Sensing and Bio-Sensing Research 32 (2021) 100408

Contents lists available at ScienceDirect

Sensing and Bio-Sensing Research

journal homepage: www.elsevier.com/locate/sbsr

Digital Livestock Farming

Suresh Neethirajan [*], Bas Kemp

Adaptation Physiology Group, Department of Animal Sciences, Wageningen University & Research, Wageningen, Netherlands

ARTICLE INFO

Keywords:
Precision Livestock Farming
digitalization
Digital Technologies in Livestock Systems
sensor technology
big data
blockchain
data models
livestock agriculture

ABSTRACT

As the global human population increases, livestock agriculture must adapt to provide more livestock products and with improved efficiency while also addressing concerns about animal welfare, environmental sustainability, and public health. The purpose of this paper is to critically review the current state of the art in digitalizing animal agriculture with Precision Livestock Farming (PLF) technologies, specifically biometric sensors, big data, and blockchain technology. Biometric sensors include either noninvasive or invasive sensors that monitor an individual animal's health and behavior in real time, allowing farmers to integrate this data for population-level analyses. Real-time information from biometric sensors is processed and integrated using big data analytics systems that rely on statistical algorithms to sort through large, complex data sets to provide farmers with relevant trending patterns and decision-making tools. Sensors enabled blockchain technology affords secure and guaranteed 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. Thanks to PLF technologies, livestock agriculture has the potential to address the abovementioned pressing concerns by becoming more transparent and fostering increased consumer trust. However, new PLF technologies are still evolving and core component technologies (such as blockchain) are still in their infancy and insufficiently validated at scale. The next generation of PLF technologies calls for preventive and predictive analytics platforms that can sort through massive amounts of data while accounting for specific variables accurately and accessibly. Issues with data privacy, security, and integration need to be addressed before the deployment of multi-farm shared PLF solutions becomes commercially feasible.

Implications

Advanced digitalization technologies can help modern farms optimize economic 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. This trend has the potential to fuel more research on the use of novel biometric sensors, big data, and blockchain technology for the mutual benefit of livestock producers, consumers, and the farm animals themselves. Farmers' autonomy and data-driven farming approaches compared to experience-driven animal management practices are just several of the multiple barriers that digitalization must overcome before it can become widely implemented.

1. Introduction

By 2050, the projected global human population is over 9 billion [1], approximately 2 billion more than the current population [2]. This population growth will occur primarily in developing countries, particularly in sub-Saharan Africa [2]. Population growth and increased development in these countries will create 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. 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 [3]. Water and land will become increasingly competitive resources, meaning livestock producers will need to maximize production while employing their limited resources sustainably [4]. The European Union aims to be climate neutral by 2050. Moreover, societal attitudes, especially of consumers, are changing drastically which further fuels incentives for responsible research and innovation to solving pressing problems in livestock farming through circular and sustainable ways.

* Corresponding author.
E-mail address: Suresh.Neethirajan@wur.nl (S. Neethirajan).

https://doi.org/10.1016/j.sbsr.2021.100408
Received 11 December 2020; Received in revised form 18 February 2021; Accepted 22 February 2021
Available online 27 February 2021

Digitalization will help to advance these goals. 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 PLF technologies to digitalize livestock agriculture. This critical review paper focuses on PLF technologies - namely biometric sensors, big data, and blockchain technology - that can help farmers increase production while addressing consumer concerns. The paper in addition throws a spotlight upon the impact of PLF technologies upon livestock farming, particularly as they relate to improving animal health and welfare.

1.1. Current trends in livestock farming

The last decade has seen major improvements, including automated feeding systems, milking robots, and manure management, and maximizing production efficiency through instrumentation, animal breeding, genetics, and nutrition. Despite this progress, significant challenges remain. Intensive livestock management is necessary to meet the increasing demand for animal products, but the confined and crowded nature of livestock housing makes it difficult for farmers to closely monitor animal health and welfare [5]. As climate change intensifies, the risk of disease, heat stress, and other health issues among livestock animals will increase [6]. This in turn will create a greater urgency to identify health issues and disease outbreaks preemptively or early on, understand disease transmission, and take preventative measures to avoid large-scale economic losses [7,8]. These issues, as well as escalating concerns over animal welfare, transparency, and environmental sustainability, have led to growing interest in digitalizing livestock agriculture through precision livestock farming technologies [9].

Precision livestock farming (PLF) technologies utilize process engineering principles to automate livestock 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 [10]. 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 [8]. PLF technologies can also help farmers monitor infectious diseases within livestock agriculture, improving food safety and availability [11]. The use of PLF technologies will ultimately improve animal health and welfare while reducing food safety issues and maximizing efficient resource use [12].

