

Review: Digitalization of Animal Farming

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Running title: Digitalization of Animal Farming

Abstract

As the global human population increases, animal agriculture must adapt to provide more animal products while also addressing concerns about animal welfare, environmental sustainability, and public health. The purpose of this review is to discuss the digitalization of animal farming with Precision Livestock Farming (PLF) technologies, specifically biosensors, big data, and block chain technology. Biosensors are noninvasive or invasive sensors that monitor an animal's health and behavior in real time, allowing farmers to monitor individual animals and integrate this data for population-level analyses. The data from the sensors is processed using big data-processing techniques such as data modelling. These technologies use algorithms to sort through large, complex data sets to provide farmers with biologically relevant and usable data. Blockchain technology allows for traceability of animal products from farm to table, a key advantage in monitoring disease outbreaks and preventing related economic losses and food-related health pandemics. With these PLF technologies, animal agriculture can become more transparent and regain consumer trust. While the digitalization of animal farming has the potential to address a number of pressing concerns, these technologies are relatively new. The implementation of PLF technologies on farms will require increased collaboration between farmers, animal scientists, and engineers to ensure that technologies can be

used in realistic, on-farm conditions. These technologies will call for data models that can sort through large amounts of data while accounting for specific variables and ensuring automation, accessibility, and accuracy of data. Issues with data privacy, security, and integration will need to be addressed before there can be multi-farm databases. Lastly, the usage of blockchain technology in animal agriculture is still in its infancy; blockchain technology has the potential to improve the traceability and transparency of animal products, but more research is needed to realize its full potential. The digitalization of animal farming can supply the necessary tools to provide sustainable animal products on a global scale.

Keywords: Digitalization, sensor technology, block chain technology, data models, livestock

Implications

Advanced technologies can help modern farms optimize their contribution per animal, reduce the drudgery of repetitive farming tasks, and overcome less effective isolated solutions. There is now a strong cultural emphasis on reducing animal experiments and physical contact with animals in-order-to enhance animal welfare and avoid disease outbreaks. These restrictions have the potential to fuel more research on the use of sensors, big data and blockchain technology for the benefit of farm animals. Farmers' autonomy and data-driven farming approaches compared to experience-driven animal management are just a few of the several barriers that Digitalization must overcome before it can become widely implemented.

Introduction

By the year 2050, the global human population is projected to reach over 9 billion (FAO, 2011), approximately 2 billion more than the current population (UN, 2019). This population growth will occur primarily in underdeveloped countries, particularly in sub-Saharan Africa (UN, 2019). As a result of population growth and increased development in these countries, there will be an increased demand for animal products. Livestock production in developing countries provides stable food sources, jobs, and opportunities for increased income. Much of the demand for animal products will be met by local production in these countries. However, despite the growing population and demand for animal protein, consumers are becoming more concerned about the negative impacts of livestock farming on the environment, public health, and animal welfare (Baldi and Gottardo, 2017; Ochs *et al.*, 2018). Water and land will become competitive resources, meaning livestock producers will need to maximize production while using their limited resources sustainably (Baldi and Gottardo, 2017).

In order to meet the growing demand for animal protein while addressing concerns about environmental sustainability, public health, and animal welfare, farmers and animal scientists may rely increasingly on precision livestock technologies to digitalize animal agriculture. The purpose of this review is to showcase the influence and impact of sensor technology, block chain technology, and big data on livestock farming, particularly as they relate to animal health and welfare.

Current trends in livestock farming

The last decade has seen major improvements in maximizing production efficiency through animal breeding, genetics, and nutrition. However, in light of burgeoning concerns over animal welfare, transparency, and environmental sustainability, there is growing interest in digitalizing animal agriculture through precision livestock farming technologies (Klerkx *et al.*, 2019). Confined livestock systems are necessary to meet the increasing demand for animal products, but the crowded nature of these systems makes it difficult for farmers to closely monitor animal health and welfare (Helwatkar *et al.*, 2014). As climate change intensifies, the risk of disease, heat stress, and other health issues among livestock animals will increase (Bernabucci, 2019). This will create a greater need to identify health issues and disease outbreaks early on, understand disease transmission, and take preventative measures to avoid large-scale economic losses (Thornton, 2010; Neethirajan, 2017). Precision livestock farming (PLF) technologies provide solutions to these growing issues in animal agriculture.

PLF technologies utilize process engineering principles to automate animal agriculture, allowing farmers to monitor large populations of animals for health and welfare, detect issues with individual animals in a timely manner, and even anticipate issues before they occur based on previous data (Benjamin and Yin, 2019). Examples of recent developments in PLF technologies include monitoring cattle behavior, detecting vocalizations such as screams in pigs, monitoring coughs in multiple species to identify respiratory illness, and identifying bovine pregnancy through changes in body temperature (Neethirajan, 2017). PLF technologies can also help farmers monitor infectious diseases within animal agriculture, improving food safety and availability (Neethirajan *et al.*, 2018).

The use of PLF technologies will ultimately improve animal health and welfare while reducing food safety issues and maximizing efficient resource use (Norton *et al.*, 2019).

Challenges of traditional business models

One major challenge in monitoring animal welfare is that most available methods are time-consuming, labor-intensive, and costly (Benjamin and Yik, 2019; Jorquera-Chavez, 2019). Livestock farmers often rely on observations from stock people to detect health and welfare issues, but many commercial facilities have large stockperson-to-animal ratios. For example, a commercial pig farm may have one stockperson for every 300 pigs (Benjamin and Yik, 2019). Even vigilant and well-trained stock people might overlook animals in critical condition. Third-party auditing programs offer comprehensive welfare assessments, but these programs can also be time-consuming, costly inconsistent across auditors. For example, the Common Swine Industry Audit (CSIA) uses 27 criteria, including direct observation of animals to monitor body condition score, lameness, and lesions, all of which can be subjective measures. The CSIA contains criteria for critical failures such as animal abuse or animals in critical condition that need to be humanely euthanized (Benjamin and Yik, 2019). Ideally, these conditions would be rectified long before reaching the point of registering as a critical failure in a third-party audit. The use of PLF technologies, particularly biosensors, would contribute to consistent, objective, and regular welfare monitoring in real time, allowing farmers to address concerns and implement preventative measures to avoid critical failures. Precision technologies could also help reduce resource use; a more proactive and individualistic approach to animal health would ultimately reduce the need for medications, particularly antibiotics (Neethirajan, 2017).

