



A Systematic Literature Review on the Uses, Benefits, Challenges, and Prospects of Digital Twins in Livestock Farm Management

MD KAMRUL HASAN^{1,2}, HONG-SEOK MUN^{1,3}, KEIVEN MARK BIGTASIN AMPODE^{1,4}, EDDIEMAR BAGUIO LAGUA^{1,5}, HAE-RANG PARK^{1,5}, YOUNG-HWA KIM⁶, MD SHARIFUZZAMAN^{1,7}, CHUL-JU YANG^{1,5*}

¹Animal Nutrition and Feed Science Laboratory, Department of Animal Science and Technology, Suncheon National University, Suncheon, Republic of Korea; ²Department of Poultry Science, Sylhet Agricultural University, Sylhet, Bangladesh; ³Department of Multimedia Engineering, Suncheon National University, Suncheon, Republic of Korea; ⁴Department of Animal Science, College of Agriculture, Sultan Kudarat State University, Tacurong, Philippines; ⁵Interdisciplinary Program in IT-Bio Convergence System (BK21 Plus), Suncheon National University, Suncheon, Republic of Korea; ⁶Interdisciplinary Program in IT-Bio Convergence System (BK21 Plus), Chonnam National University, Gwangju, Republic of Korea; ⁷Department of Animal Science and Veterinary Medicine, Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj, Bangladesh.

Md Kamrul Hasan and Hong-Seok Mun contributed equally to this work.

Abstract | Digital twin (DT), an artificial intelligence (AI) technology, has garnered significant attention recently due to its potential applications across various industries, including the livestock sector. To facilitate the adoption and integration of DT technologies in livestock farming systems, this study aims to discern and appraise the most recent advancements by assessing scientific and technological progressions. The objective of this study is to conduct a comprehensive review of the literature to determine the status of DT application in livestock farm management with its benefits, challenges, and prospects. Scientific databases, PRISMA guidelines, and systematic bibliometric methodologies were used for searching and sorting the most fit articles. This study found that DT technology is new to the livestock industry and mainly used for environmental control, feed management, farm planning, greenhouse gas reduction, and behavior monitoring. Key barriers to DT deployment include high establishment costs, risk of market monopolization, and technical knowledge gaps. The amalgamation of government subsidies, localized technology production, and the provision of training facilities can be instrumental in enabling farmers to overcome the obstacles. The application of DT is limited in monitoring animal behavior and farm environment. However, DT technology has the potential for broader use, such as predicting growth, feed consumption, and improving the supply chain. Although these new areas are yet to be explored in real farm conditions. Along with expanding the new area of using DT in livestock farm management, future collaborative research should concentrate on creating new machine learning and/or deep learning models.

Keywords | Digital twin, Animal behavior monitoring, Environmental control, Farm operation, Livestock supply chain, Precision agriculture

Received | May 26, 2024; **Accepted** | June 27, 2024; **Published** | October 23, 2024

***Correspondence** | Chul-Ju Yang, Animal Nutrition and Feed Science Laboratory, Department of Animal Science and Technology, Suncheon National University, Suncheon, Republic of Korea; **Email:** yangcj@snu.ac.kr

Citation | Hasan MK, Mun HS, Ampode KMB, Lagua EB, Park HR, Kim YH, Sharifuzzaman M, Yang CJ (2024). A systematic literature review on the uses, benefits, challenges, and prospects of digital twins in livestock farm management. *Adv. Anim. Vet. Sci.* 12(12): 2301-2314.

DOI | <https://dx.doi.org/10.17582/journal.aavs/2024/12.12.2301.2314>

ISSN (Online) | 2307-8316; **ISSN (Print)** | 2309-3331



Copyright: 2024 by the authors. Licensee ResearchersLinks Ltd, England, UK.

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

According to the United Nations (World Population Prospects 2022: Summary of Results, 2022), it is assumed that the total population of the world will be 8.5, 9.7, and 10.4 billion in the year 2030, 2050, and 2100 respectively. It has been predicted that in order to meet the projected food demand resulting from population growth, global crop production will need to at least double by 2050 (Tilman *et al.*, 2011; Alexandratos and Bruinsma, 2012). Different agricultural technologies with the combination of Information and Communication Technology (ICT) are developing to provide sufficient food for the ever-increasing population (Saidu *et al.*, 2017; Mat *et al.*, 2018; Farooq *et al.*, 2019; Farooq *et al.*, 2022). Agriculture 4.0 (da Silveira *et al.*, 2021) is a part of industrial and agricultural revolutions and driven by technological advancements such as edge computing (Zhang *et al.*, 2022), artificial intelligence (AI) (Smith, 2018), real-time sensing and wireless sensor networks (WSNs) (Loukatos and Arvanitis, 2021), and the internet of things (IoT) (Paraforos and Griepentrog, 2021), which are opening the door for data-driven farming. With its emphasis on sustainable development, Agriculture 5.0 (Kaklauskas, 2018) is generating interest in digital twin (DT) and their potential applications in agriculture (Tzachor *et al.*, 2022). DT is the digital and virtual counterparts of any physical object (Fuller *et al.*, 2020). Nowadays it is used in different industries (Errandonea *et al.*, 2020), and can track and forecast the state and condition of the machines (Aivaliotis *et al.*, 2019). DT is used to monitor animal behavior (Zhang *et al.*, 2023) with future predictions (Han *et al.*, 2022), reduce methane emissions from dairy farms (An and Chen, 2021), optimize production lines in poultry feed factories (Tarek *et al.*, 2022), and manage feeding (Raba *et al.*, 2022) and environment control (Jo *et al.*, 2019; Jeong *et al.*, 2023) in animal farms. Various ICTs, IoT, cameras, radiofrequency identification (RFID), and sensors are used in precision livestock farming (PLF) to identify animals and behavior, monitor farm animals and the environment, detect diseases early, and manage farms optimally (Besteiro *et al.*, 2018; Pezzuolo *et al.*, 2018; Benjamin and Yik, 2019; da Fonseca *et al.*, 2020; Hristov *et al.*, 2021; Pandey *et al.*, 2021; Halder *et al.*, 2022).

Several review articles about the use of DT in agriculture have been published (Sreedevi and Santosh Kumar, 2020; Pylaniadis *et al.*, 2021; Verdouw *et al.*, 2021; Nasirahmadi and Hensel, 2022; Peladarinos *et al.*, 2023). To the best of the authors' knowledge, there is not enough research that addresses the use of DT in livestock farm management specifically. This study aims to evaluate research progress and application of DT in livestock farm management by analyzing recent case studies and to guide future investigations into the advancement of DT.

A systematic review was carried out in compliance with PRISMA guidelines (Page *et al.*, 2021), and by using the methodology suggested by systematic and bibliometric reviews (Agnusdei *et al.*, 2021; Salazar-Moya and Garcia, 2021; Ahn and Kim, 2023). The review was carried out in five stages: firstly, identifying the research questions; secondly, choosing sources of information; thirdly, organizing the search process; fourthly, specifying the qualifying requirements; and finally, choosing the papers.

IDENTIFYING THE RESEARCH QUESTIONS

The primary aim of this paper is to conduct a literature search on the use of DT in livestock farm management and to evaluate the research findings in order to identify the prospects and obstacles associated with this area of study. The following research questions (RQs) therefore serve as a summary of these objectives.

- RQ1. What are the advantages of deploying DT for animal behavior monitoring and environment control?
- RQ2. What are the economic, social, technological, ethical, and environmental challenges of deploying DT in livestock farms?
- RQ3. What purposes does the livestock farm management hope to achieve from DT?

CHOOSING SOURCES OF INFORMATION

Three academic research databases were searched: Google Scholar, Web of Science (WoS), and Scopus. They are well known for maintaining strict selection criteria, only accepting scholarly content from high-quality journals and conference proceedings, thereby ensuring the inclusion of top-tier research. Indirect inclusion was made for contributions that are indexed in ScienceDirect, IEEE-Xplore, and SpringerLink.

ORGANIZING THE SEARCH PROCESS

Various keywords closely aligned with the research inquiries were utilized during the literature search process. The phrase "digital twin" was chosen as the main keyword. There were other keywords which are as follows: "livestock farming", "application", "cattle", "pig", "welfare", and "environment". These keywords were linked to the Boolean operators "AND" for better searching of literature. There was keyword selection bias because synonymous keywords were not used across different databases. Moreover, there were language and time frame limitations in this study due to its focus exclusively on English-language articles published within the last five years.

SPECIFYING THE QUALIFYING REQUIREMENTS

Articles from peer-reviewed journals, conference proceedings, and doctoral consortiums that highlight the uses of

DT in the livestock sector were included. Reviews of the literature and comparative studies were not included because this study focused on trial-based results. The literature search was restricted to English-language works, and contributions from all over the world in the last 5 years (2018-2023) were included due to the recent development of DT in livestock farm management. Conference proceedings as well as accepted and published articles from journals with an index were included.