1.2. Challenges to traditional business models

The major challenges in effectively monitoring animal welfare revolve around three key factors: cost, validity, and timing of insights. Most available methods are time-consuming, labor-intensive, and therefore costly [13]. Livestock farmers often rely upon observations from stockpeople to detect health and welfare issues, but many commercial facilities have high stockperson-to-animal ratios. For example, a commercial pig farm may have one stockperson for every 300 pigs [10]. Even vigilant and well-trained stockpeople might overlook animals in critical condition. Third-party auditing programs offer comprehensive animal welfare assessments, but these, too, often are costly and time-consuming. The Common Swine Industry Audit (CSIA), for example, employs 27 criteria, many of which require direct animal observation. With large herd sizes, this can be prohibitively expensive.

The CSIA also raises concerns regarding the validity of the obtained data. The monitoring criteria applied include body condition score, lameness, and lesions, all of which can be subjective measures. Inconsistency across auditors is of particular concern; however, application of more objective, but invasive measures, present practical limitations. Animals typically must be restrained by stockpeople when monitoring physiological stress signs, such as elevated heart rate, cortisol levels, and body temperature, which inevitably cause additional stress, thus potentially influencing the physiological measurements being taken [13]. Even with non-invasive observations, animals will react to the presence of a person nearby, often rendering these observations not especially useful for monitoring 'typical' animal behavior [13]. Timing of insights has a direct consequence for the ability of farmers to take corrective action. The CSIA stipulates criteria for critical failures, such as animal abuse or animals in critical condition that need to be humanely euthanized. Ideally, so not to prolong an animal's suffering, these conditions should be rectified long before reaching the point of registering as a critical failure through a third-party audit.

The use of PLF technologies, particularly biometric sensors, would contribute to consistent, objective, and regular welfare monitoring of livestock in real time, allowing farmers expeditiously to identify problems and implement preventative measures to avoid critical failures. Precision livestock farming technologies allow for non-invasive sampling, helping farmers and researchers to obtain realistic measures that can be used to address welfare concerns [13]. PLF technologies could also help reduce resource use; a more proactive and individualistic approach to animal health ultimately would reduce the need for medications, particularly antibiotics [8].

As consumers become more concerned with the sustainability and welfare of animal products, they are demanding more transparency from livestock farmers (Figure 1). Blockchain technologies will allow farmers to be transparently accountable 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 [10].

2. Biometric sensing

Biometric sensors monitor behavioral and physiological parameters of livestock, allowing farmers to evaluate an animal's health and welfare over time [8]. Today's wide variety of available biometric sensors are either non-invasive or invasive. Non-invasive sensors, that can be deployed around the barn, include surveillance cameras and sensors in the feeding systems to monitor animal weight and feed intake. Non-invasive sensors also include sensors easily attached to animals, such as pedometers, GPS (global positioning system), and MEMS (micro-electromechanical) based activity sensors, that can be used to monitor behavior [5]. Invasive sensors, which are less commonly studied in livestock, typically are swallowed by or implanted in an animal. This class of sensors is useful for monitoring internal physiological measures, such as rumen health, body temperature, and vaginal pressure in dairy cows [5].

The livestock industry has adopted the use of biometric sensor technologies as a way to monitor more animals without increased contact time and number of employees, and to provide reliable, objective measures of animal health and welfare [5,8]. The sensors collect data that is then stored in databases and processed by algorithms - sets of instructions or calculations that are sequentially executed to solve specific problems. With livestock biometric sensors, specialized algorithms process the raw sensor data to provide biologically relevant information, such as the total time animals engage in specific behaviors on a certain day, or how activity level changes over particular time periods [10]. These sensors can also monitor behaviors within specified 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 [8]. Combining biometric sensors with big data analytics (see below), artificial intelligence, and bioinformatics technologies, such as those used in genomics, could identify animals with desirable qualities and select them for breeding programs [14].

The use of biometric sensors in livestock farming and other animal health sectors is expected to increase in the next decade [8]. This is due to their significant advantages in terms of real-time output, accuracy, and the large amounts of data they are able to acquire. Obtaining information relating to animal welfare as early as possible allows early

