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Review

Digital Twins in Livestock Farming

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Simple Summary: A digital twin can be described as a digital replica of a real-world entity. It simulates the physical state and may be the biological state and behavior of the real-world entity based on input data. It helps in predicting, optimizing, and improved decision making. It has revolutionized the industrial world, especially the manufacturing industry, construction & healthcare sector, smart cities, and energy industry. In this critical review, we explore the development and implementation of the digital twin in the modern animal farming. In addition to showcasing potential applications, this review provides in-depth insights about the implementation and characterization of digital twins in modern animal farming.

Abstract: Digital twin technology is already improving efficiencies and reducing costs across multiple industries and sectors. As the earliest adopters, space technology and manufacturing sectors have made the most sophisticated gains with automobile and natural resource extraction industries following close behind with recent investments in digital twin technology. The application of digital twins within the livestock farming sector is the next frontier. The possibilities that this technology may fuel are nearly endless as digital twins can be used to improve large-scale precision livestock farming practices, machinery and equipment usage, and the health and well-being of a wide variety of farm animals. Currently, many pioneers of digital twins in livestock farming are already applying sophisticated AI technology to monitor both animals and environment around the clock, which leads to a better understanding of animal behavior and distress, disease control and prevention, and smarter business decisions for the farmer. Mental and emotional states of animals can be monitored using recognition technology that examines facial features such as ear postures and eye white regions. Used with modeling, simulation and augmented reality technologies, digital twins can help farmers build more energy-efficient housing structures, predict heat cycles for breeding, discourage negative behaviors of livestock, and potentially much more. As with all disruptive technological advances, the implementation of digital twin technology will demand a thorough cost and benefit analysis by individual farms. Digital twin application will need to overcome challenges and accept limitations that arise. However, regardless of these issues, the potential of digital twins promises to revolutionize livestock farming in the future.

Keywords: Digital twin; precision livestock farming; digitosome; digital cohort; animal farming

1. Introduction

Today, more than ever before, vast quantities of information are being captured, stored, processed and used digitally. For the first time in human history, more than half the world's population is connected via the internet. In 1990, before the first internet browser was released by Berners-Lee, less than 0.5% of the world's population was online. Over the last three decades, the internet exploded and today is home to more than half the world's population [1].

On the other hand, computing power and storage technologies have also increased several folds over the last five decades. To put things into perspective, the latest smartphones that we use, typically have 4GB of RAM. When compared to the Apollo guidance computer (AGC) [2] on Apollo 11 – the first human-crewed spacecraft to land on the moon, this is more than one million times its RAM capacity [3]. And the number of transistors per microprocessor has doubled about every two years over the past five decades [4]. More transistors per microprocessor mean more computing power. This explosive growth in computing power, storage capacity and the internet have paved the way for numerous smart devices to exist today.

Smart devices come in a range of sizes and shapes. They can be as simple and inexpensive as an internet-enabled heat sensor. Or they can be as complicated and expensive as a high-end smartphone. But most importantly, all smart devices are connected to some network and can receive as well as transmit digital information seamlessly [5]. In 2020, it is estimated that almost 200 billion smart devices are connected to each other via the internet [6]. This is almost a hundred-fold increase in smart devices since 2006. In other words, on average, we now have almost 26 smart devices per person on this planet.

And increasingly, as smart devices generate more and more digital data, we turn our attention towards technologies such as artificial intelligence (AI), big data and machine learning (ML) to make sense of it. Without these technologies, it is impossible to make sense of this enormous influx of data. To give you some perspective, it is estimated that we now generate about 2.5 quintillion bytes of data every day. And more than 90% of all data was created in the last two years [7]. Clearly, this volume of data is beyond human comprehension. But newer advances in artificial intelligence (AI), big data and machine learning (ML) have the ability to process such a large volume of data and help us make sense of it. This has opened up new possibilities that never existed before. One such opportunity is digital twins.