Another major issue with current welfare monitoring techniques is their invasive nature. Animals typically must be approached and restrained by stock people when monitoring physiological signs of stress such as heart rate, cortisol levels, and body temperature, causing additional stress and potentially influencing the physiological measures being taken (Jorquera-Chavez *et al.*, 2019). Even with non-invasive observations, animals will react to the presence of a person nearby, making these observations useless for monitoring 'typical' behavior (Jorquera-Chavez *et al.*, 2019). Precision livestock technologies allow for non-invasive sampling, helping farmers and researchers obtain realistic measures that can be used to address welfare concerns (Jorquera-Chavez *et al.*, 2019).

As consumers become more concerned with the sustainability and welfare of animal products, they will demand more transparency from livestock farmers (Figure 1). Modern technologies such as blockchain will allow farmers to be transparent with consumers about where food is traveling without requiring more of the farmers' time. The time saved here can be better spent monitoring animal welfare, public safety, and environmental sustainability issues (Benjamin and Yik, 2019). The following sections will address PLF technologies that can help farmers increase production while addressing consumer concerns, including biosensors, big data, and blockchain technology.

Biosensing

Biosensors monitor behavioral and physiological parameters of livestock, allowing farmers to evaluate an animal's health and welfare over time (Helwatkar *et al.*, 2014; Neethirajan, 2017; Benjamin and Yik, 2019). The animal production industry adopted the use of sensor

technology as a way to monitor more animals without having to increase contact time and number of employees, and to provide reliable, objective measures of animal health and welfare (Helwatkar *et al.*, 2014; Neethirajan, 2017). The sensors collect data that is then stored and processed by algorithms, sets of instructions or calculations that are followed in sequence to solve specific problems. With livestock sensors, algorithms process the raw data to provide biologically relevant information such as the total time animals spend on specific behaviors on a certain day or how activity level changes over specific time periods (Benjamin and Yik, 2019). These sensors can also monitor behaviors within specific ranges and alert farmers when an animal's behavior is abnormal, allowing them to check the animal and respond appropriately to improve health and welfare (Neethirajan *et al.*, 2017). Combining biosensors with other technologies, such as those used in genomics, could identify animals with desirable qualities and select them for breeding programs (Ellen *et al.*, 2019).

The use of biosensors in livestock farming and other animal health sectors is expected to increase in the next decade (Neethirajan, 2017). These sensors can be used to monitor body temperature, behavior, sound, and physiological measures such as pH, metabolic activity, pathogens, and the presence of toxins or antibiotics in the body. The overuse of antibiotics in animal agriculture is currently a huge concern with serious repercussions for human health (Mungroo and Neethirajan, 2014). Being able to monitor the presence of antibiotics allows farmers to treat animals for illness while providing safe, nutritious animal products to the global population (Mungroo and Neethirajan, 2014; Neethirajan *et al.*, 2018). Biosensing technologies can also be used to detect problematic pathogens such as avian influenza, coronavirus (Ahmed *et al.*, 2017; Ahmed *et al.*, 2018; Weng and

Neethirajan, 2018), and Johne's disease, a detrimental bacterial infection in ruminants that can result in huge economic losses for farmers (Chand *et al.*, 2018). Biosensors can also detect biomarkers of inflammation for widespread disease monitoring (Tuteja and Neethirajan, 2018). Ultimately, they will allow farmers to improve animal productivity and welfare while cutting costs.

Biosensors such as heart rate monitors can even detect affective states in animals. With the use of biosensors, researchers were able to detect changes in heart rate in response to both positive and negative stressors in real time, compare individual responses across animals, and track how heart rate changed over time in response to different stressors. In a study with pigs, a negative stressor caused an elevated heart rate for one minute following a loud noise. A positive stressor, a towel to play with, also caused an elevated heart rate for two minutes after the stressor was provided. More traditional or delayed measures of welfare may not be able to detect these subtle differences (Joosen *et al.*, 2019). Heart rate monitors are also useful for monitoring overall health and metabolic energy production. Biosensors, such as photoplethysmographic sensors, can easily be added to ear tags to continuously monitor livestock heart rates (Nie *et al.*, 2020).

Today's wide variety of available sensors can be broken down into non-invasive and invasive. Non-invasive sensors include sensors around the barn, such as surveillance cameras or sensors in the feeding systems to monitor weight and feed intake. Non-invasive sensors also include sensors easily placed on animals, such as pedometers, GPS (global positioning system) sensors, and MEMS (microelectromechanical)-based accelerometers that can be used to monitor behavior (Helwatkar *et al.*, 2014). Invasive

sensors are typically swallowed by or implanted in an animal (Helwatkar *et al.*, 2014), and are less commonly studied in livestock. These types of sensors are useful for monitoring physiological measures within an animal, such as rumen health, body temperature, and vaginal pressure in dairy cows (Helwatkar *et al.*, 2014).

The most common non-invasive sensors used for monitoring livestock animals are currently thermometers, accelerometers, microphones, and cameras. They allow farmers to monitor temperature, activity levels, sound levels in the barn (i.e., vocalizations, sneezing, and coughing), and specific behaviors (i.e., aggression in pigs) (Benjamin and Yik, 2019). Thermal infrared (TIR) imaging can be used to monitor body temperatures in place of invasive thermometers that require restraint and handling of animals. TIR of the area around the eye and general skin temperature can monitor stress and detect disease 4-6 days earlier than traditional methods. TIR has also been used on images of feet to detect foot disease (Jorquera-Chavez *et al.*, 2019). Physiological monitors such as TIR and heart rate monitors can measure stress in animals prior to slaughter and be compared with meat quality metrics to improve the consistency and quality of consumer products (Jorquera-Chavez *et al.*, 2019). Algorithms for video images can detect changes in animals' posture that may indicate lameness and other health concerns (Jorquera-Chavez *et al.*, 2019). Image analysis from cameras can monitor animal weight, gait, water intake, individual identification, and aggression (Norton *et al.*, 2019). Sound analysis using microphones can be used to monitor vocalizations and coughing, alerting farmers to welfare issues before they become severe. Microphones also have the advantage of being easily placed in barns to monitor large groups of animals without worrying visibility (Mahdavian *et al.*, 2020). Livestock farmers are increasingly utilizing radio-frequency

identification (RFID), which may be placed in ear tags and collars or implanted in animals directly to monitor a wide variety of behaviors such as general activity, eating, or drinking (Neethirajan, 2017).