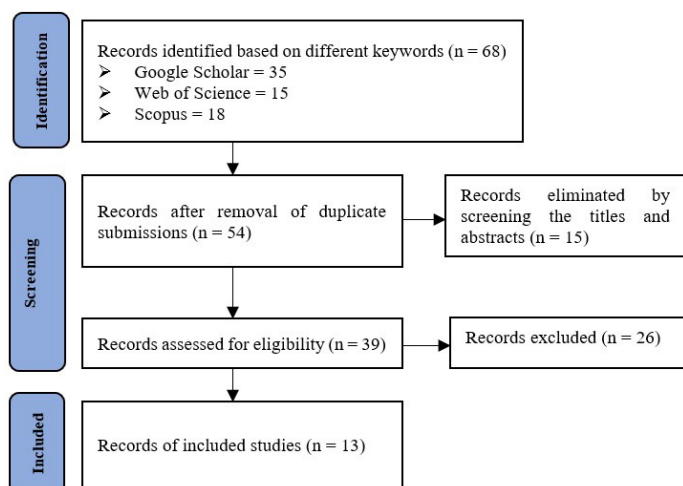


Figure 1: PRISMA flowchart for choosing papers.

CHOOSING THE PAPERS

A total of 393 papers were produced because of the initial selection of contributions based only on the topic of “digital twin” and “livestock farming” with a time frame from 2018 to 2023; of these, 360 were indexed in Google Scholar, 15 in the WoS, and 18 in the Scopus. The use of DT in livestock farm management was our topic and considering the research questions a total of 325 papers were eliminated from the Google Scholar searches based on searches produced by connecting the specified keywords- “livestock farming”, “application”, “cattle”, “pig”, “welfare”, and “environment”. A total of 68 papers were selected (35 papers were Google Scholar-indexed, 15 papers were WoS-indexed, and 18 papers were Scopus-indexed). Papers containing duplicate submissions, titles exhibiting a close resemblance, and content failing to meet the primary criteria were subsequently excluded through the meticulous screening of their titles, abstracts, and keywords. Manual examination was used to find and remove duplicate entries from each article. After a thorough review of the title and abstracts, the publication details were examined in order of priority. Due to the use of three databases in this investigation, duplicate articles were found that appeared repeatedly in different databases. Prioritizing research questions led to the establishment of distinct inclusion and exclusion criteria, which were tailored to specific topics, experimental designs, publication types, and involved stages such as title and abstract review, full-text assessment, real-world application, and the initial phases of DT model development. As a result, the relevant

article came down to 39. A methodical process of removing irrelevant articles was followed, with an emphasis on including those that showed practical applicability in actual farming environments. Articles with potential for the future but not immediately applicable to farm conditions today were also included in the study. To ascertain the relevance and accomplishment of the study’s objectives and to reduce the chance of missing any crucial information, each of these 39 papers was examined separately. A total of 13 papers were kept for this study, after being carefully evaluated for their scope, the particular subject matter, and the required qualifications. The procedure for choosing papers is schematically depicted in line with the PRISMA flow-chart (Figure 1).

USE OF DIGITAL TWIN IN LIVESTOCK FARM MANAGEMENT

According to the analysis of the 13 papers published recently on the use of DT in livestock farm management, three of the papers concentrated primarily on animal behavior and welfare monitoring, three on real-time environmental and energy control in livestock farms, and three on livestock supply chains. Furthermore, there were two papers addressing livestock farm operation, one focusing on decision-making processes concerning animal feed factories, and another centered-on strategies for mitigating greenhouse gas emissions from livestock farms. Different physical objects were used in various papers, with cattle appearing as more specific animal species of interest. All these papers—aside from (Keates, 2019) and (Tarek *et al.*, 2022)—have a close connection with animal welfare and management.

To identify the feeding behavior of cows, Zhang *et al.* (2023) suggested a pioneering architectural framework for cows utilizing DT technology, designed to encapsulate the entirety of the cow’s lifecycle. A method was used to create the cows’ digital shadow by gathering real-time location and neck movement data from cows of different stages (calf, heifer, and adult) using an inventive custom-made intelligent collar that included ultra-wideband (UWB) chips and inertial measurement units (IMUs). Based on the data dependency, the whole architecture was classified into three levels: barn integration, pasture agent, and cloud. Besides, there were five layers- physical entity, integrated, data management and information, modeling and simulation, and decision and user interface. They used three machine learning (ML) models- support vector machines (SVM), k-nearest neighbor (KNN), and a deep learning (DL) model- long short-term memory (LSTM), and the accuracy was highest in LSTM (94.97%). Petrov and Atanasova (2021), created a 3D real-time virtual reality (VR)/ augmented reality (AR) model of farm animals to monitor animal behavior and welfare. Following the five domains for assessing animal welfare—the physical envi-

ronment, health, mental state, behavioral interactions, and nutrition—the model was created using data gathered from IoT devices. ML software was used to analyze the data in a meaningful way, alerting farmers when values seemed to deviate from the predetermined ranges. The software also offers details on potential issues that could result from the measured deviations as well as prompt action items for resolving the issue. At its nascent developmental phase, this model has yet to showcase any evaluation outcomes. [Han et al. \(2022\)](#) implemented DT for the identification and future prediction of different behaviors of cattle—resting, rumination, high activity, medium activity, panting, eating, grazing, and walking. Through the utilization of sensor data retrieved from an IoT farm system, this innovative solution constructs a DT of cattle utilizing DL (LSTM), enabling real-time monitoring of the physiological cycles of cattle, and forecasting the state of subsequent physiological cycles. This model exhibited a training error of 0.58 with a future prediction error of 5.12, and their findings indicate that DT can predict the future behavior of cattle, which can help the farmers in monitoring animal health and welfare.

[Jo et al. \(2018\)](#) conducted a feasibility study for controlling the environment of the pigsty by using DT technology. The two-tiered framework of smart livestock farms—the digital farm engine and the digital farm framework—was outlined, and a brief description of an easily deployable service scenario for automatic control in livestock farms was given to illustrate how physical and digital livestock farms interact. They define a DT for pig enlargement optimization, which was achieved by controlling a barn system that maintains temperature and air quality within a pre-set collection. To find scenarios that lead to the desired outcome, a combination of big data and model-based simulations were used to provide decision support and mechanize the pigsty control system. The farm control mechanism was needed to control both automatic window openings and airflow to achieve the desired state. They found that DT can efficiently regulate the animal shed's environment, helping to improve the welfare of animals on livestock farms. The DT of this framework is in the initial stage of development, and till now it is not applied in real livestock farm conditions. Moreover, [Jo et al. \(2019\)](#) proposed a DT to simulate a pigsty's energy consumption to offer decision support for the best pigsty construction with optimal energy use. Six different models of ventilation fans (SLF-300D2-6, SLF-350A4-6, SLF-500A4-6, SLF-500D4-6, SLF-730A6-5, and SLF-960A6-3) were utilized in the pigsty. EnergyPlus, an energy simulation program used to model energy consumption for heating, cooling, and ventilation, was employed in the pigsty. A variety of ventilation fan models were employed in combination to determine the optimal configuration for energy savings. Among the different fan combinations, case number 4 (2 fans of the SLF-300D2-6 model and 4 fans of the SLF-960A6-3 model) exhibited the lowest electricity

consumption (approximately 550 MJ). This study suggests that DT can reduce farm expenses by reducing electricity costs. Furthermore, [Jeong et al. \(2023\)](#) deployed DT in pig farms for making virtual pig houses which provided information for the efficient use of heating, ventilation, and air conditioning (HVAC) systems in the real pig house to maintain the best environment for the pigs, and helped to solve the problem related to HVAC system before it appears in the real pig house. Energy consumption of heating systems and ventilation fans in proportional, conventional, optimal, and fixed (60°C) operating methods were examined. DT technology aided in finding the best operating method which was the 'optimal method' that consumed the lowest amount of electricity for operating ventilation fans (67.01 kWh) and heating purposes (1051 kWh) than others. This study suggests that DT can effectively manage environmental conditions in animal sheds while minimizing electricity costs.

