilitates communication among the layers and the physical entity. Open Platform Communication-Unified Architecture (OPC-UA) is essential for data exchange between these layers. Layer 4 converts data into useful information using IoT technologies, connecting Layer 3 to Layer 5. Layer 5 stores historical data, improving the DT's availability and accuracy, while Layer 6 monitors machine health and contains historical information about the physical twin. This layer allows users to interact with a virtual version of the physical twin, helping with decision-making and predictions. Tools like Siemens Tecnomatix Plant Simulation, OPC-UA, and artificial intelligence assist in analysis and optimization. Recent advancements in DT technologies and the five-dimensional DT model developed by a previous author [31] have also made it possible to implement DTs effectively.

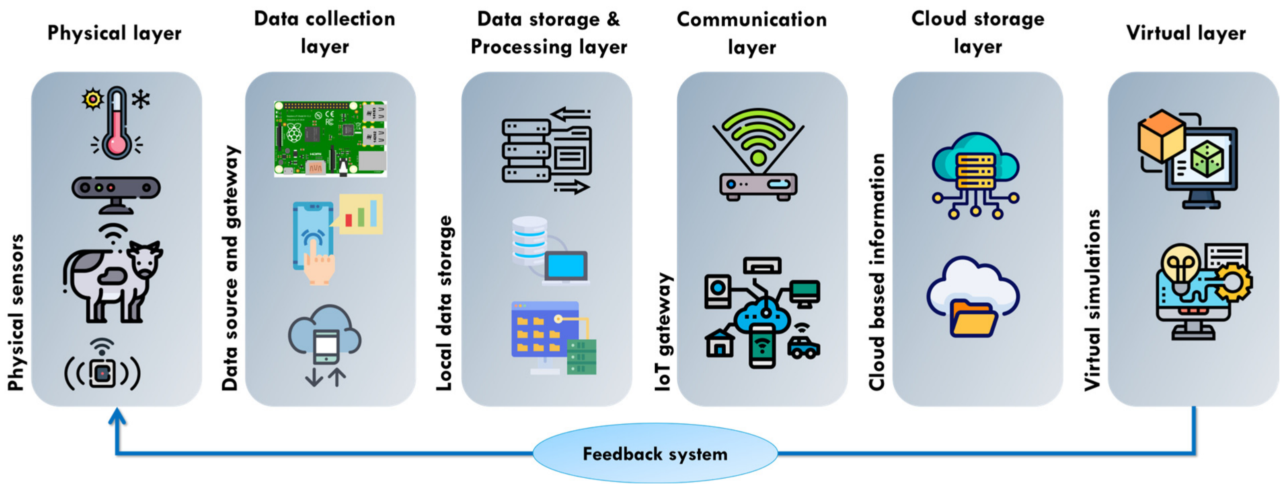

Figure 4. Digital twin with six layered architectures.

4. Potential Areas of Digital Twin Applications in Livestock Management

Over the past few years, DT technology has become more widespread in livestock management, including animal monitoring, environmental management, precision agriculture, and supply chain optimization. The subsequent sections present a comprehensive summary of DTs' primary application areas and use cases in the livestock industry. The summary of recent applications of DTs in the livestock sector is shown in Table 1. Besides a conceptual framework of potential possibilities of DT in livestock sector is explained in Figure 5.

4.1. Environmental Management

General environmental control in animal husbandry involves constantly observing and controlling temperatures, humidity, air, and water quality within those premises. The latest DT technologies have sensors and IoT devices that continuously monitor environmental parameters in real time, with indoor climate conditions, ventilation efficiency, and pollutant levels. For example, a previous study [16] developed a DT-based framework for real-time environmental control in a pig housing facility. This research used energy consumption estimation of virtual objects and their optimum operational strategies as scenarios to evaluate the energy performance of virtual HVAC systems that were not installed physically in a pig house through data synchronization between digital and physical spaces. The study concisely described how real-time and virtual environments interact. Based on simulated conditions in a virtual pig house using real data, the most energy-efficient solutions within the study were identified. A DT framework for pig housing was presented that enables comfortable feeding conditions while improving functionality within the livestock sector. Through DT-based dynamic simulation, the framework identifies energy-efficient solutions in the design phase and proposes guidelines for the optimal control of HVAC systems during operation. DTs have potential to analyze environmental data and optimize control systems to help farmers maintain optimum conditions for animal health, welfare, and productivity using minimal resources and causing minimal environmental impact.