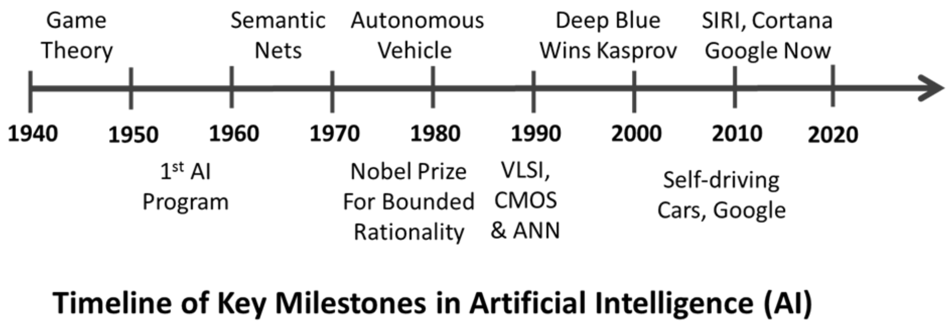

Figure 1. A timeline that shows key milestones in Artificial Intelligence

This paper looks at the concept of digital twins from two perspectives. First, it looks at the origins and practical applications of digital twins that have been adopted across industries and sectors until now. Secondly, but more importantly, it looks at how digital twins' technology can benefit livestock farming in the near future. Traditionally, livestock farming has been a very experiential and manual industry. Experienced farmers simply used their knowledge or the knowledge of previous generations to run their operations and care for their livestock. Because of this, farming tends to be an imperfect, unpredictable and inefficient industry. Digital twins promises to revolutionize potentially all aspects of livestock farming. By combining big data, real-time information from the individual farm, and AI, farmers can obtain a much more precise picture of what's occurring with their livestock, housing structures, and equipment. As such, digital twins technology promises to help farmers better predict and discourage negative animal behaviours, track and prevent diseases from spreading or becoming serious, improve energy efficiency as well as animal comfort and well-being in housing structures, and reduce costs of livestock losses and breeding operations.

The Evolution of Digital Twins

At the most simple level, digital twins are realistic virtual representations of a physical entity. This physical entity can be anything from an automobile, windmill, or a manufacturing unit [8]. Sometimes it can even be something as complex as an entire city like Singapore [9]. To better understand the concept behind digital twins, let's look at the origins of digital twins and how the concept has evolved until now.

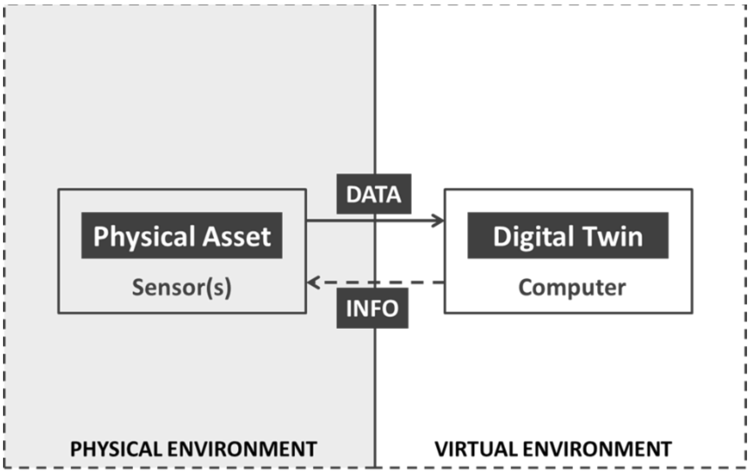

Figure 2. A conceptual representation of digital twin technology and its relation with a physical asset

The First Digital Twin

As early as 1991, in his book Mirror Worlds, David Gelernter wrote about the possibility of software models that represent some chunk of reality [10]. But even before that, NASA was one of the first organizations that used complex simulations of spacecrafts [11]. About fifty years ago, in 1970, the Apollo 13 mission had an unexpected explosion in its oxygen tank [12]. This damaged their main engine and pushed the spacecraft away from its trajectory by about 400 miles a minute. To make things worse, the crew's oxygen supply was slowly leaking into space. But the mission team quickly modified several high-fidelity simulators to match the real-world conditions of the damaged spacecraft and used this to help the astronauts pick the right moves to land safely back on earth [13]. This was probably one of the first real-world applications of a digital twin.