[Mu et al. \(2022\)](#) illustrated the results of a case study on the use of DT in China's Qinghai Meadow, and the purpose of this case study was to create a livestock supply chain. The two essential elements that comprised the foundation of this approach were the commercial supply chain and the information technology (IT) operating system. The IT operating system underwent categorization into three distinct tiers: physical, data, and virtual. Information obtained from sensors within the physical layer underwent transmission to the data layer for subsequent processing, evaluation, management, and archival purposes. Subsequently, data processed within the data layer was relayed to the virtual layer, where advanced AI and ML models were employed for further data refinement, and then provided sophisticated feedback to the physical layer. The main purpose of this process was to help in early disease diagnosis and prevent losses from severe weather. For this reason, regardless of the animal or the surroundings, alarms were set off whenever the system noticed unusual behavior; however, this solution has not yet shown any evaluation outcomes. Besides, [Keates \(2019\)](#), described a DT to enhance livestock value chains, and the goal of this DT was to serve as a tool for gathering and disseminating important metrics and assessing each one's performance in comparison to a reference model. One of the main use cases mentioned was the creation of missing data by simulating the actual supply chain using the reference model, which improved supply chain comprehension. The life cycle of meat animals, ranging from 2 to 10 years, posed significant challenges in collecting individual animal data. Due to the lack of individual animal data, this DT framework is still in its initial stages of development and has not yet been applied to actual circumstances. Furthermore, to attain 'zero-waste,' [Valero et al. \(2023\)](#), provided a framework of DT in several areas of a circular meat supply chain, one of which is animal management. The framework of DT in the animal management

area can monitor, predict, and influence animal behavior and environmental conditions which provide valuable insights into the health and welfare of animals. The physical objects include information about individual animals (for example their activity, resting status, and grazing behavior) as well as environmental information in their shed (for example temperature, humidity, and lighting); however, this framework of DT is still at the conceptual level.

Erdélyi and János (2019), proposed a DT of the porker model in MATLAB Simulink environment, which can predict future feed intake, body weight gain, and final body weight of pigs. Details of the porker model were not explained in their paper. This DT framework can help farmers in their pig farm management and future planning; however, the DT of the porker model is still being developed, and it has not been used on a real pig farm yet. Raba *et al.* (2022) applied DT technology for better feed management and optimization of the animal feed delivery chain. This was accomplished at the farm level using a DT-based strategy, which remotely monitored the amount of feed in feed bins, using RGB-D (red, green, blue-depth) camera images, processed by combining biased-randomization techniques with a simheuristic framework. The results exhibited that both farmers and feed producers can remotely manage their feedstock levels using DT. This study suggests that by deploying DT on their farms, farmers can enhance feeding management. Tarek *et al.* (2022) implemented DT in a poultry feed manufacturing factory by using a four-layer software architecture (physical, data, analytical, and presentation layer) to monitor the whole feed manufacturing process. All the assets, for example, IoT sensors, machines, storage facilities, and containers, were included in the physical layer, whereas model definitions and the relationships between assets were contained in the data layer. The analytic layer was affixed to the data layer, and it offered service modules and provided a description of the feed factory's assets and production line processes. The simulation model to replicate various factory operating conditions was included in the analytic layer, and the dashboard, which was used to display and examine data, was part of the presentation layer. Moreover, the graphs that exhibited the connections between the factory's assets for poultry feed were included in the presentation layer. This DT technology helped in decision-making on whether to use single or multiple production lines to meet the demand for the quantity of feed production.

An and Chen (2021), used swarming unmanned aircraft vehicles (a group of drones) on the dairy farm to provide real-time data updates for the DT which assisted in the measurement and reduction of methane emissions from the dairy farm. To deploy the DT platform, they used web app, gazebo, robot operating system, and unmanned aerial vehicle toolbox. In addition, unmanned aerial vehicles were

also utilized as mobile sensors and actuators to monitor the diffusion of methane and to minimize methane emissions by spraying methane neutralizers (biochar). At various altitudes, they observed the 3D flight path of an unmanned aerial vehicle waypoint within an unmanned aerial vehicle toolbox. Additionally, the entirety of the unmanned aircraft vehicles' flight paths within the gazebo was observed. Finally, observations were made of the methane diffusion process. Their results suggest that greenhouse gas emissions from livestock farms can be reduced by using DT technology.

A summary of research on the application of DT in livestock farm management is shown in Table 1.

BENEFITS OF USING DIGITAL TWIN IN LIVESTOCK FARM MANAGEMENT

Because only seven of the thirteen studies mentioned above have used DT technology in actual farm settings, the literature review exhibits that the technology is still in its early stages of development. However, DT technology has several benefits for livestock farm management. DT exhibited positive results in the animal shed model in operating ventilation fans and windows (Jo *et al.*, 2018), therefore, farmers can use a laptop or smartphone to automatically control the farm environment from a distance.

According to Jo *et al.* (2019), the most energy-efficient ventilation fan combinations can be effectively detected using DT, and farmers can use these fan combinations in farms to reduce production costs. DT can be effectively harnessed to ascertain the optimal energy-efficient operating methods for running the HVAC system in animal sheds (Jeong *et al.*, 2023) and through the identification and removal of operational inefficiencies, DT can assist farmers in reducing their farm expenses.

DT technology can monitor a comprehensive range of animal behaviors—including resting, rumination, high and medium activity levels, panting, eating, grazing, and walking—and can also provide predictive analytics (Han *et al.*, 2022), thereby assisting farmers in enhancing overall farm management practices. With an accuracy of 94.97%, DT with LSTM model identified animals' feeding behavior (Zhang *et al.*, 2023), assisting farmers by providing important information about animal health and welfare status. Continuous monitoring of daily feed consumption can be successfully done by DT (Raba *et al.*, 2022) and such kind of monitoring can assist farmers in early detection of animal health and welfare issues and making better future planning for farm operations. DT can be significantly used in making decisions regarding the selection of the production line (single or multiple) for manufacturing livestock feed (Tarek *et al.*, 2022) which can assist farmers in manufacturing desired amounts of feed within a short period. DT can be successfully utilized to accurately measure and

Table 1: An overview of research on the application of digital twins in livestock farm management.

DT with AI model	Purpose	Field application	Physical object (No.)	Findings						Ref.
DT with ML (SVM, KNN), and DL (LSTM)	Identification of feeding and non-feeding behaviors.	Yes	Cattle (5)	Model	Accuracy (%)	Recall (%)	Precision (%)	F1 score (%)	Specificity (%)	(Zhang <i>et al.</i> , 2023)
				SVM	88.83	89	89.90	89.45	88.64	
				KNN	90.53	90.20	92	91.09	90.91	
				LSTM	94.97	93.86	99.99	95.21	99.99	
DT with ML	To monitor animal behavior and welfare.	No	All livestock animal	DT assists in monitoring animal behavior and welfare.						(Petrov and Atanasova, 2021)
DT with ML	To build a livestock supply chain.	No	Cattle	Both early disease detection and prevention of catastrophic weather are possible by DT.						(Mu <i>et al.</i> , 2022)
DT with DL (LSTM)	Identification and future prediction of behaviors.	Yes	Cattle (98)	Training error 0.58 Future prediction error 5.12						(Han <i>et al.</i> , 2022)
DT of the livestock value chain	To create a DT to enhance Australia's livestock value chains.	No	Value chain of livestock	DT aids in gaining a deeper comprehension of the livestock supply chains.						(Keates, 2019)
DT of meat supply chain	To build a meat supply chain that has zero-waste.	No	Supply chain of meat	DT aids in reducing waste in the meat supply chain.						(Valero <i>et al.</i> , 2023)
DT of the porker model	To build a DT for smart pig farming.	No	Pig	DT assists in the future prediction of feed consumption, body weight gain, and final body weight of fattening pigs.						(Erdélyi and János, 2019)
DT of dairy farm	To assist in quantifying and reducing the methane emissions from dairy farms.	Yes	Dairy farm (1)	DT can detect and reduce methane emissions.						(An and Chen, 2021)
DT of poultry feed factory	For smart manufacturing of poultry feed.	Yes	Poultry feed factory (1)	DT assists in deciding the production line (single or multiple) to produce the required quantity of poultry feed.						(Tarek <i>et al.</i> , 2022)
DT with simheuristic framework based on biased randomization techniques	To supply precise real time data for tracking daily feed consumption, and future planning to prevent runouts of feedstock. To alter the feed company's approach by shifting the maintenance of the feedstock's workload.	Yes	Feed bin (325)	Farmers can do better feeding management in livestock farms by using DT. DT assists feed producers in making better plans for future feed production.						(Raba <i>et al.</i> , 2022)
DT of pigsty	To automatically regulate the pigsty's environment.	No	Pigsty	Decision-making by farmers regarding automated environmental control systems in pigsty is aided by DT.						(Jo <i>et al.</i> , 2018)

DT of pigsty	Energy planning for automated environmental control in the pigsty.	Yes	Pigsty (1)	Case Number		Energy consumption (MJ)	(Jo <i>et al.</i> , 2019)
				Case number 1 (10 fans of SLF-300D2-6 and 15 fans of SLF-350A4-6)		Approximately 710	
				Case number 2 (6 fans of SLF-500A4-6 and 4 fans of SLF-500D4-6)		Approximately 850	
				Case number 3 (4 fans of SLF-500D4-6 and 4 fans of SLF-730A6-5)		Approximately 750	
				Case number 4 (2 fans of SLF-300D2-6 model and 4 fans of SLF-960A6-3 model)		Approximately 550	
DT of pigsty	To run the HVAC system in a pigsty with minimal energy consumption.	Yes	Pigsty (1)	Operating methods	Electricity consumption of ventilation fans (kWh)	Heating energy consumption (kWh)	(Jeong <i>et al.</i> , 2023)
				Proportional	95.41	1138.61	
				Conventional	91.55	-	
				Optimal	67.01	1051	
				Fixed (60°C)	-	1288.61	

SVM-support vector machines, KNN-k nearest neighbor, LSTM-long short term memory, HVAC-heating, ventilation, and air conditioning, MJ-Megajoule, and kWh-kilowatt-hour.