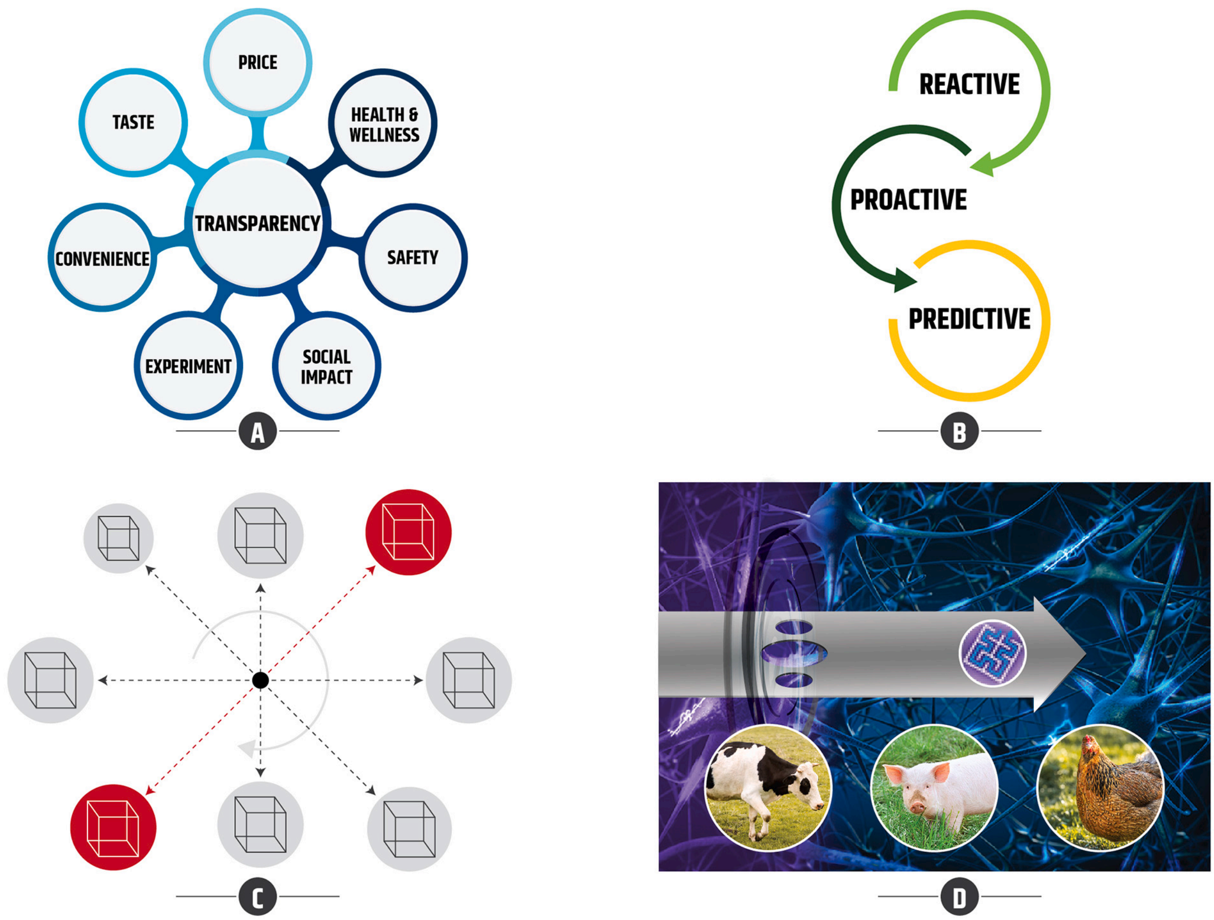

Figure 1. Prosumer values and concerns that then links the Precision Livestock Farming technologies that addresses them. Digital technologies in modern animal farming aims to (b) avoid risks and enhance welfare/productivity by providing reactive to predictive approaches, (c) bridge the scales including 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.

intervention and often minimizes further required interventions. Thermal infrared (TIR) imaging, for example, can be used to monitor body temperatures in place of invasive thermometers that require restraint and handling of animals. TIR of the eye region and general skin temperature can monitor stress and detect disease 4-6 days earlier than traditional methods [15], thus affording prompt treatment and reducing the ability for illness to spread throughout flocks or herds [16]. The most commonly used non-invasive sensors for monitoring livestock animals are thermometers, accelerometers, and radio-frequency identification (RFID) tags, microphones, and cameras. These allow farmers to monitor temperature, activity levels, sound levels in the barn (e.g., vocalizations, sneezing, and coughing) and specific behaviors (e.g., aggression in pigs) [10].

Thermometers, along with physiological sensors, 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 [13]. With the use of biometric sensors, researchers are able in real time to detect changes in heart rate in response to both positive (eustress) and negative stressors, compare individual responses across animals, and track how heart rate changes over time in response to different stressors. In a study with pigs, a negative stressor caused elevated heart rate for one minute following a loud noise. A positive stressor (a towel to play with) also caused elevated heart rate for two minutes after the stressor was provided. More conventional or indirect measures of welfare may not be able to detect these subtle differences [17]. Heart rate monitors also are useful for monitoring overall health and metabolic energy production. Biometric sensors, such as photoplethysmographic sensors, can easily be attached to ear tags or other body parts to continuously monitor livestock heart rates [18].

Livestock farmers increasingly are utilizing RFID devices, which may be embedded in ear tags and collars or implanted subcutaneously, to monitor a wide variety of behaviors such as general activity, eating, and drinking [8]. Acoustic analysis, using microphones, allows monitoring of vocalizations and coughing, alerting farmers to welfare issues before they become severe. Microphones also have the advantage of being easily and inconspicuously installed in barns to monitor large groups of animals [19]. Cameras, similarly, are easy to place in barns and can be used to capture a wide variety of actionable information. Algorithms for video images can detect changes in animals' posture that may indicate lameness and other morbidities [13]. Camera image analysis allows monitoring of animal weight, gait, water intake, individual identification, and aggression [12].