However, it is important to note that digital twins were not a familiar concept back in 1970. But this specific example met several key characteristics of a digital twin. For instance, the simulators sensed the real-world condition of the spacecraft and used that information to modify themselves. And more importantly, it helped the team address what-if scenarios that were never considered in the design plan.

Lower Costs Mean Greater Benefits

As one can imagine, space crafts are extremely costly, mission-critical and inaccessible by anyone not on it. So, in a sense, they were the perfect real-world applications for digital twins – because the high costs were well worth the potential benefits it could offer. At least this was true until a few decades ago. But as discussed earlier, the cost of sensing, sending, storing, and processing real-world changes in physical entities was becoming exponentially lower. This opened newer opportunities for several other industries including biomedical and agricultural livestock sectors to also benefit from digital twins.

Early Publications

Around the turn of the 21st century, John Vickers of NASA first coined the term digital twin in 2002 [14]. A research professor called Dr Michael Grieves worked with John Vickers around the same time to adapt the concept of digital twins as a way to improve product lifecycle management (PLM) in the manufacturing sector [15]. Initially, he called it the 'Conceptual Ideal for PLM'. But even during this early stage, he touched upon several key properties of Digital Twins [16]. In his 2003 paper, Grieves spoke about the difference between real and virtual spaces. He also highlighted the need for exchange of data and information between the real and virtual entities to mirror each other.

The Following Years

Since 2003, the concept of Digital Twin has grown in interest by leaps and bounds. Gartner now includes hyper-automation as the number one key strategic technology trends for 2020. And digital twins are a big part of hyper-automation [17]. Initiatives such as Digital Futures and the movement towards the Industry 4.0 paradigm are key factors in this growth of interest. In addition to this, several key advances across technologies such as IoT (Internet of Things), big data, and real-time sensors have driven costs down.

Together, all this has allowed several new applications of digital twins, that weren't possible earlier. A range of sensors can now collect data from a smart device and mirror that state in a digital twin in real-time [18]. In other words, we now have the technology to make a reasonably accurate digital twin copy that mimics the properties of real-world assets such as (but not limited to) its shape, status and movement.

According to Gartner, about thirteen percent of organizations that were implementing IoT projects were already using digital twins. But more importantly, another sixty-two percent of organizations reported that they were in the process of establishing digital twins [19]. In other words, today, seventy-five percent of organizations implementing IoT projects have already implemented or plan to implement a digital twin. Clearly, the concept is beginning to gain traction, at least among the early adopters. A recent Markets and Markets research estimated the digital twins' market at 3.8 billion dollars in 2019. It also projected that this market would grow by almost nine times to reach 35.8 billion dollars in market value by 2025 [20].

Real World Digital Twin Examples

Today, digital twins are being used in a number of ways, across sectors and industries. For example, the world's largest aeroplane manufacturer – Boeing is betting big on digital twins. In a 2018 interview, its CEO Dennis Muilenburg attributed a forty percent improvement in the first-time quality of parts and systems by using the digital twin asset development model. He also added that this digital twin asset development model was bound to deliver the biggest production efficiency improvements for Boeing over the next decade [21].

Similarly, Halliburton Company, one of the world's largest oil field service companies, is also now turning its attention towards capturing massive amounts of information while drilling new oil and gas wells. In a 2017 interview, the VP for Global Innovation, Greg Powers shared how the company is now using different sensors to capture as much as one terabyte of data per day for a single well in real-time. And how this, along with other simulations and virtual models, helps them drill wells more efficiently [22].

In another example, Dassault Systèmes, a French software company, is pushing the boundaries of what digital twins far beyond windmills, bridges and automobiles. They are in the process of using digital twins for various parts of the human body. Thus, helping people benefit from less invasive and more personalized medical interventions [23]. The company has already begun this journey and has initiated a project to develop and validate personalized digital human heart models [24].