Farm operation	Environmental control	Welfare monitoring
• Remotely farm operation • Measure daily feed consumption • Reduce farm expenses • Effective farm planning • Decision-making for feed production line operation	• Fix environmental issues • Optimal energy use in animal shed • Reduce greenhouse gas emissions	• Animal behavior identification • Predict future animal behavior

Figure 2: Benefits of using DT in livestock farm management.

subsequently reduce methane emissions from animal farms (An and Chen, 2021), and assist farmers in solving environmental problems and creating more environmentally friendly farming practices that will lessen greenhouse gas emissions. The overall benefits of DT in different aspects of livestock farm management including farm operation, environmental control, and welfare monitoring are summarized in Figure 2.

DIGITAL TWIN DEPLOYMENT CHALLENGES AND POSSIBLE SOLUTIONS

With the deployment of DTs, a variety of economic, social, technological, ethical, and environmental challenges have emerged (Neethirajan, 2023). In terms of economic challenges, high switching costs will be required to incorporate DT in livestock farms for the setup of sensors, devices, hardware, and software (Neethirajan and Kemp, 2021). The infrastructure for PLF varies, which makes it difficult to use DT in this setting (Mallinger *et al.*, 2022). Round-the-clock internet facilities, the cost of laptops and desk-

top computers, training costs of farmers, additional energy costs, and other costs to run this technology effectively are to be added. There are deployment and operational costs to run the DT effectively which can vary based on farm size and the use of AI technologies. The deployment costs include PLF tools for monitoring farm animals and the environment, the development of AI software, farm structure development for setting PLF tools, and internet connectivity. Operational costs include annual maintenance fees (for updating software, and changes of broken sensors and devices), costs related to data (for integration, processing, and analysis), and training costs (for skill development and proper operation of DT). Government subsidies, credit options, and tax exemptions could aid farmers in overcoming their financial obstacles. For example, subsidies and tax incentives assisted in the quick adoption of different DT technologies in the manufacturing sector of Germany (Platform Industrie 4.0, 2024). It also helped to reduce the production cost and increase efficiency.

In the social aspect of challenges, if the DT is only accessible by large-scale farmers, then medium and small-scale farmers will be unable to establish it on their farms which may create a monopolization market, and there will be a high chance of increasing international dependencies (Mallinger *et al.*, 2022; Malik *et al.*, 2023). Moreover, it may create social discrimination among farmers which may affect the variation in the health and welfare status of animals (An and Chen, 2021). Farmers' support to overcome social challenges could come from the domestic production of digital devices and technology, coupled with the provision of accessible credit facilities.

In terms of technological aspects of challenges, technical proficiency in fields of data analytics, IoT, and AI is required for operating DT effectively, and many farmers might not possess the required abilities (Mallinger *et al.*, 2022); lacking assistance, and training. Appropriate installation of animal-attached sensors, for example, accelerometer, pedometer, radar-based sensor, and respiratory rate sensor is challenging (Neethirajan, 2020), and if they are not installed correctly, they may fall out of the body. Furthermore, most of the sensors rely on batteries for operation (Dewan *et al.*, 2014); therefore, if the batteries run out of power (Oudenhoven *et al.*, 2012), the sensor's ability to provide real-time animal data may be compromised, potentially disrupting the entire DT system. ML and/or DL models are used in DT technology (Petrov and Atanasova, 2021; Han *et al.*, 2022; Mu *et al.*, 2022; Zhang *et al.*, 2023), and these models rely on large and high-quality data (Zhang *et al.*, 2018; Upadhyay and Khandelwal, 2019; Prior *et al.*, 2020; Zhang *et al.*, 2022); integrating these data is still challenging (Davis *et al.*, 2017; Zhang *et al.*, 2018; Jarrahi *et al.*, 2023). When there is insufficient data, the DL model exhibits unsatisfactory accuracy due to its sensitivity to data sources (Han *et al.*, 2022). Furthermore, improper labeling and the use of skewed training datasets can affect future animal behavior prediction by DT technology (Han *et al.*, 2022). By implementing comprehensive training, creating a user-friendly interface, and optimizing and integrating AI models, farmers can effectively navigate and overcome technological hurdles.

In ethical aspects of challenges, special concern is needed about human-animal relationships (Neethirajan, 2023). The relationship between the farmer and the animal could suffer if DT is used because sensors and/or devices will gather all the data required to run the technology. DT technology uses the ML model which assesses different aspects of health and nutrition effectively, but it lacks the intuitive understanding of animal needs that humans have (Seibel *et al.*, 2020). In PLF, PLF tools (sensors and devices) treat animals like objects and only gather certain parameters from them (Bos *et al.*, 2018). 'Treating as an object' and 'turning into an object' are the two categories of objectification

(Brom, 1997), and objectification using PLF tools has detrimental effects (Bos *et al.*, 2018). 'Treating as an object' refers to treating an animal like a mere object and never considering its inherent worth (Bos *et al.*, 2018). 'Turning into an object' refers to focusing more on the economic worth of animals (milk, meat, and eggs) and never considering their welfare (Bos *et al.*, 2018). Consequently, the overall sustainable development of industrial farming can be impacted by viewing an animal as nothing more than an object and concentrating only on its financial worth. It is crucial to keep in mind that animals are sentient beings with social and emotional needs (Proctor, 2012; Proctor *et al.*, 2013; Kumar *et al.*, 2019), and using DT should never lead to a disrespect for animal welfare or a failure to uphold human responsibility for animals. The development of a DT model that prioritizes the social and emotional needs of animals may have the potential to address ethical challenges. Moreover, animal welfare guidelines for the ethical use of PLF tools should take into account the behavioral needs and economic characteristics of animals in order to achieve a balanced approach between PLF tools and animal ethics.

In terms of environmental challenges, it is still up for debate how best to evaluate and lessen the environmental impact of DT (Neethirajan, 2023). Along with carbon emissions from the manufacture and disposal of digital infrastructure and devices, the use of DT in livestock farming can also produce electronic waste (Liu *et al.*, 2019; Neethirajan, 2023). Energy is needed for data processing and to run the DT even though this technology can assist with sustainability by automatic environment controlling of animal sheds with minimal energy consumption (Jo *et al.*, 2019; Jeong *et al.*, 2023). Maximizing the utility of digital devices alongside the exploration of alternative energy sources may present a viable strategy for farmers to surmount environmental challenges. For long-term sustainability, the use of renewable energy sources (solar, wind, and other new energy sources) for operating DT in livestock farms can minimize the environmental footprint of DT. For example, photo-voltaic power generation saved 2×10^4 KWh of electricity and 20 t of CO₂ emissions annually from a dairy farm (Zhang *et al.*, 2017). By integrating renewable energy sources and efficiency-improving methods, such as borehole thermal energy storage and heat pump technology, the photovoltaic-thermal system supplies the pig farm's reliance on fossil fuels for energy, culminating in a decrease of 20,850 kg in CO₂ emissions annually (Murali *et al.*, 2024).

Moreover, there exist additional challenges. DT is used in monitoring animal behavior and welfare (Petrov and Atanasova, 2021; Han *et al.*, 2022; Zhang *et al.*, 2023), and environmental control (Jo *et al.*, 2018; Jo *et al.*, 2019; Jeong *et al.*, 2023); however, it may be difficult to integrate all aspects of the livestock production cycle, spanning from

PROSPECTS OF DIGITAL TWIN IN LIVESTOCK FARM MANAGEMENT

Innovations in IoT, AI, cloud, and edge computing have the potential to assist farmers in real-time data processing. Data privacy and cybersecurity will increase the faith of farmers. Data integration and visualization can help farmers for better farm operation and planning. Additionally, the use of renewable energy sources for operating DT technology may minimize production costs and greenhouse gas emissions. User-friendly interfaces and regulatory standards will ensure the optimal use of DT while considering the animal welfare issue. These innovations are believed to drive the future of DT application in different aspects of livestock farming. Various AI models, for example, convolutional neural networks (CNN), ML, DL, artificial neural networks (ANN), adaptive neural fuzzy inference systems, and pattern recognition, are employed in precision livestock farming to identify animals and diseases, monitor farm animal behavior and welfare, observe daily body weight growth, and monitor the farm environment (White *et al.*, 2004; Kashiha *et al.*, 2014; Kashiha *et al.*, 2014; Khoramshahi *et al.*, 2014; Lee *et al.*, 2019; Nasirahmadi *et al.*, 2019; Alameer *et al.*, 2020; García *et al.*, 2020; Bao and Xie, 2022). Every single AI model has some limitations for the explanation and accuracy of results (Birhane, 2021), for example, the ML model exhibits biases (Alelyani, 2021; Chakraborty *et al.*, 2021). Therefore, priority should be given in making an appropriate design that has no hidden biases that, through computational feedback mechanisms bination of two or more AI models in the design of DT technology, for example, deep hybrid learning (a combination of DL and ML), which may increase accuracy. could magnify unfavorable effects on livestock productivity

Figure 3.