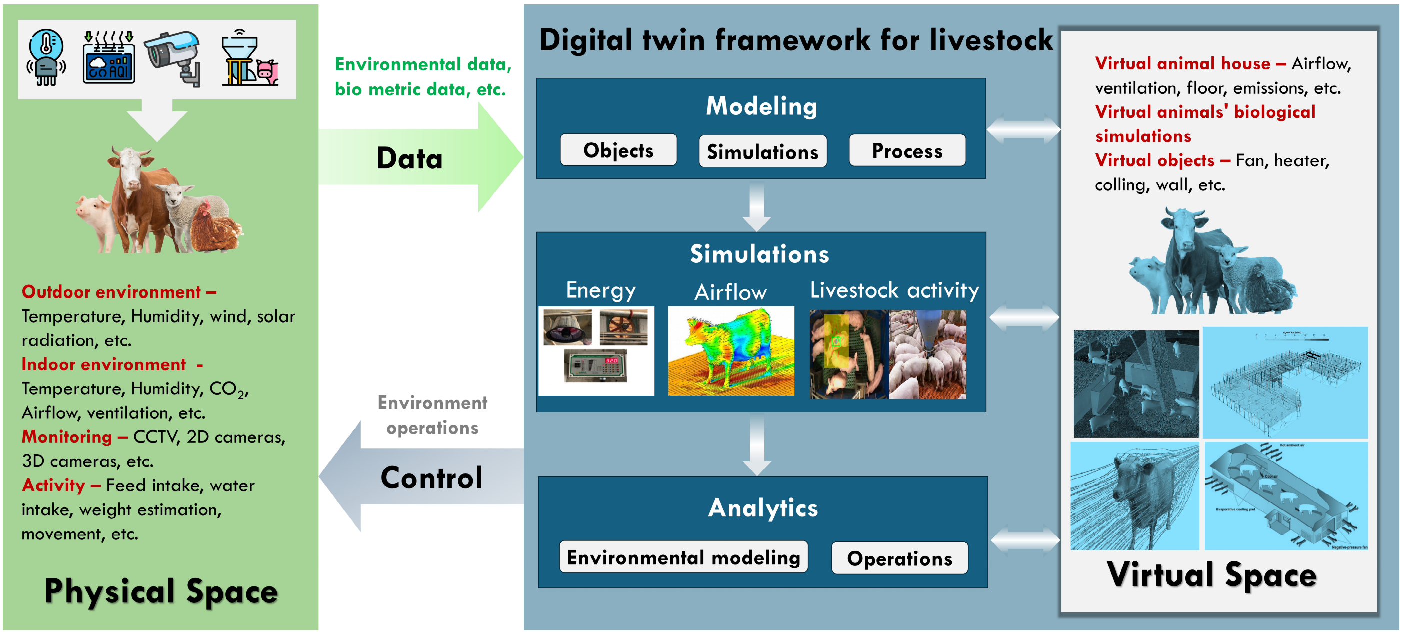

Figure 5. Potential application of digital twins in overall livestock management.

In addition, DTs offer a robust, multifaceted tool for advancing sustainable practices in livestock agriculture, with applications extending to waste management, climate adaptation, and resource efficiency. DTs provide insights that help reduce waste and enhance recycling and composting efforts by tracking and analyzing waste production. For instance, manure monitoring from livestock can be easily reused for biogas production or as mineralized fertilizers, hence closing the loop of agricultural waste management, which is part of reducing environmental impact. In addition, there is great potential to integrate climate modelling approaches into DTs to adapt the livestock system towards climate change. General circulation models (GCMs) and regional climate models (RCMs) project temperature, humidity, and extreme weather changes by reproducing atmospheric and environmental events. Embedding these projections within DTs enables proactive adjustments to climate scenarios, such as the effects of rising temperatures and humidity on indoor air quality and methane emissions. This climate-enhanced DT framework could inform management practices supporting animal welfare and environmental goals, making livestock systems more resilient and adaptive. Integrating these capabilities into our low-cost indoor air quality monitoring system and ML model would further improve methane management and help to ensure sustainable animal farming [47,48].

4.2. Farm Mangement

DT technology in farm management opens up a wide avenue for transformation by creating virtual models of real-time farm activities. With its adoption, farmers can have high accuracy tracking of the health and behavior of the livestock, as well as the prevailing environmental conditions. DTs merge sensor data with weather forecasts and animal health records to do scenario simulations, optimize resources, and predict potential problems and outbreaks of disease or feed shortages. For instance, Jo et al. performed a feasibility study on the preliminary design of an intelligent pig farm based on DTs for improving the living conditions of animals. This research focuses on the two-layer architecture of smart livestock farming: the DT engine and the DT framework. It also briefly outlines an autonomous control system, showing how physical and DT are integrated; however, the results need to be assessed, and the research has been expanded in subsequent work [22]. The same author has examined energy-related performance concerning various virtual objects in a pig barn, building on the previous study. An energy planning framework for a pigsty to ensure optimal feeding conditions was developed in that study [21]. The energy consumption analysis involved utilizing fans with differing capacities in the pigsty. The results yielded insights into projected energy consumption and provided recommendations for installing new fans.