Other notable examples of digital twins come from leading companies such as Unilever, Royal Dutch Shell and Bridgestone [25]. FMCG giant Unilever is using digital twins to create virtual models of its factories. They use this information to track and improve key factory performance parameters such as

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temperature, motor speed and other production variables. They estimate that this has helped them save up to 2.8 million dollars already from their Valinhos, Brazil factory. Similarly, Shell, the world's largest Oil and Gas Company, is using digital twins to design valuable assets in locations that are hard to reach. By using data from sensors along with AI and ML models, they can recreate realistic real-time models of the assets and as a result, reduce maintenance costs as well as downtime. And finally, Bridgestone, the leading tire manufacturer, is experimenting with real-time data from tire sensors to improve precision safety systems.

Table 1. A list of digital twin case studies across industries and sectors

Industry	Sector	**Digital Twin types and advantages**	**Reference**
Boeing	Aero Manufacturing	Digital twin asset development model has shown a 40% quality improvement in first-time parts/systems to deliver huge productivity gains over the next.	[21]
Halliburton	Oil Field Service	Using different sensors to capture different dimensions of data while drilling oil wells. Uses this with virtual models to make drilling more efficient.	[22]
Dassault	Software	Using digital twins for various parts of the human body. Thus, helping people benefit from less invasive and more personalized medical interventions.	[23]
Unilever	FMCG	Create virtual models of its factories to track and improve key factory performance parameters and production variables. Helped save 2.8 million dollars.	[25]
Royal Dutch Shell	Oil and Gas	Using digital twins to design and recreate realistic real-time models of valuable assets. As a result, are able to reduce maintenance costs as well as downtime.	[25]
Bridgestone	Tire Manufacturer	Experimenting with real-time data from tire sensors to improve precision safety systems.	[25]

As one can see from all these examples, there are two common trends. First, digital twins are being applied by industry market leaders across sectors. And second, digital twins are being applied in areas mission-critical areas that have the potential to improve or transform their market position significantly. This is because digital twin technology is still its nascent stages. In other words, it has high learning, experimentation and implementation costs. Often, these projects cost millions of dollars per year.

So naturally, not many companies can afford such a significant investment into something that may not have immediate payoffs, unless of course, they are market leaders and are looking to consolidate their leadership further. Also, this helps us better appreciate their big bets. They want their huge investments to pay off with massive returns. This is probably why they are going for the big home runs with the digital twin technology. But does this mean that other smaller companies that can't innovate with digital twins? And what about sectors like agriculture and livestock production that may not have large R&D budgets? To understand all this better, let's look at what it means to implement digital twins.

Implementing Digital Twins

Key Properties

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As discussed earlier, digital twins are virtual representations of a physical asset. Let us expand on this definition and look at some of the key properties needed to implement a digital twin.

First, to realistically represent a physical asset and mirror its behaviour, the twin needs to get real-time feedback on how the physical or the biological asset is interacting with its environment, workload and other variables. This requires different sensors that can send and receive specific forms of data via the internet or some other privately secured network.

Second, we need the twin to be able to receive, store and process the large volumes of data in real-time. This requires a significant amount of computing, storage and data processing capacity. In other words, it has to make use of the latest advances in big data, data management and cloud servers.

Third, the twin must be able to make sense of the large volumes of continuously transmitted data. Since this is beyond the computing abilities of most humans, invariably, this means using AI algorithms to discern between useful and non-useful information. It also means using AI algorithms to suggest recommendations and actions.

Fourth, the twin must be able to learn about different cause-effect scenarios over time and be able to apply the learnings to improve the performance of the physical asset. This involves running several alternate scenarios, test cases and what-if simulations. Again, this level of complexity is beyond human comprehension. This means that ML algorithms need to be trained under specific circumstances to learn, experiment and evolve the best possible course of action.

And finally, all this must be readily available to key human decision-makers via an interactive digital user interface. Typically, this will be some form of a display and processing unit such as computers, tablets or even smartphones.