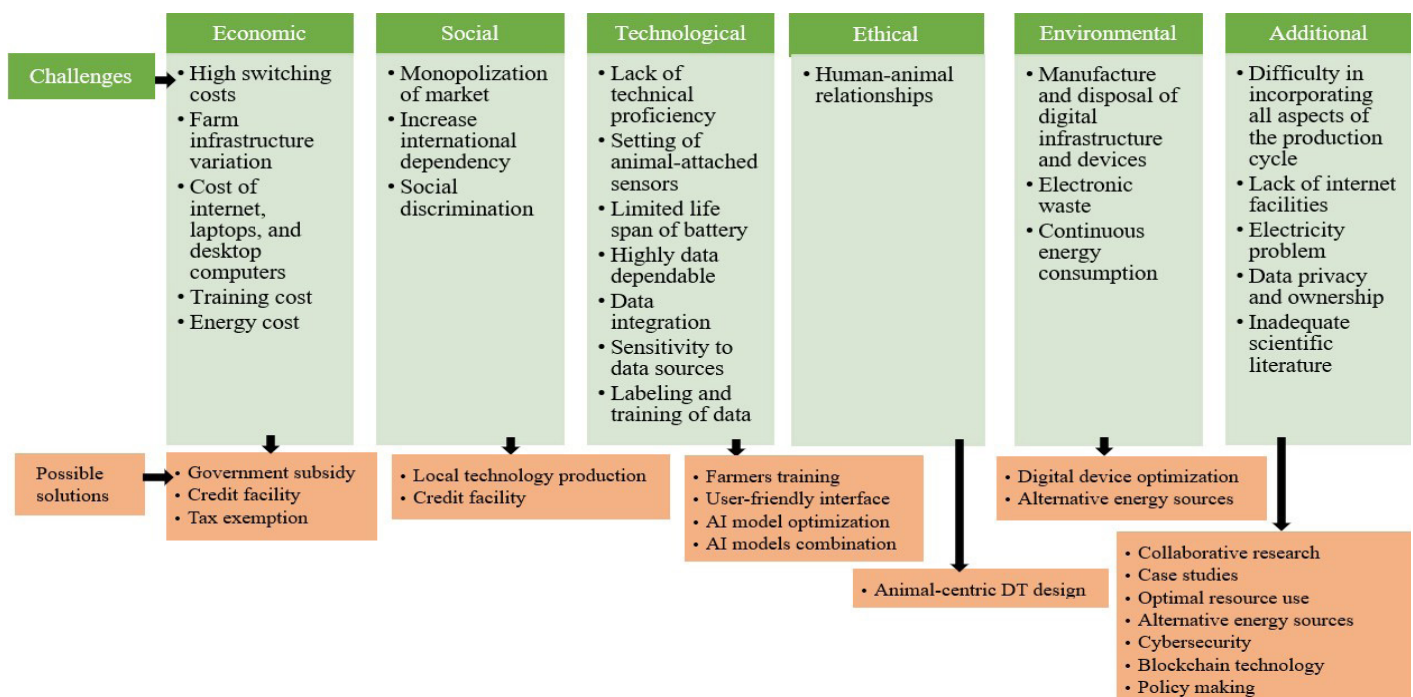


Figure 3: DT deployment challenges and possible solutions.

(Malik *et al.*, 2023). In the future, there may be a comThe hybrid blended deep learning (HyBDL) model exhibited higher accuracy (98.03%) than CNN, gated recurrent units (GRU), LSTM, CNN-GRU, and CNN-LSTM for milk adulteration detection (Mhapsekar *et al.*, 2024). Optimization of the AI model is essential for a higher level of accuracy (Abdolasol *et al.*, 2021). When the inertial measurement units (IMUs) and indoor position detection data were combined in the DL model of a DT technology, it identified the feeding behavior of cows with a higher degree of accuracy (94.97%) than when the IMUs data was used alone (91.05%) (Zhang *et al.*, 2023), showing a considerable amount of improvement can be achieved. In the days ahead, anticipate the increasing sophistication and advancement of AI models that analyze different parameters related to animal health and welfare. Farm animal affective states and behaviors may be simulated and predicted in the future through the use of DT (Neethirajan, 2022). DT might be developed that could tailor care plans for specific animals according to their distinct behaviors, emotions, and health requirements. In the coming days, there will be species-specific biometric sensors (Neethirajan, 2022), and they will collect different parameters related to the health, welfare, production, and reproduction of animals that are needed to run the DT technology effectively. A next-generation method for achieving real-time flow of biometric data is offered by DT models of individual animals (Jo *et al.*, 2018; Neethirajan and Kemp, 2021).

A DT reference model is necessary for the development of animal twins. Generally, the DT reference model framework consists of the physical object, communication layer, and digital object layer (Lu *et al.*, 2020). The communication layer transfers data between the physical object and the digital object layer (Lu *et al.*, 2020). The data processing section of the digital object layer processes the data that has been collected from the physical object by the information model of the digital object layer (Lu *et al.*, 2020). For developing the DT reference model there are several steps: firstly, setting of the objectives and scope. Secondly, the identification of stakeholders and understanding of their expectations regarding the use of DT. Thirdly, strategy planning for data collection and integration using PLF tools. Fourthly, designing the architectural framework for data processing and storage. Fifthly, the selection of the appropriate ML model and visualization tools (mobile apps) for data analysis and user decision implementation. Sixth, accuracy and reliability testing for improving performance. Seventh, trail basis and farm condition testing to see applicability in the real farms. Training farmers and gathering feedback for efficient use and continuous improvement. Eighth, a user manual for written documentation and making maintenance schedules for better operation of the DT. There are no DT reference models that can direct research toward the creation of animal twins

(Neethirajan, 2022). In the forthcoming days, researchers may create animal twins with the aid of DT reference models. Low latency and quick analysis are expected to be the future of DT using edge computing. Moreover, by protecting livestock farm data privacy, blockchain technology may help to increase faith among DT technology provider companies and farmers. Technology providers are expected to develop more user-friendly DT. Currently, most publications exploring the implementation of DT technology into livestock farms are in their embryonic phases, and in the foreseeable future, these foundational frameworks hold potential for application in livestock farming to enhance the credibility of this technology. The potential for efficient farm operations and improving animal health and welfare through DT technology is promising. This can be done by addressing the drawbacks and issues, looking into potential future directions, and making use of the automation and comprehensive management capabilities of DT.

According to predictions made by industry research firm Gartner (Top 10 Strategic Technology Trends for 2019: Digital Twins, 2024), DT technology was among the top ten strategic technology trends in 2019. The market value of DT is projected to reach 131.09 billion US dollars by 2030, which was only 6.3 billion US dollars in 2021 (Digital Twin Market, 2022). This indicates that in the future there will be more applications of DT technology in different industries including the livestock industry.

The potential for efficient farm operations and improving animal health and welfare through DT technology is promising. This can be done by addressing the drawbacks and issues, looking into potential future directions, and making use of the automation and comprehensive management capabilities of DT. The installation cost of DT technology in livestock farms should be subsidized by the government, and collaboration should be increased between the government, technology companies, engineers, farmers, and animal scientists. The government can take some initiatives to introduce and adopt DT. This can include, offering partial compensation (10-25%) or arranging low-interest credit facilities; tax reduction (up to 10%) on PLF tools and AI software; encouraging researchers by offering grants; exhibiting pilot DT model for potential stakeholders; ensuring uninterrupted internet facilities in rural areas; arranging training and workshop; fostering innovation by encouraging public-private partnerships; ensuring efficient and secure farm data sharing and, distributing awards among stakeholders for sustainable use of DT. The incorporation of DT in farm management is expected to improve animal welfare and sustainably increase livestock output with further study and conscientious application.

DT assists in livestock farm operations by monitoring and predicting animal behavior, facilitating early disease detection, and controlling the farm environment remotely. However, currently, there are several challenges- high establishment costs, lack of technological knowledge, data privacy, lacking human-animal relationships, and sustainability issues. In the future, more emphasis should be given to collaborative research on developing protocols for data collection and integration, improving AI models, analyzing the cost-benefit ratio, monitoring animal behavior and welfare, evaluating environmental impact, guaranteeing cybersecurity, developing stakeholders' training, and broadening the application area. It is expected that these kinds of efforts may improve the accuracy of the DT model, assist in investment decisions, ensure better animal behavior and welfare, improve resource management for sustainable farming, increase trust among stakeholders, raise DT adoption rates, and elevate livestock production. Governments and private sectors need to come forward with adequate funding, facilitating collaborative research, which will assist in expanding the domain of DT application in livestock farming systems.