Facial detection technology is another growing area of interest in automated animal welfare monitoring. Facial detection technologies rely on machine learning computer algorithms to detect features on an animal's face for identification of individuals, or to monitor changes related to affective states [20]. Several animal welfare researchers are developing animal "grimace scales" to help stockpeople better to monitor animal affective states, particularly pain [21]. Livestock animals frequently are subjected to painful procedures such as dehorning, tail docking, and castration [21,22]. Facial expression analysis can be specific enough to determine behavioral intent in animals. Distinct facial differences have been noticed in pigs initiating aggression, and those retreating or avoiding aggression [23]. Facial detection also has been proposed as a lower-cost alternative to RFID tags for individual animal identification [20].

One of the most important roles for biometric sensors is in reducing the impact and spread of disease. These sensors can be used to monitor temperature changes, behavior, sound, and physiological measures including pH, metabolic activity, pathogens, and the presence of toxins or antibiotics in the body. The overuse of antibiotics in livestock agriculture is currently a huge concern with serious repercussions for human health [24]. 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 [11]. Biosensing technologies can also be used to detect problematic pathogens such as avian influenza, coronavirus [25–27], and Johne's disease, a detrimental bacterial infection in ruminants that can result in huge economic losses for farmers [28]. Biometric sensors can also detect biomarkers of inflammation for widespread disease monitoring [29]. TIR, for example, has been used on images of feet to detect foot disease [13].

Each type of livestock has its own welfare needs and distinct challenges. The use of biometric sensors or the integration of multiple sensors in farming will, therefore, always be species-specific. As a result, it is advantageous to consider the role of biometric sensors in each of the main livestock categories.

2.1. Biometric and biological sensors for cattle

The use of biometric and biological sensors in the cattle industry has allowed for better monitoring of major welfare concerns as well as facilitating routine husbandry activities and providing valuable insights into productivity measures. Welfare concerns that can be improved through the use of biometric sensors include mastitis, cystic ovarian disease, lameness, displaced abomasum, and ketosis, whilst productivity measures that have been researched for automation include general activity, affective state, estrus detection, and milking behavior [5].

Cattle present to farmers specific husbandry challenges. Individual animals are a high-value investment and a wide array of factors can influence the overall profitability of a herd. Being able to measure the timing of fertility cycles (estrus) with real-time results is of particular importance for herd maintenance, whilst precision control of nutrition and calorific energy are essential to maximize milk production. The use of biometric sensors to detect estrus has been of particular interest. Pedometers have shown some success for dairy cows [5], whilst a recent study by Röttgen et al. (2019) investigated automated detection and identification of the vocalizations of an individual cow within the herd, with reported sensitivity at 87% and specificity at 94%, as a potentially viable method for monitoring dairy cow estrus [30].

Nutrition and energy balance are essential to efficient milk production by dairy cattle. Circulating levels of non-esterified fatty acids (NEFA) indicate negative energy balance and can be symptomatic of 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, decreased milk production, reproductive issues, mammary infections, and immune system dysfunction. Biosensors that monitor NEFA currently are in development and have the potential to be extremely useful on dairy farms [31]. Ketosis, another serious health concern for dairy farms, is often preceded by elevated levels of beta-hydroxybutyrate (BHBA). This can be detected by a quantum dots-based biosensor sensor developed by Weng et al. (2015) [32]. An alternative approach was taken by Tuteja et al. (2017) [33] using 2D MoS_2 nanostructure based electrochemical immunosensors for the detection of BHBA in dairy cattle. This method showed high specificity and sensitivity, was reproducible and comparable to commercially available kits. Additionally, Veerapandian et al. (2016) [34] successfully used electrochemical biometric sensors of ruthenium dye-sensitized graphene oxide (GO) nanosheets to detect BHBA. Screen-printed electrode (SPE) sensors also are being developed to detect both NEFA and BHBA [35]. Field-based devices for BHBA [32] and smartphone-based technologies will soon allow for rapid on-farm testing and response. Jang et al. (2017) [36] demonstrated a portable diagnostic reader that can detect progesterone in milk. The development of biosensors that would allow for rapid biomarker detection and a proactive farmer response ultimately would improve dairy cattle health and welfare while reducing overall resource use.

Whilst many of these biosensor technologies are yet to be widely adopted by dairy farmers, there are a few commercially available biometric sensors for livestock usage. The most common sensors successfully used within the industry include thermometers, accelerometers, and microphones [5]. Among the more innovative methods, in addition to the previously mentioned TIR-based ocular imaging system used for noninvasively monitoring stress in cattle, several other recent approaches are noteworthy. MooMonitor is a wearable biometric sensor developed specifically to measure the grazing behavior of dairy cows, which so far has demonstrated a high correlation with traditional observation methods [37]. Biometric sensors had been demonstrated to monitor cattle water intake. A study by Williams et al. (2020) [38], using RFID tags and accelerometers observed 95% accuracy with the correct classification of animal behavior patterns. Sensor technologies also have the potential to grant animals a degree of autonomy by replacing some of the animal husbandry tasks, 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 [8]. These milkers are becoming increasingly popular in the dairy industry, as they allow remote monitoring of cow health [9].