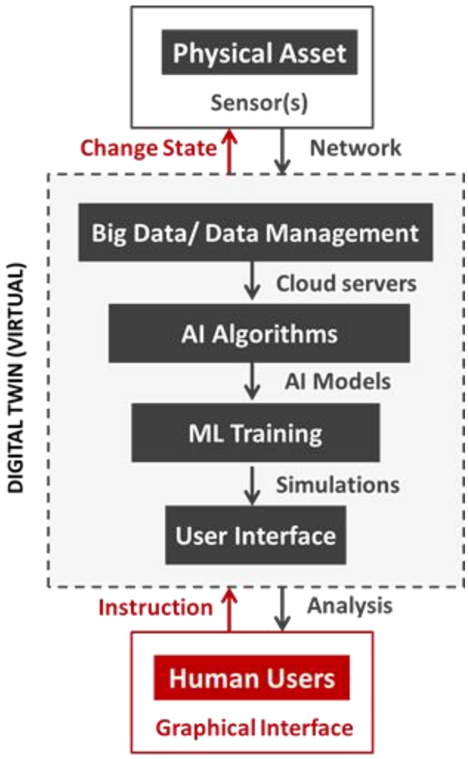

Figure 3. The flow of information between physical asset, digital twin and human users

Key terms involved in the process of implementing digital twins are (1) The actual physical asset, (2) The virtual representation (digital twin), and (3) the human decision-makers.

In addition to this, there are several interconnections, information flows and states that can exist between these three entities. Most of them will vary from project to project, depending upon the scope of the digital twin. But, broadly any digital twin implementation is likely to have the following terms:

Table 2. A summary of key terms used in implementing digital twins

Key Terms	Description
Physical Environment	Environment where the physical asset exists. Often not easily accessible.
Virtual Simulation	Environment where the virtual digital twin exists. Easily accessible.
Sensory States	Different possible states representing changes in the physical asset.
Changes in State	Switching between various states in the physical asset or digital twin.
Twinning	Synchronization of states between the physical asset and digital twin.
Twinning Rate	The rate at which this synchronization occurs. As close to real-time.
System Processes	Various processes that cause state changes to the asset or twin.

Beyond Computer Models and Dealing with Uncertainty

Many industries already use computer models and simulations to reduce costs and improve efficiencies. In one sense, digital twins are also simulated, computer models. Though there several differences.

The most significant difference is that computer models are built to explore or predict a wide range of cases. For example, we might have a computer model to determine the spread of coccidiosis among farm animals in a particular region. But, a digital twin, by definition is a virtual representation of a single physical asset. In other words, a digital twin can't help you make general predictions about a coccidiosis outbreak in a region. Instead, it can only help monitor key health parameters of Stacy, the dairy cow in farm 1073 at Kentucky.

So the scope of a digital twin is only one individual asset. But because of this focus, a digital twin is able to go beyond the limitations of most computer models. Digital twins can mirror changes of the physical assets in real-time, with only minor delays ranging between a microsecond to a few minutes. Digital twins also collect and analyze a lot more data compared to most computer models. And as a result, digital twins are also able to draw up more realistic what-if scenarios. Dr Matthew Smith recently published an online resource that talked about these key differences [26].

Table 3: Dr Matthew Smith's INDRA.

A digital twin needs to be	
Individual	It must represent a specific thing, e.g. "Daisy the cow" rather than a gener-ic cow.
Near real-time	This also means that the Digital Twin should be "always on"; available for as long as its real-world counterpart exists
Data informed	It must be updated via a digital measurement of the real-world thing, e.g. a soil moisture meter or a regular satellite observation
Realistic	The twin must be a sufficiently realistic surrogate for the real-world thing.

Actionable	Information from the real-world twin must have the potential to lead to an action.

Computer models are known to have gaps in understanding reality. This is why most computer models give erroneous results. This is also why computer models use several error-correcting algorithms to reduce errors stemming from wrong assumptions about the environment. But a digital twin can capture any missing data as the situation arises and therefore allows us to deal with uncertainty effectively

Also, unlike most generic computer models, to use a digital twin effectively, the user need not know about all the technical details of how it works. On the contrary, users can instead focus all their efforts on learning about how the digital twin behaves under specific conditions. Much like they would do with any asset in the real world, with almost instant feedback. This is a massive advantage over generic computer models.