Likewise, Mu et al. (2023) [49] integrated the digital twin into animal husbandry in a case study of the Qinghai Meadow that explored how to integrate DTs into the traditional method of pasture management by creating a livestock supply chain. It is based on two main flows: the first is horizontal communications between suppliers and consumers for the commercial supply chain, and the second covers the IT operating system, structured into three layers: physical, data, and virtual. According to this model, data received by sensors in the physical layer are submitted to the data layer for processing, evaluation, management, and storage. The physical layer further routes the information to the virtual layer, where AI and ML process the data transmissions and feed the results back into the physical layer. This minimizes losses due to severe weather and predicts diseases that would be identified using machine learning during the animal's life cycle. The system will raise an alarm when abnormal behaviors or environmental anomalies are detected. Unfortunately, the study was unable to include any evaluation results of the solution.

4.3. Animal Monitoring

The significant applications of DTs are relatively simple in monitoring animals. AI and ML are integral to animal husbandry, facilitating constant surveillance of animals and their surroundings. This continuous monitoring facilitates enhanced understanding of animal behavior, more efficient disease management and prevention, and superior decision-making for farmers. DT technology has emerged as a promising innovation, building upon these technologies. In contrast to conventional models, DTs generate real-time digital representations of physical entities, consistently refreshed with data. DTs, while enhancing efficiency and decreasing costs across multiple sectors, possess considerable potential for livestock farming. They could transform large-scale precision agriculture, optimize the utilization of machinery and equipment, and improve the health and welfare of various livestock. In support of this, a previous study [20] cited a study where sensor-based decision-making technology for animals will be able to simulate and predict, in real time, their emotional states and behaviors. While these proposals sound promising, they are mostly theoretical and have not been empirically validated. The study claims that all factors concerning physical and emotional well-being, social interaction, and environmental conditions can be considered in comparative studies for an experimental group of farm animals with DT technology and a control group without. A previous study [50] introduced the reference architecture for a DT system to be applied to a smart animal welfare platform to predict farm animal behavior. It typically consists of several interconnected parts in the architecture: remote and wearable sensors gathering data from animals, cloud servers that interface with sensors and process data, AI models for pattern recognition, ML models for predictive analytics, and a user interface through which users can manipulate the information and predictions coming from DT systems. They also highlighted the possible applications of technology in animal husbandry, monitoring animal emotions, and early detection of severe diseases in livestock.

Furthermore, Yi Zhang et al. (2023) [51] introduced a universal DT architecture for dairy cows that encompasses their entire lifecycle to enhance animal welfare and production efficiency. A bespoke collar incorporating ultra-wideband (UWB) chips and inertial measurement units (IMUs) was employed to gather real-time location and neck movement data, facilitating the creation of a digital shadow of the cow for analyzing feeding and non-feeding behaviors. Three layers, namely the perception, network, and service layers, were introduced to develop a cow behavior monitoring system. Five layers are included in the implementation architecture: integration, data management and information, model and simulation, partial decision-making, and visualization. They found that, with this setting, a custom-made collar, an anchor point, and integration with the local server reached an accuracy of 95.07% in classifying feeding versus non-feeding behavior. The research stated that this proposed DT architecture would be very beneficial in providing relevant insights toward the development of similar systems for livestock.

In another recent study, Xue Han et al. [52] proposed an AI-based DT model for detecting and predicting cattle behaviors as imminent physiological cycles. They categorized cattle behaviors into different classes: rest, rumination, panting, high activity, eating, grazing, walking, and medium activity. They used an identification of cattle behavior based on LSTM, while an intelligent decision tree was used to model their conditions. This deep learning decision tree model uses sensor data provided through an IoT farm system to monitor the physiological cycles of cattle with real-time prediction of their next cycle state. While the model performed well on big datasets, accuracy was lower for smaller sample sizes.