Facial detection technology is another growing area of interest in automated animal welfare monitoring. Facial detection technologies rely on computer algorithms and machine learning to detect features on an animal's face for identification or to monitor changes related to affective states (Marsot *et al.*, 2020). Many animal welfare researchers are developing grimace scales for animals to help researchers and animal managers better monitor affective states in animals, particularly pain (Viscardi *et al.*, 2017). Livestock animals are frequently subjected to painful procedures such as dehorning, tail docking, and castration (Viscardi *et al.*, 2017; Müller *et al.*, 2019). Facial expression is also specific enough to determine behavioral intent in animals. Camerlink and colleagues (2018) noticed distinct facial differences in pigs initiating aggression and those retreating or avoiding aggression (Camerlink *et al.*, 2018). Facial detection is also being proposed as a lower-cost alternative to RFID tags for individual animal identification (Marsot *et al.*, 2020).

Cattle

The use of sensors in the dairy industry has allowed for better monitoring of major welfare concerns such as mastitis, lameness, cystic ovarian disease, displaced abomasum, and ketosis, among others (Helwatkar *et al.*, 2014). Sensor technology is particularly useful in monitoring dairy herd health and productivity measures such as general activity, affective state, estrus detection, and milking behavior (Helwatkar *et al.*, 2014). The most beneficial

sensors for the dairy industry include temperature, accelerometer, and microphone (Helwatkar *et al.*, 2014). Examples include pedometers, which are useful for detecting dairy cow estrus (Helwatkar *et al.*, 2014), and thermal infrared images, which have been used to noninvasively monitor stress in cattle, using the temperature around the eye as an indicator (Jorquera-Chavez *et al.*, 2019). MooMonitor is a wearable biosensor developed specifically to measure the grazing behavior of dairy cows. It has so far demonstrated a high correlation with traditional observation methods (Werner *et al.*, 2019). Biosensors can also be used to monitor cattle water intake – a study by Williams and colleagues (2020) using RFID tags and accelerometers observed 95% accuracy with animal behavior.

A recent study by Röttgen and colleagues (2019) investigated the use of automated detection of individual vocalizations as a method of monitoring dairy cow estrus. The researchers used collar-based cattle call monitor microphones and an algorithm that matched vocalizations to individual cows. With reported sensitivity at 87% and specificity at 94%, this study shows that advancements in technology and automated systems may allow farmers to monitor animals at the level of the individual, even with complex measures such as vocalizations (Röttgen *et al.*, 2019). Sensor technologies also have the potential to give animals a new degree of autonomy over their own husbandry practices, as has been observed in robotic milking systems for dairy cattle. Robotic milkers utilize wearable sensors on the cow to record her milking and feeding behavior (Neethirajan, 2017). These milkers are becoming increasingly popular in the dairy industry as they allow remote monitoring of cow health (Klerkx *et al.*, 2019).

In dairy cattle, nutrition and energy balance are essential to efficient milk production. Circulating levels of non-esterified fatty acids (NEFA) indicate negative energy balance and can be indicative of other health risks that need to be addressed immediately. Metabolic disorders, indicated by high levels of NEFA in the blood, can lead to loss of appetite, decrease in milk production, reproductive issues, mammary infections, and immune system dysfunction. Currently in development, biosensors that can monitor NEFA have the potential to be extremely useful on dairy farms (Tuteja and Neethirajan, 2017). Ketosis is another serious health concern on dairy farms that is often preceded by elevated levels of β -hydroxybutyrate (β HBA). Research by Weng and colleagues (2015) developed a quantum-based biosensor to detect β HBA. When Tuteja and colleagues (2017) investigated 2D MoS₂ nano-structure-based electrochemical immunosensors for the detection of β HBA in dairy cattle, they found that this method had high specificity and sensitivity, was reproducible, and stood its ground against commercially available kits. Additionally, Veerapandian and colleagues (2016) successfully used electrochemical biosensors of ruthenium dye-sensitized GO nanosheets to detect β HBA. Screen-printed electrode (SPE) sensors are also being developed to detect NEFA and β HBA (Tuteja *et al.*, 2017). Field-based devices for β HBA (Weng *et al.*, 2015) and smartphone-based technologies will soon allow for rapid on-farm testing and response; one particular model designed by Jang and colleagues (2017) is able to detect progesterone in milk. The development of sensors that would allow for rapid biomarker detection and a proactive farmer response would ultimately improve dairy cattle health and welfare while reducing overall resource use.

Consumers grow increasingly concerned about the carbon footprint of livestock production, especially when it comes to cattle. Biosensors are being investigated as a way to monitor methane emissions (Muñoz-Tamayo *et al.*, 2018), thus improving the environmental sustainability of industrialized animal agriculture.

Swine

Major welfare challenges in the swine industry include lameness, aggression in group-housed animals, body condition, and health issues like prolapse and illness. Benjamin and Yik (2019) provide an overview of how precision livestock farming is being implemented in the swine industry to address these welfare concerns. Sensors being used for swine include 2D and 3D cameras, microphones, thermal infrared imaging, accelerometers, radio frequency identification (RFID), optical character recognition, and facial recognition. Pressure-sensing mats have been used to detect lameness in pigs, primarily by putting the mats within electronic sow feeders and in gestation or breeding crates. Accelerometers can also be used to detect lameness by monitoring overall activity levels, posture, and gait. Pigs are likely to chew devices that are placed almost anywhere on the body or in the pen, making ear-tag RFID technology the most promising in swine. Future research hopes to incorporate motion tracking and thermal imaging to detect lameness and aggression in sows (Benjamin and Yik, 2019). To monitor and address concerns over aggression, researchers are investigating the use of automated video monitoring and depth imaging tracking. These technologies are generally able to monitor overall activity patterns but cannot yet track individual behavioral patterns (Wurtz *et al.*, 2019). Infrared thermography has been used to identify illness in piglets (Benjamin and Yik, 2019).

Sound detection technologies have been successful in detecting differences in vocalizations and coughs in swine (Benjamin and Yik, 2019; Friel *et al.*, 2019). The implementation of sound detection software in a barn would help farmers identify welfare issues such as aggression, tail biting, heat stress, and respiratory illness (Benjamin and Yik, 2019). The use of sound analysis to detect coughing can allow farmers and veterinarians to diagnose respiratory illnesses up to two weeks before they could without the use of sensors (Norton *et al.*, 2019). Sound analysis can also distinguish different coughs, such as those of a healthy pig with minor irritation from dust or those of pigs with respiratory illness (Norton *et al.*, 2019).