ACKNOWLEDGMENTS

The authors would like to acknowledge the Korea Institute of Planning and Evaluation for Technology in Food, Agriculture and Forestry (IPET) and Korea Smart Farm R&D Foundation through the Smart Farm Innovation Technology Development Program, funded by the Ministry of Agriculture, Food and Rural Affairs (MAFRA) and Ministry of Science and ICT (MSIT) and Rural Development Administration (RDA) (421023-04). Also, work was supported by the Korea Institute of Planning and Evaluation for Technology in Food, Agriculture, Forestry (IPET) through Agri-Food Export Enhancement Technology Development Program, funded by Ministry of Agriculture, Food and Rural Affairs (MAFRA) (RS-2023-00231738).

NOVELTY STATEMENT

This study presents a comprehensive analysis of the literature concerning the application of digital twin technology in livestock farm management, an area that has remained relatively underexplored until now. The review opens the door for more studies and developments in the field of precision livestock management.

AUTHOR'S CONTRIBUTIONS

Conceptualization: Md Kamrul Hasan, Hong-Seok Mun,

Young-Hwa Kim, Chul-Ju Yang; Methodology: Md Kamrul Hasan, Hong-Seok Mun; Writing - original draft preparation: Md Kamrul Hasan, Hong-Seok Mun, Keiven Mark Bigtasin Ampode, Young-Hwa Kim, Eddiemar Baguio Laguna, Md Sharifuzzaman; Writing - review and editing: Md Kamrul Hasan, Hong-Seok Mun, Keiven Mark Bigtasin Ampode, Young-Hwa Kim, Eddiemar Baguio Laguna, Hae-Rang Park, Md Sharifuzzaman, Chul-Ju Yang; Formal analysis: Md Kamrul Hasan, Hong-Seok Mun; Supervision: Chul-Ju Yang.

CONFLICTS OF INTEREST

The authors have declared no conflict of interest.

REFERENCES

- Abdolrasol MGM, Hussain SMS, Ustun TS, Sarker MR, Hannan MA, Mohamed R, Ali JA, Mekhilef S, Milad A (2021). Artificial Neural Networks Based Optimization Techniques: A Review. *Electronics*, 10: 2689. <https://doi.org/10.3390/electronics10212689>
- Agnusdei GP, Elia V, Gnoni MG (2021). Is Digital Twin Technology Supporting Safety Management? A Bibliometric and Systematic Review. *Appl. Sci.*, 11: 2767. <https://doi.org/10.3390/app11062767>
- Ahn EY, Kim SY (2023). Digital Twin Application and Bibliometric Analysis for Digitization and Intelligence Studies in Geology and Deep Underground Research Areas. *Data*, 8: 73. <https://doi.org/10.3390/data8040073>
- Aivaliotis P, Georgoulas K, Chrysosouris G (2019). The use of Digital Twin for predictive maintenance in manufacturing. *Int. J. Comput. Integr. Manuf.*, 32: 1067–1080. <https://doi.org/10.1080/0951192X.2019.1686173>
- Alameer A, Kyriazakis I, Dalton HA, Miller AL, Bacardit J (2020). Automatic recognition of feeding and foraging behaviour in pigs using deep learning. *Biosyst. Eng.*, 197: 91–104. <https://doi.org/10.1016/j.biosystemseng.2020.06.013>
- Alalelyani S (2021). Detection and Evaluation of Machine Learning Bias. *Appl. Sci.*, 11: 6271. <https://doi.org/10.3390/app11146271>
- Alexandratos N, Bruinsma J (2012). World agriculture towards 2030/2050: the 2012 revision, ESA Working Papers 12-03. <https://doi.org/10.22004/ag.econ.288998>
- An D, Chen Y (2021). Digital Twin Enabled Methane Emission Abatement Using Networked Mobile Sensing and Mobile Actuation. In: *IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI)*, IEEE, Beijing, China, pp. 354–357. <https://doi.org/10.1109/DTPI52967.2021.9540133>
- Arulmozhi E, Bhujje A, Moon BE, Kim HT (2021). The Application of Cameras in Precision Pig Farming: An Overview for Swine-Keeping Professionals. *Animals*, 11: 2343. <https://doi.org/10.3390/ani11082343>
- Bao J, Xie Q (2022). Artificial intelligence in animal farming: A systematic literature review. *J. Clean. Prod.*, 331: 129956. <https://doi.org/10.1016/j.jclepro.2021.129956>
- Benjamin M, Yik S (2019). Precision Livestock Farming in Swine Welfare: A Review for Swine Practitioners. *Animals*, 9: 133. <https://doi.org/10.3390/ani9040133>
- Besteiro R, Arango T, Rodríguez MR, Fernández MD, Velo R

- (2018). Estimation of patterns in weaned piglets' activity using spectral analysis. *Biosyst. Eng.*, 173: 85–92. <https://doi.org/10.1016/j.biosystemseng.2017.06.014>
- Birhane A (2021). Algorithmic injustice: a relational ethics approach. *Patterns*, 2: 100205. <https://doi.org/10.1016/j.patter.2021.100205>
- Bos JM, Bovenkerk B, Feindt PH, van Dam YK (2018). The Quantified Animal: Precision Livestock Farming and the Ethical Implications of Objectification. *Food ethics*, 2: 77–92. <https://doi.org/10.1007/s41055-018-00029-x>
- Brom FWA (1997). Onherstelbaar verbeterd : biotechnologie bij dieren als een moreel probleem / Frans W.A. Brom - F.W.A. Brom Vlaamse catalogus. Available online: https://bibliotheek.be/catalogus/fwa-brom/onherstelbaar-verbeterd-biotechnologie-bij-dieren-als-een-moreel-probleem/boek/library-marc-vlacc_1821755?branch=/root/bibnet/West-Vlaanderen (accessed 20 Jun 2024)
- Chakraborty J, Majumder S, Menzies T (2021). Bias in machine learning software: why? how? what to do?, In: Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. Association for Computing Machinery, New York, NY, USA, pp. 429–440. <https://doi.org/10.1145/3468264.3468537>
- da Fonseca FN, Abe JM, de Alencar Nääs I, da Silva Cordeiro AF, do Amaral FV, Ungaro HC (2020). Automatic prediction of stress in piglets (*Sus scrofa*) using infrared skin temperature. *Comput. Electron. Agric.*, 168: 105148. <https://doi.org/10.1016/j.compag.2019.105148>
- da Silveira F, Lermen FH, Amaral FG (2021). An overview of agriculture 4.0 development: Systematic review of descriptions, technologies, barriers, advantages, and disadvantages. *Comput. Electron. Agric.*, 189: 106405. <https://doi.org/10.1016/j.compag.2021.106405>
- Davis SE, Lasko TA, Chen G, Siew ED, Matheny ME (2017). Calibration drift in regression and machine learning models for acute kidney injury. *J. Am. Med. Inform. Assoc.*, 24(6): 1052–1061. <https://doi.org/10.1093/jamia/ocx030>
- Dewan A, Ay SU, Karim MN, Beyenal H (2014). Alternative power sources for remote sensors: A review. *J. Power Sources*, 245: 129–143. <https://doi.org/10.1016/j.jpowsour.2013.06.081>
- Digital Twin Market (2022). By Enterprise (Large Enterprises, Medium Enterprises, Small Enterprises), By Industry (Infrastructure, Retail, Agriculture, Oil and Gas, Aerospace, Telecommunication, Automotive and Transportation, Energy and Utilities, Healthcare, Other Industries), By Application (Product Design, Product Development, Inventory Management, Predictive Maintenance, Performance Monitoring, Business Optimization, Other Applications), Global Report by Size, Industry Analysis and Forecast, 2021–2030. Available at: <https://www.strategicmarketresearch.com/market-report/digital-twin-market> (accessed 23 Apr 2024)
- Erdélyi V, Jánosi L (2019). Digital Twin and Shadow in Smart Pork Fatteners. *Int. J. Eng. Manag. Sci.*, 4: 515–520. <https://doi.org/10.21791/IJEMS.2019.1.63>
- Errandonea I, Beltrán S, Arrizabalaga S (2020). Digital Twin for maintenance: A literature review. *Comput. Ind.*, 123: 103316. <https://doi.org/10.1016/j.compind.2020.103316>
- Farooq MS, Riaz S, Abid A, Abid K, Naeem MA (2019). A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming. *IEEE Access*, 7: 156237–156271. <https://doi.org/10.1109/ACCESS.2019.2949703>
- Farooq MS, Riaz S, Helou MA, Khan FS, Abid A, Alvi A (2022). Internet of Things in Greenhouse Agriculture: A Survey on Enabling Technologies, Applications, and Protocols. *IEEE Access*, 10: 53374–53397. <https://doi.org/10.1109/ACCESS.2022.3166634>
- Fuller A, Fan Z, Day C, Barlow C (2020). Digital Twin: Enabling Technologies, Challenges and Open Research. *IEEE Access*, 8: 108952–108971. <https://doi.org/10.1109/ACCESS.2020.2998358>
- García R, Aguilar J, Toro M, Pinto A, Rodríguez P (2020). A systematic literature review on the use of machine learning in precision livestock farming. *Comput. Electron. Agric.*, 179: 105826. <https://doi.org/10.1016/j.compag.2020.105826>
- Haldar A, Mandal SN, Deb S, Roy R, Laishram M (2022). Application of Information and Electronic Technology for Best Practice Management in Livestock Production System. In: Kumar A, Kumar P, Singh SS, Trisasonko BH, Rani M (Eds.), *Agriculture, Livestock Production and Aquaculture: Advances for Smallholder Farming Systems Volume 2*. Springer International Publishing, Cham, pp. 173–218. https://doi.org/10.1007/978-3-030-93262-6_11
- Han X, Lin Z, Clark C, Vucetic B, Lomax S (2022). AI Based Digital Twin Model for Cattle Caring. *Sensors*, 22: 7118. <https://doi.org/10.3390/s22197118>
- Hristov H, Dimitrov K, Penev T (2021). Use of Infrared Thermography to Monitor the Physiological Condition of Dairy Cows. In: 12th National Conference with International Participation (ELECTRONICA), pp. 1–4. <https://doi.org/10.1109/ELECTRONICA52725.2021.9513724>
- Jarrahi MH, Memariani A, Guha S (2023). The Principles of Data-Centric AI (DCAI). *Communications of the ACM*, 66: 84–92. <https://doi.org/10.1145/3571724>
- Jeong DY, Jo SK, Lee IB, Shin H, Kim JG (2023). Digital Twin Application: Making a Virtual Pig House Toward Digital Livestock Farming. *IEEE Access*, 11: 121592–121602. <https://doi.org/10.1109/ACCESS.2023.3313618>
- Jo S-K, Park D-H, Park H, Kim S-H (2018). Smart Livestock Farms Using Digital Twin: Feasibility Study. In: International Conference on Information and Communication Technology Convergence (ICTC), pp. 1461–1463. <https://doi.org/10.1109/ICTC.2018.8539516>
- Jo S-K, Park D-H, Park H, Kwak Y, Kim S-H (2019). Energy Planning of Pigsty Using Digital Twin. In: International Conference on Information and Communication Technology Convergence (ICTC), IEEE, Jeju Island, South Korea, pp. 723–725. <https://doi.org/10.1109/ICTC46691.2019.8940032>
- Kaklauskas A (2018). Agriculture 5.0: Smart Agriculture, AI, IoT, Society 5.0, Big Data Analytics, Blockchain, Digital Twins, Robotics, Drones and Immersive Reality. Available online: <https://ir.lib.ruh.ac.lk/xmlui/handle/iruor/13735>
- Kashiha M, Bahr C, Ott S, Moons CPH, Niewold TA, Ödberg FO, Berckmans D (2014). Automatic weight estimation of individual pigs using image analysis. *Comp. Electron. Agric.*, 107: 38–44. <https://doi.org/10.1016/j.compag.2014.06.003>
- Kashiha MA, Bahr C, Ott S, Moons CPH, Niewold TA, Tuytens F, Berckmans D (2014). Automatic monitoring of pig locomotion using image analysis. *Livest. Sci.*, 159: 141–148. <https://doi.org/10.1016/j.livsci.2013.11.007>
- Keates O (2019). The Design and Validation of a Process Data Analytics Methodology for Improving Meat and Livestock Value Chains. In Doctoral Consortium of the 17th International Conference on Business Process Management