Consumers are growing increasingly concerned about the environmental sustainability of livestock production, especially concerning cattle. Mitigation efforts include, for example, biometric sensors that are being investigated as a way to monitor methane emissions [39].

2.2. Biometric sensors for swine

Major welfare challenges in the swine industry include lameness, aggression in group-housed animals, body condition, and health issues like prolapse and illness. Proactive livestock management, including verification of high welfare standards, is of increasing concern to consumers and producers alike [40].

Biometric sensors are currently being used to improve health and wellbeing of animals, as well as to ameliorate behavioral issues. Current technologies in common use for swine farming include 2D and 3D cameras, microphones, thermal imaging, accelerometers, radio frequency identification (RFID), and facial recognition.

Acoustic detection technologies have been successful in detecting differences in vocalizations and coughs in swine [41]. 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. The use of acoustic 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. 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 [12].

Pig vocalizations are distinct and indicate affective state [41]. For instance, pig screams often indicate pain or distress caused by 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 to potential danger but is also used during periods of play, which can, therefore, also be used as an indicator of positive welfare [12]. Friel et al. (2019) found that the duration of vocalizations in pigs is also an important indicator of affective state [41]. Longer calls, especially long grunts, were used in situations of negative valence, whereas shorter duration vocalizations were more common in situations of positive valence.

Attempts to address lameness in swine have focused on the use of pressure-sensing mats, primarily by placing the mats within electronic sow feeders and in gestation or breeding crates. For less sophisticated analysis, accelerometers can also be used to detect lameness by monitoring overall activity levels, posture, and gait.

A major welfare concern in the swine industry is aggression among group-housed pigs. To monitor and address concerns over aggression researchers are investigating the use of automated video monitoring and depth imaging tracking. These technologies generally are able to monitor overall activity patterns but cannot yet track individual behavioral patterns [42]. Other researchers are taking a different approach, including decoding hours of video of pigs fighting, to learn more about how to intervene to reduce aggression. Image analysis and the use of automated detection technologies are being explored to efficiently decode aggression in videos [12]. Future research hopes to incorporate and integrate both motion tracking and thermal imaging to detect lameness and aggression in sows [10].

Researchers also are 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 weighing scales, which can be time-consuming and/or stressful for the pigs [10].

One of the biggest obstacles to more widespread use of biometric sensors in swine is the curious nature of the pigs themselves. 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 solution. RFID tags can be used to monitor individual feeding and drinking behavior, which are important indicators of health and welfare in swine [12]. 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. Although placing an RFID tag in the ear is the most secure option with pigs, it presents challenges for sensors such as accelerometers. Wireless sensor networks (WSNs) 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 locomotion issues for individual animals, and providing temperature readings of individual pigs [10].

2.3. Biometric and biological sensors for poultry

A major concern with poultry production is the spread of disease. Pathogens spread easily between birds and even between farms. Poultry also requires significantly more accurate temperature control than the other livestock discussed so far. This is both to maintain good health in adult birds and also to promote the proper environment for chick embryonic development [43,44]. As a result, poultry farming is highly reliant upon real-time analysis of data and prompt responses, both of which are key advantages of sensor technologies used in PLF.

PLF sensing modules and platforms have the potential to monitor temperature in animal environments and alert farmers to intervene as needed. In addition to influencing embryonic development of poultry, temperature also is the primary reason for heat stress in broilers [45]. Infrared thermometers have been used to monitor the body temperature of broilers with high accuracy compared with implanted temperature loggers [45]. Non-invasive heart rate monitors have been used to monitor the incubation temperature [43] and detect cardiovascular defects of chicken embryos [46]. Smartphone apps with compatible sensors have been developed for easy monitoring of embryo heart rate, which allows farmers to intervene as needed to prevent the loss of embryos during incubation [44].

Similar to swine, acoustic analysis is an important way in which sensors can provide important information about poultry welfare. Chicken vocalizations can indicate issues with thermal comfort, social disturbances, feather pecking, disease, or growth [19,47]. Chicken vocalizations have a distinct diurnal pattern [48]; increased vocalizations within a barn or deviations from normal diurnal patterns can be used an indicator of stress in chickens, especially stress related to thermal comfort [47,48]. Recent research demonstrated that the use of machine learning to monitor chicken vocalizations was a reliable way to non-invasively monitor welfare and detect warning signs early on [47]. Analysis of pecking sounds can be used to monitor feed intake in chickens [12] and exploratory pecking in turkeys [49]. Sneeze detection can be used to monitor respiratory illness [50].