While the studies try to simulate the DT models, their aim is still at the virtual modelling of physical entities rather than 3D data. A previous study [8] has suggested that a real-time 3D virtual model of the barn and the animals can be generated, showing their precise locations based on gathered data from IoT devices. In developing the DT model with IoT devices for data collection, a five-domain model for assessing welfare was proposed, which includes the physical environment, health, mental state, behavioral interactions, and nutrition. For analysis of a three-dimensional physical model, software such as Augmented Anatomy (mobile application, version 1.2.3), Easy Anatomy (mobile application, version 5.14.0), and QVIRE, (windows software, version 3.0.46) was considered in the study. The software also makes suggestions on the potential problems that can arise from the measured deviations, on the basis of which immediate remedial action can be taken to rectify the problem. Resources available in Augmented reality (AR) and virtual reality (VR) facilitate faster learning in a safe environment and can be used by veterinarians, breeders, and students. In that study, no evaluation results were presented for this solution.

4.4. Supply Chain Optimization

Likewise, DTs optimize the value chain for effectiveness and efficiency in the distribution of livestock products right from the farm to the market. DT technology provides essential tools and insights critical in optimizing operations along the supply chain, including production planning, inventory management, logistics, and distribution. For instance, a prior study [53] presents a novel framework for a digital twin that integrates essential technological enablers throughout various sectors of the meat supply chain, aiming for a "zero-waste", circular meat supply chain. The study aims to enhance the food supply chain by incorporating the entire cycle of meat production, encompassing feed crops, livestock, processing, distribution, sale, utilization, and disposal of food products. They evaluate physical entities, including land management, animal management, food processing, food products and packaging, transportation, retail, household and hospitality, and waste management, to optimize the supply chain utilizing the digital twin model. In animal management, the tangible components of the framework encompass aspects related to individual animals (e.g., exercise and rest levels, grazing behaviors, and location) as well as environmental and housing conditions (e.g., temperature, humidity, luminosity, etc.). This framework is in its initial stages, and its implementation and the development of a simulation model will be addressed in future research endeavors. Due to ongoing concerns regarding decision-making in livestock production supply chains, a computer-aided system was proposed by a previous study [17] as part of the IoFEED project to manage and optimize the delivery of animal feed to multiple farms. At the farm level, a DT approach incorporated sensors to monitor inventories remotely and generate data, which was then utilized through a combination of biased randomization techniques and a simheuristic framework. The study's findings show that the suggested solution successfully enhanced feeding practices on the livestock farms. DTs can provide virtual representations of supply chain processes and assets that monitor and analyze production flows, real-time inventory levels, and transport routes to find bottlenecks, smoothen operations, and make the whole value chain more resilient and efficient. Moreover, owing to DTs, the building of traceability, quality control systems, and sustainability standards will make the value chain of livestock more transparent, trustworthy, and responsible.

Table 1. Summary of recent applications of DTs in livestock production systems.

S. No	Development Level	Application Area	Year of Publication	Reference
1	Application level	Environmental Management	2023	[16]
2	Concept level	Farm management	2018	[22]
3	Application level	Farm management	2019	[21]
4	Concept level	Farm management	2022	[49]
5	Concept level	Animal Monitoring	2022	[50]
6	Application level	Animal Monitoring	2023	[51]
7	Application level	Animal Monitoring	2022	[52]
8	Concept level	Animal Monitoring	2021	[8]
9	Concept level	Supply Chain Optimization	2022	[53]
10	Application level	Supply Chain Optimization	2021	[17]

5. Employing Precision Livestock Farming (PLF) for the Deployment of Digital Twins

Precision Livestock Farming (PLF) is a new form of animal husbandry. It enhances livestock production through the help of advanced technological developments. In other words, PLF applies data-driven decision-making through collecting, analyzing, and applying data to improve various aspects of animal husbandry. Conventional farming depends on generalized guidelines and subjective decisions while handling animals, whereas PLF brings into the field an added level of precision. Although DTs in livestock applications continue to evolve, precision livestock farming facilitates their implementation on farms. Wearable animal sensors, environmental sensors, IoT systems, and feed and nutrition sensors, coupled with AI integration, are essential instruments for DT technology adoption in the livestock sector.

5.1. Potential Applications of Sensor Technology

As mentioned earlier, the guidance of PLF is invaluable for implementing DTs in the livestock sector, whereas the accomplishment of PLF is subject to gathering data from numerous facets of livestock management along with the harmonious integration of diverse sensor technologies. Generally, these sensors function in diverse configurations and accomplish multiple purposes. An accelerometer sensor can be deployed to monitor animal activity, posture-related behavior, and feeding and drinking habits. More than one sensor will be required to provide sufficient information every so often. To resolve this issue, it may be necessary to integrate several sensors, including an accelerometer, gyroscope, magnetometer, and altimeter, into a single electronic device that functions as a wearable sensor capable of gathering multiple types of information.