- (BPM): Vienna. <https://bpm2019.ai.wu.ac.at/>
- Khoramshahi E, Hietaoja J, Valros A, Yun J, Pastell M (2014). Real-time recognition of sows in video: A supervised approach. *Inf. Process. Agric.*, 1: 73–81. <https://doi.org/10.1016/j.inpa.2014.07.002>
- Kumar S, Choudhary S, Kumar R, Kumar A, Pal P, Mahajan K (2019). Animal Sentience and Welfare: An Overview. *Int. J. Curr. Microbiol. Appl. Sci.*, 8: 635–646. <https://doi.org/10.20546/ijcmas.2019.808.074>
- Lee W, Ham Y, Ban T-W, Jo O (2019). Analysis of Growth Performance in Swine Based on Machine Learning. *IEEE Access*, 7: 161716–161724. <https://doi.org/10.1109/ACCESS.2019.2951522>
- Liu R, Gailhofer P, Gensch CO, Köhler A, Wolff F, Monteforte M, Urrutia C, Cihlarova P, Williams R (2019). Impacts of the digital transformation on the environment and sustainability. Issue Paper under Task 3.
- Loukatos D, Arvanitis KG (2021). Multi-Modal Sensor Nodes in Experimental Scalable Agricultural IoT Application Scenarios. In: Krause, P., Xhafa, F. (Eds.), *IoT-Based Intelligent Modelling for Environmental and Ecological Engineering: IoT Next Generation EcoAgro Systems*. Springer International Publishing, Cham, pp. 101–128. https://doi.org/10.1007/978-3-030-71172-6_5
- Lu Y, Liu C, Wang KI-K, Huang H, Xu X (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robot. Comput.-Integr. Manuf.*, 61: 101837. <https://doi.org/10.1016/j.rcim.2019.101837>
- Malik P, Sneha, Garg D, Bedi H, Gehlot A, Malik PK (2023). An Improved Agriculture Farming Through the Role of Digital Twin. In: 4th International Conference on Electronics and Sustainable Communication Systems (ICESC), IEEE, Coimbatore, India, pp. 667–671. <https://doi.org/10.1109/ICESC57686.2023.10193522>
- Mallinger K, Purcell W, Neubauer T (2022). Systemic design requirements for sustainable Digital Twins in precision livestock farming. In: Berckmans D, Oczak M, Iwersen M, Wagener K (Eds.), *Precision Livestock Farming*. pp. 718–725. <https://doi.org/10.34726/4644>
- Mat I, Mohd Kassim MR, Harun AN, Yusoff IM (2018). Smart Agriculture Using Internet of Things, In: IEEE Conference on Open Systems (ICOS), IEEE, Langkawi, Malaysia, pp. 54–59. <https://doi.org/10.1109/ICOS.2018.8632817>
- Mhapsekar RU, O'Shea N, Davy S, Abraham L (2024). Hybrid Blended Deep Learning Approach for Milk Quality Analysis. *IEEE Trans. Emerg. Top. Comput. Intell.*, 8: 2253–2268. <https://doi.org/10.1109/TETCI.2024.3369331>
- Mu M, Zhou Y, Wu D (2022). Digital Twins on Animal Husbandry: Insights and Application. *Procedia Computer Science*, 9th International Conference on Information Technology and Quantitative Management, 214: 1182–1189. <https://doi.org/10.1016/j.procs.2022.11.294>
- Murali D, Acosta-Pazmiño IP, Loris A, García AC, Benni S, Tinti F, Gomes J (2024). Experimental assessment of a solar photovoltaic-thermal system in a livestock farm in Italy. *Sol. Energy Adv.*, 100051. <https://doi.org/10.1016/j.seja.2024.100051>
- Nasirahmadi A, Hensel O (2022). Toward the Next Generation of Digitalization in Agriculture Based on Digital Twin Paradigm. *Sensors*, 22(2): 498. <https://doi.org/10.3390/s22020498>
- Nasirahmadi A, Sturm B, Edwards S, Jeppsson K-H, Olsson A-C, Müller S, Hensel O (2019). Deep Learning and Machine Vision Approaches for Posture Detection of Individual Pigs. *Sensors*, 19: 3738. <https://doi.org/10.3390/s19173738>
- Neethirajan S (2023). The Significance and Ethics of Digital Livestock Farming. *AgriEngineering*, 5: 488–505. <https://doi.org/10.3390/agriengineering5010032>
- Neethirajan S (2022). Affective State Recognition in Livestock—Artificial Intelligence Approaches. *Animals*, 12: 759. <https://doi.org/10.3390/ani12060759>
- Neethirajan S (2020). Transforming the Adaptation Physiology of Farm Animals through Sensors. *Animals*, 10: 1512. <https://doi.org/10.3390/ani10091512>
- Neethirajan S, Kemp B (2021). Digital Twins in Livestock Farming. *Animals*, 11: 1008. <https://doi.org/10.3390/ani11041008>
- Oudenhoven JFM, Vullers RJM, van Schaijk R (2012). A review of the present situation and future developments of micro-batteries for wireless autonomous sensor systems. *Int. J. Energy Res.*, 36: 1139–1150. <https://doi.org/10.1002/er.2949>
- Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu MM, Li T, Loder EW, Mayo-Wilson E, McDonald S, McGuinness LA, Stewart LA, Thomas J, Tricco AC, Welch VA, Whiting P, Moher D (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 372: n71. <https://doi.org/10.1136/bmj.n71>
- Pandey S, Kalwa U, Kong T, Guo B, Gauger PC, Peters DJ, Yoon K-J (2021). Behavioral Monitoring Tool for Pig Farmers: Ear Tag Sensors, Machine Intelligence, and Technology Adoption Roadmap. *Animals*, 11: 2665. <https://doi.org/10.3390/ani11092665>
- Paraforos DS, Griepentrog HW (2021). Digital Farming and Field Robotics: Internet of Things, Cloud Computing, and Big Data. In: Karkee M, Zhang Q (Eds.), *Fundamentals of Agricultural and Field Robotics*. Springer International Publishing, Cham, pp. 365–385. https://doi.org/10.1007/978-3-030-70400-1_14
- Peladarinos N, Piromalis D, Cheimaras V, Tserepas E, Munteanu RA, Papageorgas P (2023). Enhancing Smart Agriculture by Implementing Digital Twins: A Comprehensive Review. *Sensors*, 23: 7128. <https://doi.org/10.3390/s23167128>
- Petrov P, Atanasova T (2021). Digital Twins with Application of AR and VR in Livestock Instructions. *Probl. Eng. Cybern. Robot.*, 77. <https://doi.org/10.7546/PECR.77.21.05>
- Pezzuolo A, Milani V, Zhu D, Guo H, Guercini S, Marinello F (2018). On-Barn Pig Weight Estimation Based on Body Measurements by Structure-from-Motion (SfM). *Sensors*, 18: 3603. <https://doi.org/10.3390/s18113603>
- Platform Industrie 4.0 (2024). Available at: <https://www.plattform-i40.de/IP/Navigation/EN/Home/home.html> (accessed 16 Jun 2024).
- Prior F, Almeida J, Kathiravelu P, Kurc T, Smith K, Fitzgerald TJ, Saltz J (2020). Open access image repositories: high-quality data to enable machine learning research. *Clin. Radiol.*, 75: 7–12. <https://doi.org/10.1016/j.crad.2019.04.002>
- Proctor H (2012). Animal Sentience: Where Are We and Where Are We Heading? *Animals*, 2: 628–639. <https://doi.org/10.3390/ani2040628>
- Proctor HS, Carder G, Cornish AR (2013). Searching for Animal Sentience: A Systematic Review of the Scientific Literature. *Animals*, 3: 882–906. <https://doi.org/10.3390/ani3030882>