Pig vocalizations are distinct and indicate their affective state (Friel *et al.*, 2019). For instance, pig screams often indicate pain or distress and would be cause for concern. These screams could indicate a pig in pain due to tail-biting or ear-biting, or a piglet being crushed in the farrowing crate. Indicators of positive welfare are growing in popularity as people concerned with animal welfare strive to provide positive environments for animals rather than simply remove painful and stressful events. Pig barking, for example, can be an alert sound to potential danger but is also used during periods of play. The sounds of pig barking during play can be used as an indicator of positive welfare (Norton *et al.*, 2019). A study by Friel and colleagues (2019) found that the duration of vocalizations was also an important indicator of affective state. Longer calls, especially long grunts, were used in situations of negative valence, whereas shorter duration vocalizations were more common in situations of positive valence (Friel *et al.*, 2019).

Researchers are also investigating automated detection and monitoring of pig body size, especially in relation to space allowance. They hope to use 3D technology to provide weight estimates based on a pig's size and shape, rather than needing to run individual animals through scales, which is time-consuming and can be stressful for the pigs (Benjamin and Yik, 2019).

One of the major welfare issues in the swine industry is aggression among group-housed pigs. There are a number of researchers working on solutions to this issue, including decoding hours of video of pigs fighting in order to learn more about how to intervene to reduce aggression. Image analysis and the use of automated detection technologies are being explored as a way to efficiently decode aggression in videos (Norton *et al.*, 2019). RFID tags in pigs are used to monitor individual feeding and drinking behavior, which are important indicators of health and welfare in swine (Norton *et al.*, 2019). As pig farmers transition to group-housing gestating sows, they are implementing electronic sow feeders using RFID tags as a way to monitor feeding behavior in large groups of sows. Due to pigs' curious nature, sensors typically have to be placed in the ear tag, which can present challenges for sensors such as accelerometers. Wireless sensor networks are being implemented in barns to allow communication between ear tags and a base station that will provide data to the farmer regarding pig activity levels, alerting them to issues with locomotion for individual animals, and providing temperature readings at pig level (Benjamin and Yik, 2019).

Poultry

Sound analysis can provide important information about poultry welfare. Chicken vocalizations can indicate issues with thermal comfort, social disturbances, feather pecking, disease, or growth (Du *et al.*, 2020; Mahdavian *et al.*, 2020). Chicken vocalizations also have a distinct diurnal pattern (Du *et al.*, 2018). Increased vocalizations within a barn or deviations from normal diurnal patterns can be used as an indicator of stress in chickens, especially stress related to thermal comfort (Du *et al.*, 2018; Du *et al.*, 2020). Recent research determined that the use of machine learning to monitor chicken vocalizations was a reliable way to noninvasively monitor welfare and detect warning signs early on (Du *et al.*, 2020). Sound analysis can also use the sound of pecking to monitor feed intake in chickens (Norton *et al.*, 2019), monitor exploratory pecking in turkeys (Nasirahmadi *et al.*, 2020), or detect sneezes to monitor respiratory illness (Carpentier *et al.*, 2019).

In a study by Mahdavian and colleagues (2020), a voice activity detection algorithm was used to identify healthy and ill chickens by extracting animal vocalizations from ambient noise in the environment. The algorithm had a high rate of accuracy in differentiating between healthy chickens and chickens with respiratory illness. Two factors that increased error in sound detection included age and onset of illness; detection accuracy was lower for chickens with respiratory illness than for healthy birds, at 95% and 72%, respectively (Mahdavian *et al.*, 2020). One possible explanation for the decreased accuracy of vocalizations for ill chickens is that chickens with respiratory disease produce abnormal vocalizations. A study by Liu and colleagues (2020) investigated a group of broiler chickens' coughs and scores, vocalizations made when suffering from respiratory

diseases, and reported 93.8% accuracy. Multiple studies have shown that sound analysis correlates well with overall activity observed in video monitoring (Carpentier *et al.*, 2017; Du *et al.*, 2017). Carpentier and colleagues (2017) found that sound correlated highly with broiler chicken activity, ranging from 58.6%-80.5% – this suggested that sound can be just as useful for monitoring chicken behavior and welfare as video. Video analysis can also be used to monitor foot health in broiler chickens by observing activity and occupancy patterns (Norton *et al.*, 2019).

Temperature control is an important component of poultry management, from preventing heat stress in broilers (Bloch *et al.*, 2019) to promoting the proper environment for embryonic development (Andrianov *et al.*, 2019; Phuphanin *et al.*, 2019). Biosensors have the potential to monitor temperature in animal environments and alert farmers to intervene as needed. Infrared thermometers have been used to monitor the body temperature of broilers with high accuracy compared with implanted temperature loggers (Bloch *et al.*, 2019). Non-invasive heart rate monitors have been used in chicken embryos to monitor incubation temperature (Andrianov *et al.*, 2019) and detect cardiovascular defects (Khaliduzzaman *et al.*, 2019). Smartphone technology has been developed for easy monitoring of embryo heart rate, which will allow farmers to intervene as needed to prevent the loss of embryos during incubation (Phuphanin *et al.*, 2019).

Pathogens in poultry can spread quickly between farms, so researchers have been investigating how to use biosensors to monitor disease outbreak in poultry populations. Optoelectronic sensors using gold nanobundles were highly sensitive in detecting adenovirus in fowl and were about 100 times more sensitive than conventional methods

(Ahmed *et al.*, 2018). Nanocrystals (chiral zirconium quantum dots) have been used in biosensors to detect coronavirus in chickens (Ahmed *et al.*, 2018). Chiro-immunosensors utilizing chiral gold nanohybrids are promising technology for the detection of multiple chicken pathogens including avian influenza, fowl adenovirus, and coronavirus (Ahmed *et al.*, 2017).

Big data

The use of sensors for monitoring the health and welfare of livestock results in large amounts of data that need to be processed in order to provide meaningful biological outputs for animal management. This has led to advances in big data, or large, complex sets of data (Wolfert *et al.*, 2017). Big data is defined as data sets with large numbers of rows and columns that prevent visual inspection of the data and a large number of variables or predictors that make the data messy and unsuitable for traditional statistical techniques (Morota *et al.*, 2018). Big data is defined by four key attributes known as the four V model. These attributes include volume, the quantity of data; velocity, the speed of accessing or using the data; variety, the different forms of the data; and veracity, cleaning and editing the data (Wolfert *et al.*, 2017; Koltes *et al.*, 2019). Value is also considered an important attribute to ensure high-quality data through improvements in methods and technology (Wolfert *et al.*, 2017; Koltes *et al.*, 2019). Data models contribute to the efficiency of sensor technology by sorting through data to provide meaningful output for farms, including predictions for future events (Wolfert *et al.*, 2017).