Numerous studies employed sensors to enhance overall farm management in multiple facets of livestock management, encompassing monitoring animal health, optimizing nutrition and feed management, and improving reproductive programs. Likewise, several review studies have already been conducted to explore the potential of sensors in deploying PLF effectively [54–62]. The studies provide a foundational understanding of the knowledge deficiencies in employing sensors to promote the adoption of PLF applications within DT systems for livestock, thereby providing a roadmap for advancing DT technology implementation. The studies identify the categories of sensors suitable for applying DT technology in the livestock sector as follows. However, the current review apprehends that the sensor, as mentioned earlier, will be beneficial for future DT studies; thus, a summary of comprehensive information from prior studies is presented in Table 2.

Bio-information sensors: In this regard, bio-information sensors are employed to monitor and acquire data on vital signs, activity levels, and location [63]. Non-contact bio-information sensors, including infrared temperature sensors [64], microphones [65], thermal infrared cameras [66], 2D cameras [67,68], 3D cameras [69,70], and load cells [65], have been employed in acquiring animal data by surface reading. A 2D camera can provide information regarding the activity of animals, posture detection, and behavioral classification. Infrared-based temperature sensors are also used to gather information on the body surface and rectal temperature, which can help monitor animal health. High-end biosensors have changed the method of observing and caring in the livestock sector. In particular, wearable bio-information sensors, such as RFID ear tags [71], rumination sensors [72,73], collar bands [74], and leg bands [74], produce real-time information about an animal's physiological attributes, providing information on its health and welfare [7,75,76]. RFID tags facilitate the identification and tracking of individual animals. Likewise, activity sensors can detect changes in behavior that can indicate an animal's health problems or the state of estrus of a female animal.

Feed and Nutrition Sensors: These sensors assess feed intake, ensuring that animals obtain appropriate nutrition. They can also identify dietary preferences, enabling farmers to modify feed formulations and reduce waste [77,78]. Feeding activities are indirectly assessed by detecting body movements and postures, including jaw motion. Jaw movements can be directly quantified by detecting variations in pressure or length of a sensor positioned around the nose, and indirectly by capturing and analyzing the acoustic patterns generated during feeding activities with microphones [79]. Recently, electronic feeding systems have become widespread in animal sectors, offering benefits such as monitoring feeding time and date, electronic identification of each animal, feed weight consumption, and feeding duration [80,81]. For instance, an electronic feeding system offers various functionalities that assist poultry farmers in managing their workloads, including automated feeding based on time intervals, monitoring feed and water capacities in containers and storage, and controlling overflow in water and feed containers [82].

Environmental Sensors: Environment monitoring systems installed in farmhouses, storage areas, and external spaces monitor environmental conditions necessary to ensure animal comfort and health. They monitor microclimate variables such as temperature, humidity, ventilation, and air quality. For example, if the temperature exceeds a specific threshold in animal husbandry, cooling mechanisms may be used to avoid livestock heat stress [64]. In recent decades, the utilization of environmental monitoring systems based on IoT devices equipped with low-cost sensors has noticeably developed [83–89]. IoT systems facilitate remote surveillance and instantaneous data transmission to centralized control centers [90,91]. This connectivity is crucial for thorough data analysis and informed decision-making. The emergence of low-cost sensor resources, coupled with the accessibility of open-source resources, has accelerated the proliferation of IoT-based environmental monitoring. "Open source" refers to software applications with publicly accessible source code, allowing users to modify or utilize the program as intended. Numerous studies have demonstrated that an IoT-based monitoring system can track multiple parameters, including temperature, humidity, light, CO_2, pressure, NH_3, various gases, and air quality metrics [83–89].

The consolidation of these sensors establishes a data framework in which information transitions fluidly from the animal to the farm management system. This framework is essential for analyzing the gathered data and producing practical conclusions. With technological advancements, sensor technologies are evolving to be more sophisticated, precise, and economical, thereby enhancing the accessibility and efficacy of DTs for further studies aiming to optimize their operations and tackle the challenges of contemporary livestock farming.

Table 2. Collection of reviews utilizing precision livestock farming technology.