Voice activity detection algorithms have been shown to discriminate between healthy chickens and those with respiratory illness by extracting animal vocalizations from ambient noise [19]. Detection accuracy was lower for chickens with respiratory illness than for healthy birds, at 72% and 95% respectively. Two factors that increased errors in sound detection were age and onset of illness. A possible explanation for the decreased accuracy of vocalizations for ill chickens is that respiratory disease caused abnormal vocalizations. A study by Liu and colleagues (2020) [51] investigated coughing and body condition scores for a group of broiler chickens; vocalizations made when suffering from respiratory disease and reported 93.8% classification accuracy. Several studies have shown that sound analysis correlates well with overall activity observed in video monitoring [52,53]. Carpentier et al. (2017) found that sound correlated highly with broiler chicken activity, ranging from 58.6%-80.5%, suggesting that sound analysis along with video and accelerometer-based activity measurement can be an efficient sensing module for monitoring chicken behavior, health, and welfare [52].

Optoelectronic sensors, incorporating gold nanobundles have been shown to be highly sensitive in detecting adenovirus in fowl and were about 100 times more sensitive than conventional methods [26]. Similarly, nanocrystals (chiral zirconium quantum dots) have been used in biosensors to detect coronavirus in chickens [26]. Chiro-immunosensors, utilizing chiral gold nanohybrids are promising technology for the detection of multiple pathogens, including avian influenza, fowl adenovirus, and coronavirus [25].

3. Big data analytics and machine learning

The use of biometric sensors and biosensors for monitoring the health and welfare of livestock results in huge amounts of data that need to be processed and analyzed to provide meaningful insights for animal management. This has led to advances in big data analytics – the acquisition and analysis of large, complex sets of data [54]. Big data are defined as data sets with very large numbers of rows and columns that preclude visual inspection of the data, and many variables or predictors that make the data messy and unsuitable for traditional statistical techniques [55]. Big data are characterized by four key attributes, collectively known as the "4 Vs" model: (i) volume, the quantity of data; (ii) velocity, the speed of accessing or using the data; (iii) variety, the different forms of the data; and (iv) veracity, cleaning and editing the data [54,56].

Precision livestock farming relies upon proper use of big data analytics and modeling to inform management about nutritional needs, reproductive status, and declining trends in productivity, that may indicate animal health and welfare issues. Big data models extract information from sensors, process it, and then use it to detect abnormalities in the data that may be affecting the animals. Big data models contribute to the efficiency of sensor technology by sorting through to provide meaningful output for farms, including likelihood prediction of future events, improving farmer response and decision-making, and may even allow farmers to group animals based on needs, leading to greater utilization of resources [56]. Sensor data can be broken down into animal-oriented (phenotype) data and environment-oriented data. These two types of data should be monitored simultaneously, as both affect animal health and productivity. Digitalizing livestock agriculture by using animal and environmental oriented data stands to improve overall health management, nutrition, genetics, reproduction, welfare, biosecurity, and greenhouse gas emissions [57].

There are two primary types of data modeling: exploratory and predictive. 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 [58]. 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 to remove noise [56]. The use of predictive models allows farmers to predict future outcomes and implement a more proactive management approach [54]. Big data technologies can also be useful in monitoring disease transmission by creating contact networks and identifying high-risk populations [59].

Machine learning is a branch of artificial intelligence that uses algorithms for statistical prediction and inference [55]. Data mining is similar, but the focus is on teaching databases to identify patterns in order to generate information. Machine learning (ML) - a consumer of big data - is a growing area of interest in precision livestock farming, as it allows computer algorithms to progressively learn from sensor big data sets and improve themselves accordingly, eliminating the need for a human data analyst [10].

ML techniques frequently are used in animal genetics research to predict phenotypes based on genotypic information, identifying outliers in a population, and genotype imputation. ML has also been used to detect mastitis from automated milking technologies on dairy farms, estimate body weight through image analysis, and monitor microbiome health [55]. ML and big data analytics have the potential to improve welfare and productivity in dairy cattle. They can be used to monitor and predict likelihood of lameness and mastitis in dairy cattle, these conditions being particularly pressing welfare issues that can have severe negative consequences on milk production [60–62].

Big data analytics techniques also can be used to aggregate and integrate data across farms in order to optimize production processes and systems [63]. The value of big data depends upon automation, accessibility, and accuracy of the data provided; error checking and quality control need to be implemented to ensure data quality [59]. As PLF becomes more widely implemented on farms, it will 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 [56]. Another major challenge with big data obtained on farms is privacy and security [54]; consequently, data collection on farms is currently underutilized because farmers prioritize privacy (Table 1).

Based on data obtained from biometric and biological sensors, big data analytic technology prediction models can be used to build digital farming service systems that may enhance animal production capacity, productivity, and livestock welfare. For example, through integration of Internet of Things (IoT) sensors, and big data, the MooCare predictive model has been developed to assist dairy producers in managing dairy farming, through prediction of milk production [64]. Chicken diseases have been identified and predicted using models developed from big data sets [65]. Digital data from the animals' wearable sensors and livestock husbandry sensing platforms help to create a digital fingerprint that can be exploited in predictive and adaptive decision-making models (Figure 2). The 3 'F's (Footprint, Fingerprint, and Forecast) will not only guide livestock farmers in animal production management but will also help establish integrated application models for the agricultural value, supply, and food chains [66].