Digital Twins in Livestock Farming

Clearly, there is much to gain from individualized, real-time, actionable feedback from physical assets on a livestock farm. Conventional farming has always been based on past information, the experience of the farmer, and human observations. Digital twins have the potential to radically shift that model so that future farming is based instead on real-time data, manipulated by artificial intelligence analysis, which can then fuel better business decisions, improve animal health and well-being, and maximize agricultural resources. Although still in its infancy, digital twins' applications in livestock farming are beginning to surface and are expected to quickly evolve over the next several years. Consider the following promising examples:

Emotional and Mental States of Animals

By using Generative Adversarial Networks Machine Learning Algorithms, farmers can generate real-time, 3D faces of their livestock as a virtual, digital twin. By examining things such as ear position and eye regions present on the virtual model, farmers can better predict animal behavior, anticipate livestock stress, and observe early signs of pain and disease.

Energy Management of a Pigsty

Factors such as temperature, humidity, and ammonia levels can significantly affect the comfort and health of animals feeding indoors. By generating a digital twin of a pigsty before actual construction, farmers can test the effectiveness of windows, fans, and heaters in creating the optimal conditions. Using simulations in Energy Plus and an actual commercial pigsty in Korea, researchers [27] created a digital twin to determine the most energy-efficient fans to install. Temperature and humidity data was collected at the actual pigsty and used in the simulations. Researchers tested different fan capacities and positions and used the results to select the most energy-efficient, effective solution based on the results.

Monitoring Movement of Grazing Livestock

By using GPS and WSN tracking technology, livestock farmers can not only identify the location of particular animals in a large grazing area but can observe grazing patterns and behaviours [28]. In addition, if disease is identified early on, tracking technology allows farmers to easily pinpoint which animals have been in close proximity to sick livestock, preventing the spread of disease and the loss of livestock.

Understanding Growth and Development of Dairy Animals

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Digital twins of dairy cows can be used to better understand the stages of the animal growth and development from calf to adult. Multi-agent technology platforms combine sensor and longitudinal data to develop phenotypic traits of animals. The shape, behaviour and physiological functions of the animal can be recorded and used for multi-agent planning of animal development and managing life stages and production cycles.

AI-Based Computer Vision to Key an Eye on Livestock

Cainthus, an Irish start-up, uses a smart camera system to monitor animals and operations around the clock. Coupled with advanced AI technology, this camera system translates this real-time, visual data into actionable insights for the farmer to review on a phone, desktop computer, or mobile device. Cargill, an American agricultural company, is partnering with Cainthus to track cattle health.

Augmented Reality Compares Anticipated and Actual Animal Behavior

By observing the activity of pigs and chickens and recording vital signs through sensor technology, farmers can design novel solutions using digital twins to anticipate and prevent damaging behaviors such as tail biting and feather pecking. Using real-time data and simulations, farmers can predict how pigs and chickens will respond in particular environments as well as to barn, pen and population changes. Augmented reality technology allows comparisons between predicted behavior and actual behavior, providing insight to improve the welfare of livestock.

High-Tech Pedometers Detect Heat Cycles for Breeding

As part of the Smart Agri Food and Fractals accelerator projects [29], digital twins were being used to sense movements of dairy cows using high-tech pedometers, which is helpful in detecting when a dairy cow is in estrus and ready for breeding. Such monitoring would allow farmers to maximize the efficiency of artificial insemination efforts.

Potential Application Areas

As the costs of creating accurate digital twins reduce even further, there will be opportunities to use this technology to improve precision livestock farming practices such as:

To gain insights on specific livestock conditions:

To optimize production, livestock farmers need to ensure that their animals stay healthy. Several parameters such as pregnancy hormones, body temperature, quality & quantity of feed intake and the composition of various gases in the animal sheds can act as reliable indicators.