Precision livestock farming (PLF) relies on proper use of big data and data modeling to inform management of nutritional needs, reproductive status, and changes in productivity

that may indicate welfare issues. It may even allow farmers to group animals based on needs, leading to greater utilization of resources (Koltes *et al.*, 2019). Data models extract information from sensors, process it, and then use it to detect abnormalities in the data that may be affecting the animals. Sensor data can be broken down into animal-oriented data and environment-oriented data. These two types of data should be monitored simultaneously, as they both affect animal health and productivity. Sensors and big data models can function to combine this information, improving farmer response and decision-making. Digitalizing animal agriculture by using animal- and environmental-oriented data will improve overall health management, nutrition, genetics, reproduction, welfare, biosecurity, and emissions (Piñeiro *et al.*, 2019).

There are two primary types of data modeling: exploratory models and predictive models. Exploratory models take data from previous events and determine which factors were influential, while predictive models use data to predict future occurrences based on certain criteria (Sasaki, 2019). Proper use of data modelling is important when using big data sets; the variability in data means there are a number of variables that need to be accounted for in the models, and data will need to be cleaned up to remove noise (Koltes *et al.*, 2019). The use of predictive models is highly valuable, as it would allow farmers to predict future outcomes and implement a more proactive management approach (Wolfert *et al.*, 2017). Big data technologies can also be useful in monitoring disease transmission by creating contact networks and identifying high-risk populations (VanderWaal *et al.*, 2017).

Machine learning is a growing area of interest in precision livestock farming as it allows computer algorithms to learn from the data sets and improve themselves accordingly,

eliminating the need for a human coder (Benjamin and Yik, 2019). Machine learning is a branch of artificial intelligence that uses algorithms for statistical prediction and inference (Morota *et al.*, 2018). Data mining is similar, but the focus is on teaching databases to identify patterns in order to generate information (Morota *et al.*, 2018).

Machine learning techniques are frequently used in animal genetics research to predict phenotypes based on genotypic information, identifying outliers in a population, and genotype imputation. Machine learning has also been used to detect mastitis from automated milking technologies on dairy farms, estimate body weight through image analysis, and monitor microbiome health (Morota *et al.*, 2018). Machine learning and big data analytics have the potential to improve welfare and productivity in dairy cattle. They can be used to monitor and predict lameness and mastitis in dairy cattle, huge welfare issues that can have severe negative consequences on milk production (Ebrahimi *et al.*, 2019; Taneja *et al.*, 2020; Warner *et al.*, 2020).

Based on data obtained from sensors and sensing technologies, big data analytic technology prediction models can build digital farming service systems that enhance animal production capacity, productivity, and livestock welfare. Digital footprints from the animals' wearable sensors and livestock barn sensors will help to create a digital fingerprint that can establish predictive models for forecasting through adaptive decision-making models (Figure 2). The 3 'F's (Footprint, Fingerprint and Forecast) will not only guide the livestock farmers (Tsay *et al.*, 2019) for animal production management but will also establish integrated application models of the agricultural chain.

Big data techniques can also be used to integrate data across farms in order to optimize production systems (Aiken *et al.*, 2019). The value of big data will depend on automation, accessibility, and accuracy of the data provided. Error checking and quality control will need to be implemented to ensure data quality (VanderWaal *et al.*, 2017). As PLF becomes widely implemented on farms, it will also be necessary to develop software, quality control mechanisms, database systems, and statistical methods to summarize and visualize the data, and identify the most appropriate data models. (Koltes *et al.*, 2019). Another major challenge with big data obtained on farms is privacy and security (Wolfert *et al.*, 2017). Data collection on farms is currently underutilized (Table 1) because farmers prioritize privacy (Wolfert *et al.*, 2017).

Block chain technology

As food systems become more global, animal products have to remain compliant on numerous animal welfare and sustainability protocols. Documentation on compliance must be accessible for regulators and third-party inspectors, which can be complicated when this information is stored on paper or in private databases (Motta *et al.*, 2020). Consumers are also more concerned about the sustainability and ethical concerns of animal agriculture. and they demand transparency in how food animals are raised. Food safety is also a major concern among consumers – according to the World Health Organization, 1 in 10 people experience food-related illness every year, with over 420,000 people dying annually (WHO, 2020). Digitalization of animal agriculture, especially through blockchain technology, would provide solutions for these issues (Motta *et al.*, 2020). As of 2020, animal agriculture remains one of the world's least digitalized industries, leaving plenty of room for improvement (Motta *et al.*, 2020).

A blockchain is a decentralized network where each transaction creates a node. These nodes are organized into blocks based on consensus from participating parties, and blocks are linked to create a chain. Each time there is a new transaction, another node is created in real time with information about that transaction to contribute to the blockchain (Chattu *et al.*, 2019; Motta *et al.*, 2020). The four pillars of blockchain technology are that the information systems within the blockchain are distributed, transparent, immutable, and democratic (Motta *et al.*, 2020). Within animal agriculture, this means that a unique ID would be provided to each animal at the farm. That ID would remain with that animal throughout its life and collect data on the farm(s) it lived in, the transportation used to move the animal from the farm(s) to the slaughterhouse, the veterinarian checking the animal at the slaughterhouse, the quality check after slaughter, the transport of the meat product, and finally the packager and retailer (Motta *et al.*, 2020).

Blockchain technology would provide a number of benefits to animal agriculture, including decentralized, automated transactions that could contribute to automated and more efficient auditing systems for certification and regulatory organizations (Motta *et al.*, 2020), system integration, organized records of chain transactions throughout the life of an animal from farm to table (Motta *et al.*, 2020), and greater traceability and transparency within animal agriculture (Picchi *et al.*, 2019; Motta *et al.*, 2020). Recently, there has been growing distrust between farmers and consumers. Blockchain technologies could improve that trust by providing consumers with transparency about the lifecycle of an animal.

Blockchain technology could be extremely useful in detecting and tracking disease breakouts within animal agriculture. Food safety is a huge concern to consumers,

especially in light of a number of recent outbreaks including the H1N1 flu of 2009, Foot-and-Mouth and Mad Cow diseases in Europe, Avian influenza (Lin *et al.*, 2018), and recent increases in salmonella outbreaks (Dyada *et al.*, 2020). Other food practices are harmful to the health safety of consumers as well (Lin *et al.*, 2018). Modern technologies such as blockchain technology could help trace harmful foods back to the source, increasing accountability for problematic practices within animal agriculture (Lin *et al.*, 2018). The real advantage of blockchain is that it can be shared across a network rather than be controlled and managed by one group (Figure 3). In the event of a disease outbreak within animal agriculture, farmers from around the globe could input and access disease data, actively helping to control the outbreak or prepare farmers for an outbreak they know will reach their farm (Chattu *et al.*, 2019).