4. Blockchain

A blockchain is a decentralized or distributed encrypted transactions ledger, where each transaction creates a node. These nodes are organized into records, known as "blocks", based on consensus from participating parties (peers), and blocks are linked, with unique hash codes, to form a chain. Each time there is a new transaction, another node is created in real time with information about that transaction to

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 dairy cow eats, and track the health of cow	http://www.chitaledairy.com/	India
Porphyrio	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	https://www.bovcontrol.com	United States

(continued on next page)

Table 1 (*continued*)

Company Name	Big Data Technology	Website	Location
	and genetics production; Connects farmers, processors, brands, ranchers, and technical consultants.		
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

contribute to the blockchain [67]. The four pillars of blockchain technology are distributed, transparent, immutable, and democratic. Within livestock agriculture, this means that a unique identification needs to be assigned to each animal at the farm. This unique ID would remain with that animal throughout its existence, to collect data on the farm(s) it has lived in, the transportation used to convey the animal from the farm(s) to the slaughterhouse, the veterinarian checking the animal at the slaughterhouse, the quality check following slaughter, the transport of the meat product, and finally details of the packager and retailer.

Blockchain technology would provide a several important benefits to livestock agriculture, including decentralized, automated transactions that could contribute to more efficient auditing systems for certification and regulatory organizations, system integration, organized records of chain transactions throughout the life of an animal from farm to table and greater traceability and transparency within livestock agriculture [68]. Recently, there has been growing distrust between farmers and consumers due to the demand of transparency of farm products. 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 livestock disease breakouts, such as H1N1 swine flu, Foot-and-Mouth and Mad Cow diseases in Europe, Avian influenza [69], and recent increases in salmonella outbreaks [70]. Consumers also are increasingly concerned about the sustainability and ethical concerns of livestock agriculture and they demand transparency in how food animals are raised. Food safety is also of 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 [72]. Blockchain technology could help trace harmful foods back to the source, increasing traceability and accountability for problematic practices within livestock agriculture [69]. A particular advantage of blockchain technology is that information is shared across a peer network rather than under the control and custody of a single person or group (Figure 3). In the event of a livestock disease outbreak, farmers from around the globe could securely input and access disease data, actively helping to control the outbreak or prepare farmers for an