S. No	Species	Review Objective	Sensing Technology	Reference
1	Cattle	Behavioral activities monitoring	Wearable sensors	[72]
2	Cattle, pigs and broilers	Overall animal monitoring	Non-contact radar monitoring	[92]
3	Cattle, pigs and broilers	Pasture-based activities monitoring	PLF sensors	[93]
4	Cattle, pigs and broilers	Animal health management	Wearable sensors	[54]
5	Cattle, pigs and broilers	Animal health management	Biosensors	[55]
6	Cattle, pigs, sheep and broilers	Animal health management	Wearable sensors	[56]
7	Cattle	Animal behavior and environment	Wireless sensor networks, GPS collars and satellite remote sensing	[57]
8	Cattle	Pasture-based activities monitoring	Non-contact sensors	[58]
9	sheep	Overall animal monitoring	PLF sensors	[59]
10	sheep	Overall animal monitoring	PLF sensors	[60]
11	Cattle and sheep	Pasture-based activities monitoring	PLF sensors	[61]
12	Cattle and sheep	Remote managing and monitoring system	PLF sensors	[94]
13	Cattle, pigs, sheep and broilers	Overall animal monitoring	PLF sensors	[95]
14	Cattle	Overall animal monitoring	PLF sensors	[96]
15	Cattle, pigs, and sheep	Overall animal monitoring	PLF sensors	[97]
16	Cattle	Overall animal monitoring	PLF sensors	[98]
17	Cattle	Overall animal monitoring	PLF sensors	[99]
18	Cattle, pigs, and sheep	Overall animal monitoring	Wearable sensors	[100]
19	Cattle	Overall animal monitoring	Wearable wireless biosensors	[74]
20	Broilers	Overall animal monitoring	PLF sensors	[6]
21	Cattle, pigs, sheep and broilers	Overall animal monitoring	PLF sensors	[101]
22	Cattle and pigs	Animal behavior and feed management	PLF sensors	[81]
23	Cattle	Feed management	PLF sensors	[79]
24	Cattle, pigs and broilers	Overall animal monitoring	Biosensors	[102]
25	Pigs	Animal behavior	Cameras	[67]
26	Pigs	Overall animal monitoring	PLF sensors	[65]

5.2. Implementation of Digital Twins

As has already been explained, DTs are virtual models of physical objects that look to accurately recreate their behaviors and interactions with the environment; for DTs to be employed effectively, some basic properties must be combined.

First, the twin must get real-time feedback from the physical or biological asset to properly represent its ongoing interactions. Deploying various sensors connected to the internet or at least secure private networks that may broadcast and receive certain data types is required. Second, the DTs must be capable of receiving, storing, and processing large volumes of information in real time. The idea of big data technologies and cloud server architectures thus plays a vital role by availing advanced computing resources, data storage solutions, and processing capacity. The second crucial aspect is making sense of the enormous volumes of data transmitted. Volume, in most cases, becomes an issue for human analytical abilities; therefore, there arises a great need for AI algorithms. The algorithms should sift valuable data from irrelevant information and provide recommendations and courses of action based on analyses. Finally, the twinning would allow interconnection between the physical and virtual state, allowing for data transmission from the physical system to the virtual twin and reverse information feedback to the livestock production system. The variety of techniques involved in such an establishment depends on the volume, type, and source of data and the speed and rate of achieving minimum accepted delay in both data transmission and information feedback.

In conclusion, this integrated information and analytics should be made available to concerned decision-makers through a captivating digital interface. Computers, tablets, and even smartphones can be used to access crucial information and insights that drive decision-making. The framework of sensor integration, signal interactions, feedback systems and decision-making process are illustrated in Figure 3. Conducive to accomplishing the DT deployment in the livestock sector, the following components are inevitable. A prior study [103] clarified the functions of various components of DTs and their primary roles. Although the study was carried out for DTs' application in the industrial sector, Table 3 was derived from prior research.

Hardware elements: The primary technology propelling DTs is the IoT sensors, which facilitate the exchange of information between physical assets and their digital counterparts. The hardware component also encompasses biosensors, environmental controls, and agricultural management actuators. Similarly, this includes data transmission and storage apparatus such as routers, edge servers, and IoT gateways, among others.

Middleware for data management: The fundamental component is a centralized repository for aggregating data from various sources. The middleware platform should ideally manage tasks including connectivity, data integration, data processing, data quality assurance, data visualization, data modeling, governance, and additional functions.

Software elements: The analytics engine that transforms raw observations into valuable business insights is essential in digital twinning. In numerous instances, it is driven by machine learning models. Essential components of a digital twin puzzle include dashboards for real-time monitoring, design tools for modeling, and simulation software [25].

Table 3. Collection of components and their functions which are used to implement DTs in the livestock sector [103].