To detect early onset of important livestock diseases:

More often than not, the naked human eye can detect diseases only after a particular stage. By this time, the disease would have had several opportunities to spread among other animals on the farm, leading to an outbreak. But digital twins can help farmers detect several important diseases in earlier stages as well as isolate exposed livestock from further disease spread.

To optimize livestock feed intakes:

Due to the many variables involved, it is almost impossible for farm owners and managers to pinpoint the cause and effect of various feed combinations. However, digital twins can help simulate changes in feed composition and run what-if scenarios to find out optimal feed intake strategies for a farm.

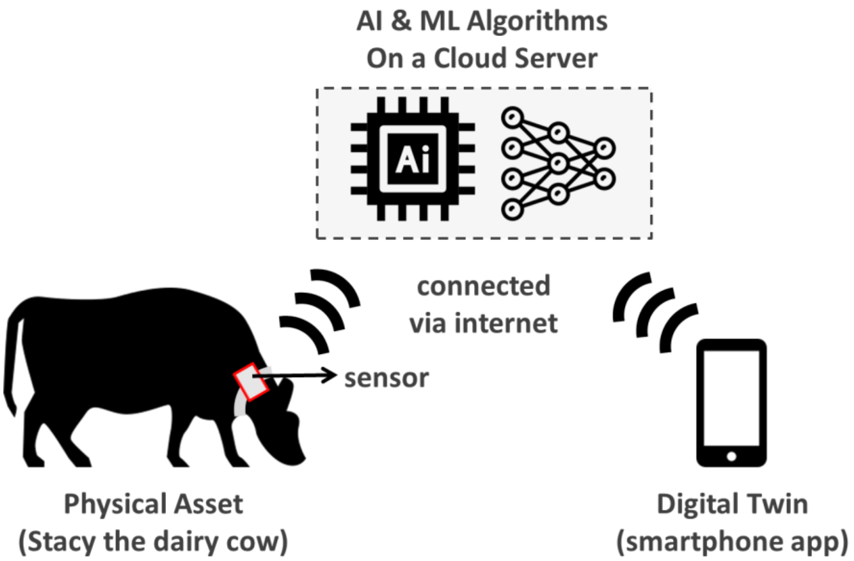

Figure 4. An illustrative case of using digital twin technology to optimize feed intake for a dairy cow

In addition to this, digital twins can be re-creating the reality of animals from a range of sensors that include [30]:

- Thermal infrared (TIR) sensors generate that can measure animal body temperatures by capturing their infrared radiation levels.
- Respiratory rate (RR) sensors that typically consist of a belt around the animal's chest (similar to a holter) to measure its thoracic and abdominal movements.
- Immuno sensors that can study animal's saliva and sweat to provide an assessment of hormones like cortisol and lactate in animal biological fluids. This also results is non-invasive tests.
- Photoplethysmography (PPG) uses infrared lights to detect changes in blood volume in the animal's microvascular bed of tissue. It is a non-invasive and cost-effective to detect blood volume changes.
- Noseband sensors also known as RumiWatch to monitor eating and ruminating activities in dairy cows can help you identify and deal with stressed animals.
- Water flow sensors can monitor the drinking behavior of large animal herds. It is considered to give accurate recommendations, even better than most experienced farm managers.
- Accelerometers use electromechanical signals to measure acceleration forces when an animal move. It has been proven to be very accurate in monitoring animal activities and movements.
- Pedometers can objectively measure the total number of steps that each animal takes in a day and calculate total distance it has covered using an algorithm. It can help identify lameness and stress.
- Wireless intraruminal bolus sensors inserted through the esophagus have been developed to monitor the temperature and pH values of the rumen and reticulum. This can help detect diseases such as ruminal acidosis and hypocalcemia.
- And finally, there is the possibility of using these sensors and several more in combination with each other to sense multiple points of stress, disease or physical pain.

Limitations of Digital Twins in Livestock Farming

Several research and industry publications have already highlighted the benefits of using digital twins. David Jones et al., did a systematic literature review and mapped the perceived benefits of using digital twins against the respective publications it was mentioned in [31].