Blockchain technology is still in early stages of development for widespread application (Table 2) within animal agriculture, with few studies investigating its impacts on animal agriculture (Picchi *et al.*, 2019; Motta *et al.*, 2020). A large number of platforms can be used, each with its own strengths and weaknesses that should be considered based on the context)in which the platforms are needed. In the future, data scientists must create criteria for deciding which blockchain platform will be the most beneficial for particular markets (Picchi *et al.*, 2019).

Future trends and gaps

Precision livestock techniques such as biosensors, block chain technology, and big data models have the potential to provide huge improvements to environmental sustainability and animal welfare in animal agriculture. As technology advances, these technologies will

become more accessible to farmers around the world, but particularly to farmers in developing countries as they expand to feed a growing population (Alonso *et al.*, 2020). Biosensor data has the potential to provide great improvements for livestock farming, but one of the primary struggles of implementing technology on farms is the conditions on these farms. Animal barns have a number of environment conditions that need to be addressed in order to successfully implement technology on farms – these conditions include moisture, dust, ammonia, and pests (Berckmans and Norton, 2017). The use of sensors also requires a wireless sensor network that may have to function over long distances to transmit data from an animal room to the base computer (Xuan *et al.*, 2017). Oftentimes, the engineers building these technologies have not physically been on farms or worked around livestock, so their sensors may fail in real farm conditions. Increased collaboration between farmers, animal scientists, bioengineers, and other professionals would help encourage and create technology that will be long-lasting and functional on farms (Koltes *et al.*, 2019). Because precision livestock farming and the use of big data are in their infancy, there are few experts in the area and a growing need to train an existing and future workforce in these technologies and skills (Koltes *et al.*, 2019).

Automated video detection software is largely nonfunctional within animal agriculture at the moment (Wurtz *et al.*, 2019). Image analysis of aggression in pigs currently struggles to distinguish between different behaviors, such as play and aggression. These technologies also cannot yet track individual animals, at least not for a long enough period of time to obtain meaningful information about behaviors of interest. Some technologies may be able to track individuals when they are up and moving but cannot track individuals when they lie in a pile and then get up again (Wurtz *et al.*, 2019). There are also issues

with distinguishing animals from the background of the environment; many video technologies were developed in specific test arenas where there was good contrast between the pen structures and the animals, so the technology can fail when applied in real-life farm situations (Wurtz *et al.*, 2019). Additionally, many of the studies testing these technologies have been done on pigs, so more work is needed to assess the applicability on other species (Wurtz *et al.*, 2019).

Data gathered from sensors on farms allows farmers to monitor their animals and use the information they obtain for proactive management. This information could also be shared between farmers to help both farms improve management or respond to specific animal health, welfare, or environmental issues (Papst *et al.*, 2019). Big agriculture companies could combine data from multiple sources to answer questions about prevalent management issues, and the use of machine learning and other technologies could provide data-driven solutions back to farmers (Papst *et al.*, 2019). However, a number of issues must first be addressed, the most important being data privacy. Farmers are typically protective of their information and would need to trust that the data from their farm would be secure before offering to share it (Papst *et al.*, 2019). Another obstacle to big data integration is the proprietary algorithms used by sensor manufacturers. Not only would the manufacturers be reluctant to share their algorithms, but it may be difficult to compare data coming from sensors built by different manufacturers if the sensors use different measures and frequencies to collect data (Papst *et al.*, 2019). New advances in machine learning are addressing these privacy concerns by developing privacy-preserving data exchange systems.

Consumers and farmers alike may be hesitant to implement PLF technologies (Berckmans and Norton, 2017). Some consumers fear that PLF will contribute to the 'factory farming' aspects of intensive animal agriculture, where animals are treated like commodities rather than sentient animals (Norton *et al.*, 2019). Farmers may also be hesitant due to wariness of technology and a fear that they will be further removed from their animals (Klerkx *et al.*, 2019). The use of technology on farms also has the potential to create inequalities within animal agriculture, creating socio-economic or socio-cultural tensions and unfairly penalizing workers that are not tech-savvy. There also appears to be gender bias in the implementation of on-farm technologies (Klerkx *et al.*, 2019). Farmers in rural areas may also be at a disadvantage due to broadband access (Koltes *et al.*, 2019). In order to implement PLF on farms, the tech and data industries must consider these issues and push to create easy-to-use software and data visualization. These goals will be key to widespread use by farmers and veterinarians (Koltes *et al.*, 2019). The use of cell phones to get real-time alerts of on-farm issues is currently being implemented on some farms as easy-to-use technology (Neethirajan, 2017).

Along those same lines, much of the literature on PLF technologies is coming from North America and Europe. As the global population grows, there will be an increasing number of farms in underdeveloped countries with unique challenges that cannot be addressed with data and information from North American and European farms. As global population growth continues and the demand for animal products increases, solutions for how to make livestock farming efficient in other global regions will become more critical than ever (Wolfert *et al.*, 2017).

Conclusions

Digitalization of animal agriculture through precision livestock farming technologies has the potential to address consumers' increasing concerns about animal welfare, environmental sustainability, and public health, while also preparing to meet the increasing demand for animal products as a result of the growing human population. Some of the most promising PLFs include biosensors, big data, and blockchain technologies. Biosensors allow farmers to collect real-time data on animal health and welfare, helping them implement proactive management strategies to maintain a sustainable and safe food supply. Big data programs take data from these sensors and turn it into meaningful biological outputs for farmers. Blockchain technology makes animal agriculture more transparent and traceable, increasing consumer trust and improving food safety. Of course, no major advances in animal agriculture come without drawbacks. PLF technologies are still in the early stages of implementation on farms, and a number of issues will need to be rectified before these technologies can be widely accepted by farmers and consumers around the world.

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Declaration of interest

The author declares no conflict of interest.

Software and data repository resources

Not applicable.

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Figure Captions

Figure 1: Prosumer values and concerns that then links the Precision Livestock Farming technologies that addresses them. Digital technologies in modern animal farming aims to (b) avoid risks and enhance welfare/productivity by providing reactive to predictive approaches, (c) bridge the scales including social, ecological and political factors in moving beyond the notion of animal productivity and beyond one-dimensional focus, and (d) move from the gross to the subtle in finding unconventional solutions.

Figure 2: Big Data for Animal Farming: The chain of sensors-based big data applications in precision livestock farming.

Figure 3: Prairies to Plate: Livestock supply chain depicting origin, storage, and flow of information as the animal products move from the farm and through processing and distribution channels to consumers. Blockchain platform enhances the supply chain visibility, product traceability and build consumer confidence.