Elements	Role of That Element
Physical entity	It functions as the counterpart of the digital twin.
IoT	This element is used to collect and transfer the data.
Continuous Bijective Function	It is utilized for synchronization and twinning.
Data	They are utilized for synchronization, analysis, and input for machine learning.
Machine learning	It is utilized for analysis and forecasting.
Security	It is utilized to avert data breaches and information compromises.
Digital entity	It is the digital twin.
Evaluation metrics/Testing	It is used to evaluate the performance of the virtual models.

6. Rationale for Adopting Digital Twins in the Livestock Industry

Despite recent advancements in DT technology, its application in the livestock sector remains in the early stages of development. Nonetheless, certain industries, including aero manufacturing [104], oil field services [105], software [42], fast- moving consumer goods [106], and tire manufacturing [106], are already harnessing the advantages of DTs. Similarly, the experiments and review literature mentioned earlier [8,15,17,20,21,24,49,51–53,106–111] enable the broad adoption of DTs in the livestock sector to enhance animal management, early disease detection, farm administration, environmental management, and optimization of feed and water resources. This study aims to bridge the knowledge gap in DT adoption in livestock by providing a comprehensive overview that builds on but expands beyond existing reviews. While previous studies focus on specific DT applications like animal management and disease detection, this review seeks to establish a foundation for broader DT integration in livestock. By identifying current limitations and suggesting areas for future research, this paper serves as a guide for advancing DT studies in this field. According to the authors' perspective, the analysis of the preceding studies and reviews indicates that DTs possess multiple advantages for enhancing livestock production. This encompasses the following:

- **Precision Livestock Farming:** Health and nutrition are optimized by technology using real-time data and monitoring down to the level of individual animals for productivity at an individual animal level. This improves animal welfare while ensuring maximum profitability at farms. While availing the possibility to simulate alternative breeding scenarios, farmers make informed decisions based on the traits that provide maximum productivity, for instance, better growth rate, fertility, or resistance to diseases. However, another approach is to accelerate genetic gains within herds. DTs identify early deviations in physiological signs and behavioral and environmental parameters associated with disease states. Predictive models can give the farmer an early warning to reduce mortality and treatment costs for health issues about to become critical. The real-time monitoring of the animal's physical condition and immediate surroundings makes spotting discomfort or stress among the animals easier. This improves general animal welfare, leading to healthier and more productive livestock.
- **Sustainability and Environmental Impact:** DTs can significantly reduce waste and environmental footprint by improving feed and water usage, among other resources. This leads to more viable farming practices that fit the growing global demand for environmentally responsible methods of producing livestock.
- **Labor Efficiency:** Automation through DTs reduces the need for further human supervision. Farmers can, from a virtual monitoring and managing system, plan several work schedules for feeding and caring for animals; hence, they can increase efficiency and eliminate most human errors.
- **Compliance with Regulations:** DTs ensure straightforward records of animal health, farm management, and environmental impact and align with local and international animal welfare and sustainability legislation. This also furthers supply chain traceability.
- **Remote Management:** DT technology will help farmers carry out remote management through cloud-based systems on livestock farming. This is also important in large-scale operations or multi-site farms, ensuring increased oversight without needing physical presence.
- **Operational Cost Efficiency:** While generally more expensive to set up, over time, the DTs optimize resource usage, cut down on waste feed, and reduce healthcare costs due to early interventions in animal care.
- **Training and Education:** The virtual replicas of the livestock system can train the staff with new management techniques that do not affect the live animals, increasing the level of skills and knowledge among farm personnel.

7. Challenges and Limitations

Despite the promising potential of digital twins, their widespread adoption necessitates addressing several practical knowledge gaps. The authors express concern regarding several open issues identified in recent research [8,10,15,17,20,21,24,49,51–53,106–111] that warrant attention in future studies. To fully leverage the advantages of DTs in livestock production systems, several unresolved issues and challenges must be addressed, as follows:

- **Complexity of Implementation:** By nature, DTs are exceptionally complex, embedding sensors, data analytics platforms, and connectivity infrastructures. Most farms do not have the respective expertise to manage such tasks independently.
- **Maintenance and Updates:** Sensors, IoT devices, and the software powering these DTs constantly need updating to make their information accurate. Faulty devices may give bad data, leading to poor decisions or effects on farm operations.
- **Resistance to the Adoption of Technologies:** Conventional modes of farming are so deeply entrenched in many areas that a few farmers would be resistant to adopting new technologies if lack of trust, perceived complexity, or costs hampered judgments associated with digital twin systems.
- **Absence of Experts:** Similarly, deploying and maintaining DT systems requires people with equally advanced knowledge in data analytics, IoT, cloud computing, and AI. The unavailability of skilled personnel may lead to poor implementation, inadequate usage, or even poor decision-making resulting from an incorrect interpretation of the data.
- **High Financial Risk:** The extremely high initial investment in establishing DT systems and continuous expenses concerning their maintenance, upgrade, and cloud services are too financially overwhelming. If farm implementation is poor, inefficient, or poor-quality data prevails, farms may not succeed in returning the investment.
- **Poor access to high-speed internet:** Most rural areas, where much livestock farming goes on, need better access to reliable high-speed internet. The complication is that implementing a cloud-based DT system requires continuous data transmission for real-time monitoring and control.
- **Data Overload and Mismanagement:** A DT system generates large amounts of data, and a farm without proper data management and analytics may not be able to act upon such information. Faulty interpretation will lead to the wrong decisions that would negatively impact animal health and productivity, impacting the overall performance of the farms.
- **Cybersecurity Threats:** Being connected and cloud-based, the DTs present a risk due to many cyber-attacks. Illegal access to farm data and systems can cause operations disruption or even theft, which may threaten farm safety.
- **Dependence on Technology:** Excessive use of the DT system implies fewer human observations and intuitive decisions. Farmers may become dependent on technology. Herein lies one of the problems: if the system is technically faulty or a cyber-attack occurs, farming operations could be utterly disrupted, affecting production.
- **Limited personalization for small-scale farms:** It would be of great help for large-scale establishments, but on small-scale farms, one could realize that such systems are not well- placed to deliver full customization for their specific needs, hence leading to inefficiencies in the way they use the technology.
- **Ethical and Animal Welfare Risks:** Continuous monitoring by sensors and data analytics can mean there is always a question of finding the right balance between productivity and animal welfare. In this context, traditional practices centered on animal well-being might be overridden by over-emphasis on technological efficiency, with consequences for animal stress or discomfort.
- **Challenges in Integration:** Most farms use both legacy systems and the latest technology; hence, integration with DT solutions among farm management software and sensor platforms will remain problematic and, therefore, require further investment in using compatible technologies.
- **Technological Failure:** DTs are highly dependent on the use of advanced technologies; should failure occur to any of these systems, such as sensors or any other element, including loss of connectivity, there would be faulty data that might even mean shutdowns of systems and therefore affect farm operations.

In resolving some of these challenges, it is expected that policymakers will be able to provide incentives through regulations and create a framework where the application of DT technologies is easier. Understandably, it is also rather important to note that the barriers included, such as the nonexistence of skilled personnel and the relatively high implementation costs, may be facilitated by close collaboration among farmers, researchers, and technology providers. Merging the technological advancement with practical, region-specific solutions will better integrate DTs into the livestock sector and ensure their future growth and sustainability.

8. Conclusions and Outlook

This study comprehensively analyzes the implementation of digital twins in livestock agriculture. Furthermore, the current study elucidates the principles of digital twins and their application in the livestock sector. The current study highlights the benefits and obstacles associated with the implementation of digital twins in accordance with the objectives. Digital twin technology exhibits significant potential for the digitization and replication of complex systems within the livestock sector. DTs present significant opportunities for improving livestock management practices, promoting animal health and welfare, increasing productivity, and fostering sustainability and resilience within the livestock sector. Advanced technologies, including IoT, AI, and cloud computing, facilitate real-time monitoring, predictive analytics, and data-driven decision-making in livestock farming. This encompasses areas such as animal monitoring, environmental management, precision agriculture, and supply chain optimization. There is a necessity for additional evidence, data, and case studies regarding digital twin technology to promote its widespread adoption among livestock farmers. The current study examines the existing literature on DT implementations; however, it remains in the conceptual and prototypical phases. Researchers are progressively developing digital twins that possess enhanced functionalities. Significant progress is still required. Future research should investigate the unique characteristics of living organisms and their interactions with virtual counterparts. It is essential to adopt a broader perspective in the design of DTs for livestock applications. Numerous challenges related to digital transformation stem from the technology's novelty, including a lack of consensus on its definition and value, absence of standards and regulations, insufficient numbers of skilled engineers and technicians, and a deficit of supporting software. Data security and ownership issues related to digital transformation require increased scrutiny, as data constitute the fundamental basis for this transformation. Policymakers might incentivize DT adoption through the consideration of regulatory schemes which could mitigate such identified barriers and allow data sharing and protection. Alongside tackling current challenges associated with digital transformation, it is essential to expand our perspective and recognize potential future issues that this technology may encounter or generate. Addressing these challenges through collaboration, innovation, and knowledge sharing enables farmers, researchers, and stakeholders to leverage digital twin technology, fostering a sustainable, efficient, and resilient livestock industry for the future.

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