- Pylaniadis C, Osinga S, Athanasiadis IN (2021). Introducing digital twins to agriculture. *Comput. Electron. Agric.*, 184: 105942. <https://doi.org/10.1016/j.compag.2020.105942>
- Raba D, Tordecilla RD, Copado P, Juan AA, Mount D (2022). A Digital Twin for Decision Making on Livestock Feeding. *Inf. J. Appl. Anal.*, 52: 267–282. <https://doi.org/10.1287/inte.2021.1110>
- Roubík H, Mazancová J (2020). Suitability of small-scale biogas systems based on livestock manure for the rural areas of Sumatra. *Environ. Dev.*, 33: 100505. <https://doi.org/10.1016/j.envdev.2020.100505>
- Saha CK, Nandi R, Rahman MA, Alam MM, Møller HB (2024). Biogas technology in commercial poultry and dairy farms of Bangladesh: present scenario and future prospect. *Biomass Convers. Biorefinery*, 2024; 14(7): 8407–8418. <https://doi.org/10.1007/s13399-022-02938-8>
- Saidu A, Clarkson AM, Adamu SH, Mohammed M, Jibo I (2017). Application of ICT in Agriculture: Opportunities and Challenges in Developing Countries. *Int. J. Comput. Sci. Math. Theory*, 3(1): 8–18.
- Salazar-Moya A, Garcia MV (2021). Lot Streaming in Different Types of Production Processes: A PRISMA Systematic Review. *Designs*, 5(4): 67. <https://doi.org/10.3390/designs5040067>
- Seibel H, Weirup L, Schulz C (2020). Fish Welfare – Between Regulations, Scientific Facts and Human Perception. *Food ethics*, 5(1): 4. <https://doi.org/10.1007/s41055-019-00063-3>
- Smith MJ (2018). Getting value from artificial intelligence in agriculture. *Anim. Prod. Sci.*, 60: 46–54. <https://doi.org/10.1071/AN18522>
- Sreedevi TR, Santosh Kumar MB (2020). Digital Twin in Smart Farming: A Categorical Literature Review and Exploring Possibilities in Hydroponics. In: *Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA)*, Cochin, India, pp. 120–124. <https://doi.org/10.1109/ACCTHPA49271.2020.9213235>
- Tarek N, El-Hefnawy NA, Abdel-Kader H, Abdelatey A (2022). A Flexible Digital Twin Framework for Poultry Feed Industrial Factory. In: *32nd International Conference on Computer Theory and Applications (ICCTA)*, IEEE, Alexandria, Egypt, pp. 253–257. <https://doi.org/10.1109/ICCTA58027.2022.10206352>
- Tilman D, Balzer C, Hill J, Befort BL (2011). Global food demand and the sustainable intensification of agriculture. *Proc. Natl. Acad. Sci.*, 108: 20260–20264. <https://doi.org/10.1073/pnas.1116437108>
- Top 10 Strategic Technology Trends for 2019: Digital Twins (2024). Available at: <https://www.gartner.com/en/documents/3904569> (accessed 23 Apr 2024).
- Tzachor A, Richards CE, Jeon S (2022). Transforming agrifood production systems and supply chains with digital twins. *Npj Sci. Food*, 6(1): 47. <https://doi.org/10.1038/s41538-022-00162-2>
- Upadhyay AK, Khandelwal K (2019). Artificial intelligence-based training learning from application. *Dev. Learn. Organ. Int. J.*, 33: 20–23. <https://doi.org/10.1108/DLO-05-2018-0058>
- Valero MR, Hicks BJ, Nassehi A (2023). A Conceptual Framework of a Digital-Twin for a Circular Meat Supply Chain. In: Kim K-Y, Monplaisir L, Rickli J (Eds.), *Flexible Automation and Intelligent Manufacturing: The Human-Data-Technology Nexus*, Lecture Notes in Mechanical Engineering. Springer International Publishing, Cham, pp. 188–196. https://doi.org/10.1007/978-3-031-18326-3_19
- Verdouw C, Tekinerdogan B, Beulens A, Wolfert S (2021). Digital twins in smart farming. *Agric. Syst.*, 189: 103046. <https://doi.org/10.1016/j.agry.2020.103046>
- White RP, Schofield CP, Green DM, Parsons DJ, Whittemore CT (2004). The effectiveness of a visual image analysis (VIA) system for monitoring the performance of growing/finishing pigs. *Anim. Sci.*, 78: 409–418. <https://doi.org/10.1017/S1357729800058811>
- World Population Prospects 2022: Summary of Results (2022). Available at: <https://www.un.org/development/desa/pd/content/World-Population-Prospects-2022> (accessed 23 Apr 2024)
- Zhang C, Campana P, Yang J, Zhang J, Yan J (2017). Can Solar Energy be an Alternative Choice of Milk Production in Dairy Farms? A Case study of Integrated PVWP System with Alfalfa and Milk Production in Dairy Farms in China. In: *Energy Procedia*, 8th International Conference on Applied Energy, ICAE2016, Beijing, China, pp. 3953–3959. <https://doi.org/10.1016/j.egypro.2017.03.822>
- Zhang Q, Yang LT, Chen Z, Li P (2018). A survey on deep learning for big data. *Inf. Fusion*, 42: 146–157. <https://doi.org/10.1016/j.inffus.2017.10.006>
- Zhang W, Gu X, Tang L, Yin Y, Liu D, Zhang Y (2022). Application of machine learning, deep learning and optimization algorithms in geoengineering and geoscience: Comprehensive review and future challenge. *Gondwana Res.*, 109: 1–17. <https://doi.org/10.1016/j.gr.2022.03.015>
- Zhang X, Cao Z, Dong W (2022). Overview of Edge Computing in the Agricultural Internet of Things: Key Technologies, Applications, Challenges. *IEEE Access*, 8: 141748–141761. <https://doi.org/10.1109/ACCESS.2020.3013005>
- Zhang Yi, Zhang Yu, Gao M, Dai B, Kou S, Wang X, Fu X, Shen W (2023). Digital Twin Perception and Modeling Method for Feeding Behavior of Dairy Cows. *Comput. Electron. Agric.*, 214: 108181. <https://doi.org/10.2139/ssrn.4463418>