Table 1: List of Companies that use Big Data in Animal Farming

Company Name	Big Data Technology	Website	Location
Cargill Inc	Dairy Enteligen Application	https://www.cargill.com/animal-nutrition/feed-4-thought/industry-insights	Italy
Cattle Watch	Uses Location Tracking System and Big Data to count the herd and enable users to pinpoint the location of individual animals.	http://www.cattle-watch.com/	Israel
Vence	Artificial Intelligence and Sensors and Sensor based big data for controlling animal movement, monitor wellbeing and creating virtual fence lines during grazing	http://vence.io/	United States
Connecterra	Big Data for predicting real time behavior of dairy farm animals using sensors and cloud based machine learning	https://www.connecterra.io/	Netherlands
Cainthus	Computer vision and deep learning to monitor animal behaviour	https://www.cainthus.com	Ireland
Rex Animal Health	Big Data for Precision Medicine to the Animal Health Sector	http://rexanimalhealth.com/	United States
Chitale Dairy	RFID tags and Sensors to collect data on how much the	http://www.chitaledairy.com/	India

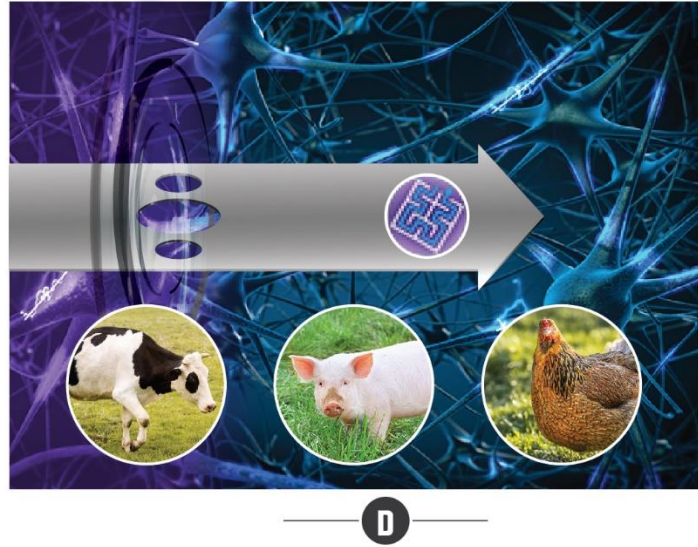
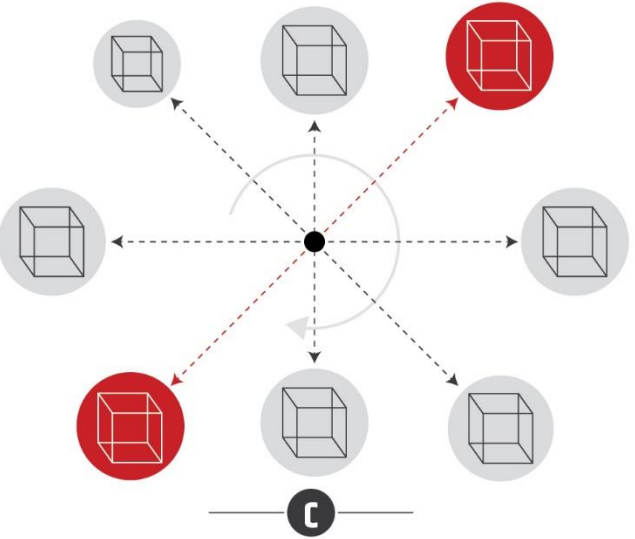
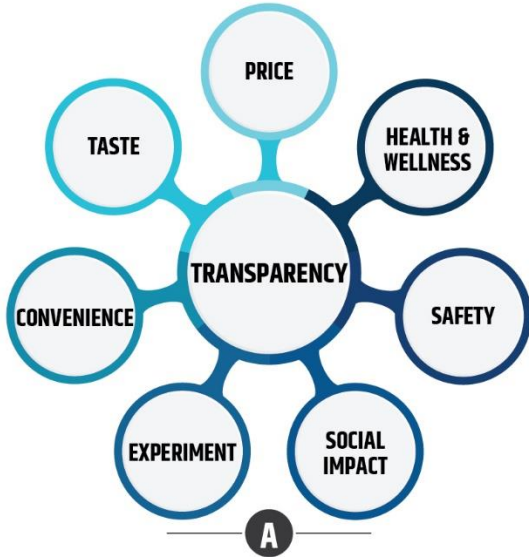
Porphyrio	dairy cow eats, and track the health of cow Predictive Egg Flow, Predictive Poultry Feedstock Management, Flock Management, Early Warning System, and Optimized Slaughter Planning	https://www.porphyrio.com/	Belgium
SmartShepherd	Collar based sensor and sensor data for building maternal pedigree (livestock breeding) through identification of relationships between animals.	https://www.smartshepherd.com.au/	Australia
Merck Animal Health (formerly QuantifiedAg)	Biometric and behavioral based big data from ear tag sensors to identify sick animals' outliers	https://quantifiedag.com/	United States
Alan-It	Cloud-based analytical service Smart4Agro; Livestock Decision Making	https://www.alan-it.ru/wkpages/default.aspx	Russia
AgriWebb	Cloud based cattle management software for connecting data from farm to supply chain	https://www.agriwebb.com/au	Australia
BovControl	Tool for data collection and analysis for improving performance on meat, milk and genetics production; Connects farmers, processors, brands, ranchers, and technical consultants.	https://www.bovcontrol.com	United States
AgriSyst	PigExpert App for recording sow, rearing, piglet, and finisher big data.	https://agrisyst.com/en/	Netherlands