Table 1: Characterizing the Digital Twin: A systematic literature review [31]

Perceived benefits of digital twins – from Characterizing the Digital Twin research	
Reduces Costs	[32], [33], [34], [35]
Reduces Risks	[35]
Reduces complexity	[36]
Improves after-sales service	[37] ,[38]
Improves efficiency	[39]
Improves maintenance decisions	[40]
Improves security	[41]
Improves safety and reliability	[42]
Improves manufacturing processes	[43], [44]
Enhances flexibility and competitiveness	[45]
Fosters innovation	[32]

However, this doesn't mean that there aren't any limitations. Next, let's look at the four biggest limitations of using digital twins in the livestock farming sector.

High Switching Costs

Livestock farmers have been optimizing their production practices for centuries together. Most of their best practices come from careful observation of animals. While new technologies such as digital twins offer new opportunities to care for animals remotely, farmers may be reluctant to change their age-old practices. Mainly because they have already invested a lot of time, effort and money into the old way of rearing animals nearby.

Asking them to adopt new systems also means that they will have to forego existing labor and processes to an extent. In other words, they face substantial switching costs. This is the most significant limitation in adopting digital twins for livestock farming.

Unknown Risks

Building on the previous point of high switching costs, farmers are used to taking only low-risk decisions. Because livestock farming has many unknown variables compared to say manufacturing. For example, in manufacturing most operations take place in a controlled closed environment. But livestock farming is dependent on several natural and biological phenomena.

Droughts, disease outbreaks, policy changes or even changes in market demand can upset farmer's plans in a matter of a few weeks. As you can see, these unknown risks are part and parcel of the farmer's life. Also, these risks are way beyond the farmer's scope of influence. So, most farmers would also want to adopt new technologies like digital twins only after they understand how it can cope up with such unknown risks. Again, this can be a significant limitation.

Lack of concrete evidence

As discussed earlier, several research papers already talk about a plethora of benefits from adopting digital twins. However, even among these papers, there are very few examples that validate these benefits. For starters, there isn't enough factual evidence available on how digital twins can improve key performance parameters and profits. Let alone comparing these improvements what is possible without adopting digital twins. It will be a few more years before the technology matures and early experiments start sharing the results.

Low Return-on-Investment

Adopting new technologies such as digital twins does not come cheap. First, there is the cost of the technology itself. This includes the cost of both hardware and software. Second, there are infrastructure costs. This might include the cost of additional energy, internet bandwidth or additional equipment to ensure that the technology can be implemented effectively. And finally, there is a learning cost. This might include training, experimentation and any losses that farmers might encounter due to mistakes. Given all these costs, it might be difficult to justify such substantial changes and expenses without any clarity on how it will pay off. In other words, farmers will continuously evaluate the costs against the potential benefits. Unless this evidence is laid out and the return on investment makes sense, it would be hard to get most farmers to adopt this technology.

5. Conclusions

It takes a balanced approach and acknowledges both the merits of the technology and at the same time also discusses the existing limitations of adopting this technology from the perspective of the livestock farmers. There is a need for more evidence, facts and case studies of this Digital Twin technology to encourage widespread adoption among livestock farmers. In the next few years, we expect to see three significant trends. First, we expect to see a significant increase in the number of funded trial projects, across the world, to validate the benefits of adopting digital twins in livestock farming. Secondly, we also expect that the primary funding for most of these trial projects will come from governments, research institutions, private investors and even business accelerators. It is quite improbable that the farmers themselves would be willing to pay for these experiments. And finally, we expect that the cost of all the associated technologies required to implement digital twins will continue to decrease even further. This will eventually make this technology more and more attractive for several specific use cases. We think that this is especially true in the livestock farming sector as labour costs increase and opportunities to run mega-scale livestock operations become more viable. However, we are still at least a few years away from the widespread adoption of digital twins in the livestock farming sector. In the meantime, the three above discussed trends will pave the way for mainstream adoption.

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