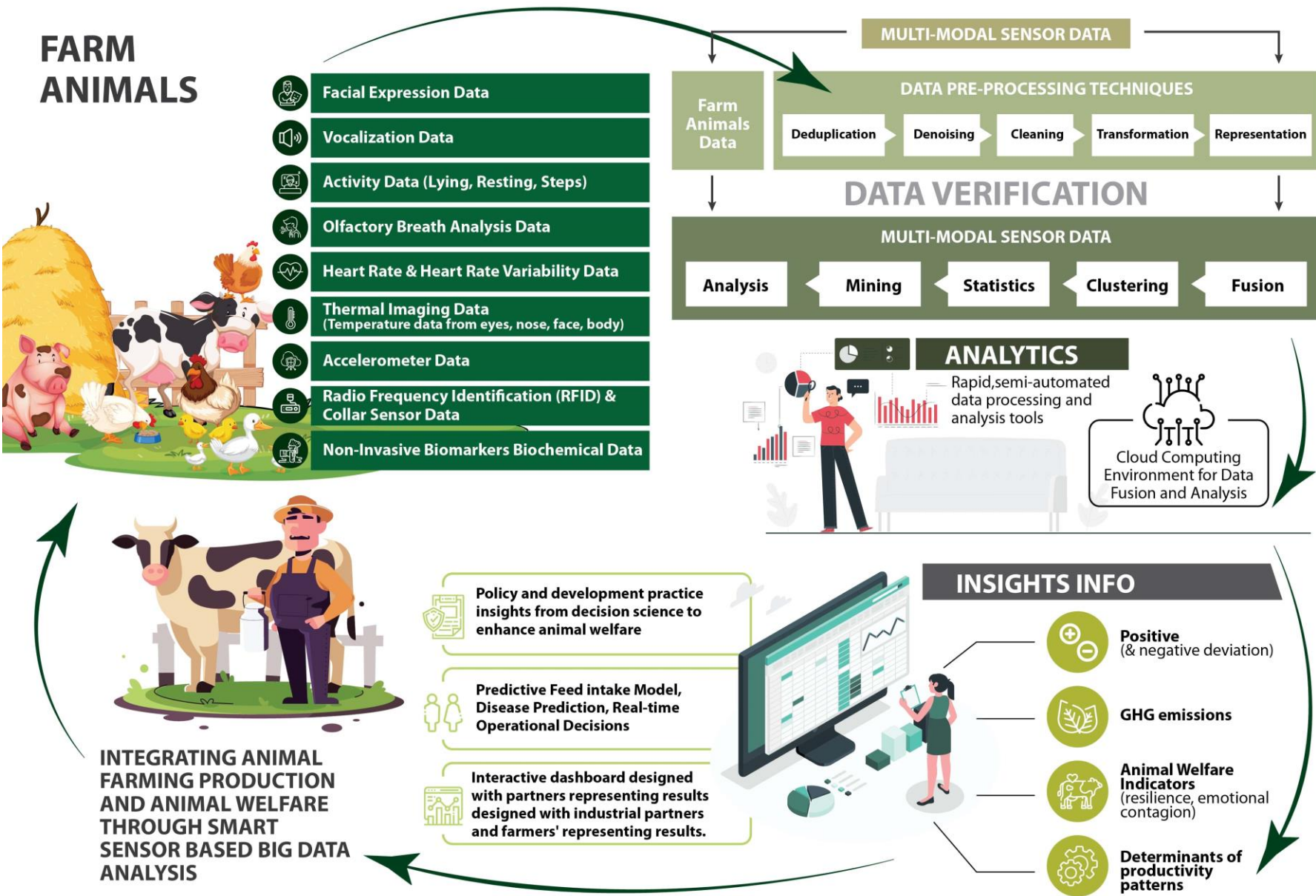
PoultryMon	Big data from sensors for remote monitoring and process monitoring for poultry hatchery operations	http://www.poultrymon.com/	India
Yingzi Technology	Big Data collected from ID cards for individual animals and traceability of the whole processes from the farm to the fork.	https://m.yingzi.com/#/frontPage	China
Parmigiano Reggiano	Big data using tags to track products, ensure quality and reduce fraud	https://www.parmigianoreggiano.com	Italy

Table 2: List of blockchain companies and their technologies employed in Livestock Industry

Company Name	Block Chain Technology	Website	Location	Animal and Veterinary Applications
OriginTrail	Ethereum Mainnet	https://origintrail.io/about-us	Slovenia & Hong Kong	Traceability solution for dairy, poultry, organic beef products.
Hunimal Blockchain Limited	Vein Recognition Technology	http://www.hunibit.com/	Hong Kong & South Korea	Animal identification technology, currently for pet companion looking to expand to other animal sector
Ripe	R3 Corda Enterprise	https://www.ripe.io/	San Francisco, USA	Food traceability platform to avoid counterfeits and food fraud and measure freshness
Acoer	Open APIS	https://www.acoer.com/	Atlanta, USA	'Hashlog' technology to determine disease transmission from livestock and farm animals to prevent pandemics
Vetbloom	Internet Based Education Platform	https://vetbloom.com/	Massachusetts, USA	In collaboration with IBM, Vetbloom established application of blockchain for learning credentials in the veterinary industry
RippleNami	Visualization platform that consolidates big data	https://www.ripplenami.com/	Kenya	Real-time livestock identification and traceability program
Ultimo Digital Technologies (UDT)	5G NB-IoT Digitized Supply Chain Ecosystem	https://www.ultimodt.com.au/	Sydney, Australia	Trace animal welfare and stop counterfeiting and measuring conditions for livestock
CattleChain	FIWARE Open Source Platform (Sentinel)	https://cattlechain.eu/	Madrid, Spain	Decision making and traceability of the beef and dairy cattle supply chain
VeChain	VeChain Thor Block Chain - Proof-of-Authority ("PoA") consensus algorithm, meta transaction features	https://www.vechain.org/	Shanghai, China	Supply chain problems in the meat export industry
Version1	Hyper-Ledger Fabric Model	https://www.version1.com	London, United Kingdom	Trace individual cuts of meat back to the cows from which they came, and share that data through QR

				codes, mobile apps, and smartphones with consumers in exchange for their feedback about the taste.
Investereum	Building Block Chain Knowledge Platform and Software Development	https://www.investereum.com/	Belgium	Combat fake food and enhance animal welfare through tracking and tracing
BatchBlock	Batch Block Extensible Platform	https://batchblock.com/	Surrey, United Kindom	Avoiding counterfeit in veterinary pharmaceutical sector and thereby enhance animal welfare
BeefChain	Azure Block Chain service	https://beefchain.com/	Wyoming, USA	Enhance traceability and humane handling; Enabling unique animal identification and ensuring origin; Rancher to Retail supply chain tracing system.
BeefLedger Ltd	BeefLedger Platform developed based on Ethereum technology	https://beefledger.io/	Australia	Product authenticity, brand value protection, disease prevention, and consumer access to the source of animal origin
AgriLedger	Distributed ledger technology and mobile apps	http://www.agriledger.io/	London, United Kingdom	Digital Identity, traceability of food origin, record keeping
AgriDigital	Cloud based management platform; Algorithm for calculating the cost of delivery using Google Maps integration.	https://www.agridigital.io/products/blockchain	Australia	Food traceability and Supply chain provenance
AgriChain	Network based transactional software platform and distributed ledger system	https://agrichain.com/	Australia	Enhance transparency, Food traceability, manage logistics







BLOCKCHAIN



Collects data from all members in the system into time-stamped blocks of digitally verified, tamper-proof information