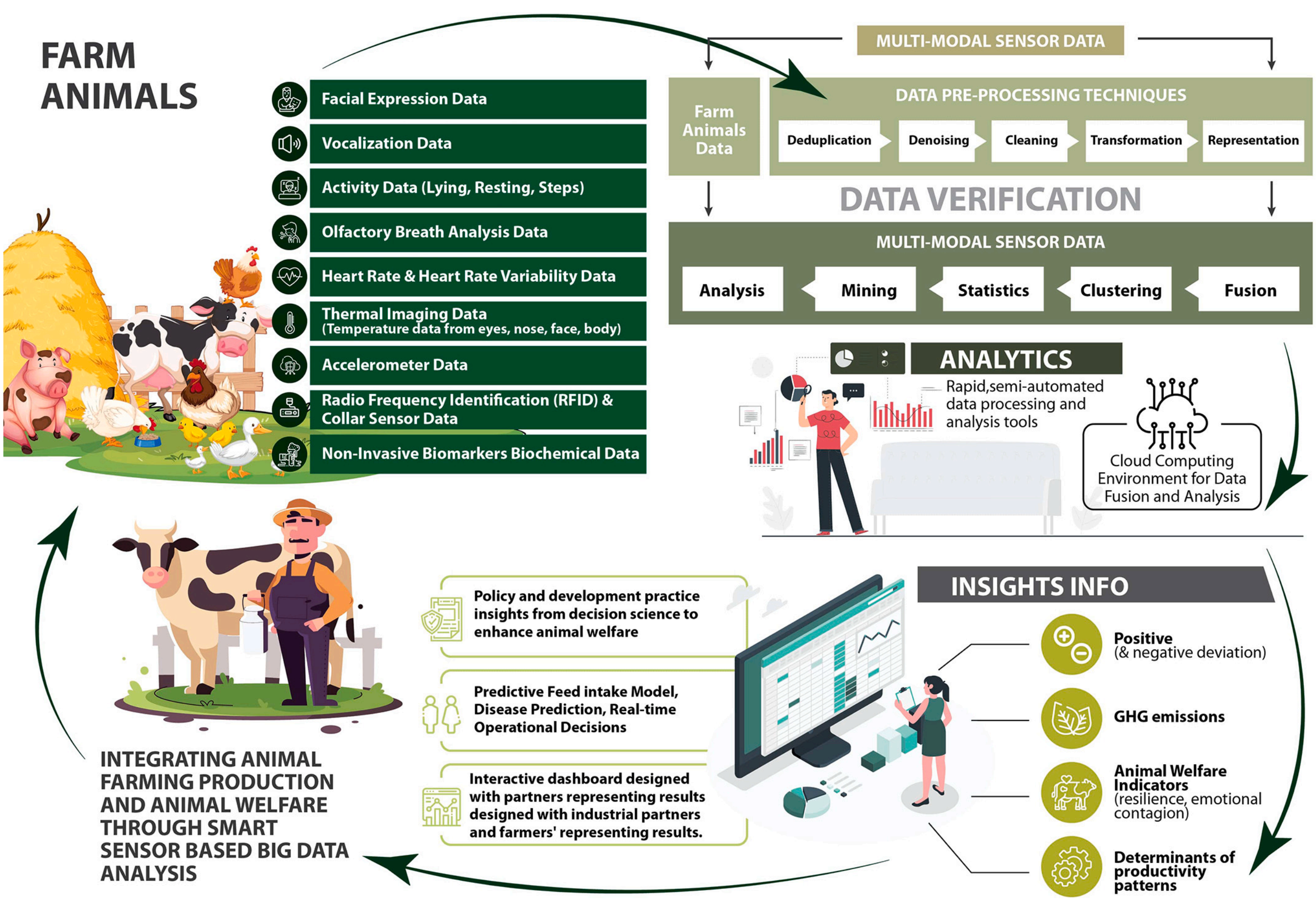

Figure 2. Big Data for Animal Farming: The chain of sensors-based big data applications in precision livestock farming.

outbreak they expect to reach their farm [67].

As food chains and systems become more global, animal products have to remain compliant with numerous animal welfare and sustainability regulations and 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 [71]. As of 2020, livestock agriculture remains one of the world's least digitalized industries, leaving plenty of room for improvement [71]. Digitalization of livestock agriculture, especially through blockchain technology, could provide solutions for the abovementioned issues concerning disease outbreaks and food safety.

Notwithstanding its potential significant benefits, blockchain technology is still in early stages of development for widespread application (Table 2) within the food industry, with only a few studies investigating its impacts on livestock agriculture [68]. Bioengineers and data scientists can play a significant role in formulating appropriate criteria for deciding which type of blockchain solution will be the most beneficial for specific livestock farming sectors.

5. Future trends and needs gaps

Precision livestock farming techniques such as sensors, blockchain technology, and big data analytics can provide significant improvements to environmental sustainability and animal welfare in livestock 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 growing populations [73].

Sensor data have the potential to deliver great improvements for livestock farming, but the primary barriers to installing PLF technologies on farms are the requisite environmental conditions and communications infrastructure. Animal barns have a number of environmental conditions that first need to be addressed in order to successfully implement PLF solutions. These include moisture, dust, ammonia (from dung), and pests [74]. 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 [75]. Oftentimes, the engineers building these technologies have not personally been on farms or worked around livestock, so their sensors may fail in real life farm conditions. Increased collaboration between farmers, animal scientists, bioengineers, and other professionals would help to foster the creation of robust technologies appropriate for long-term operation in the farm environment. Since blockchain technologies and the use of big data analytics are still in their infancy, there are relatively few experts in the discipline and consequently there is a growing need to train an existing and future workforce in these technologies and skills with end user applications in farming [56].

Automated video detection software is largely nonfunctional within livestock agriculture at the moment [42]. Image analysis in swine 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 sufficient period to obtain meaningful information about behaviors of interest. Several 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 [42]. There are issues also with distinguishing animals from the environment background; many video technologies were developed in specific test scenarios where there was good contrast between the pen structures and the animals; so, the technology likely will fail when applied in real-life farm situations [42]. Additionally, many of the studies testing these technologies have been performed on pigs; more work, therefore, is needed to assess the applicability for other species.

Data gathered from sensors on farms allow farmers to monitor their animals to exploit the information they obtain for proactive livestock husbandry. This information also could be shared between farms to improve management or respond to specific animal health, welfare, or environmental issues at the district and regional levels [76]. Large livestock agriculture companies could integrate and mine data from multiple sources, using machine learning, to provide data-driven solutions and help answer questions about prevalent animal husbandry issues.

However, several issues first must be addressed, the most important being data privacy. Farmers typically are protective of their information and would need to trust that the data from their farm will be secure before offering to share it [76]. Additional obstacles to big data integration are lack of technical standards and the proprietary algorithms used by sensor manufacturers. Not only would the manufacturers be reluctant to share their algorithms; however, it may be difficult to compare data coming from sensors built by different manufacturers if the sensors use different protocols, metrics, and frequencies to acquire data [76]. New advances in machine learning are addressing these privacy concerns by developing privacy-preserving data exchange systems.

Still, consumers and farmers alike may be hesitant to implement PLF technologies [74]. Some consumers fear that PLF will contribute to the 'factory farming' aspects of intensive livestock agriculture, where animals are treated like commodities rather than sentient beings [12]. Farmers may also be hesitant due to wariness of technology and a fear that they will be further removed from their animals [9]. The use of technology on farms also has the potential to create inequalities within livestock agriculture, creating socio-economic or socio-cultural tensions and unfairly penalizing workers who are not tech-savvy. There also appears to be gender bias in the implementation of on-farm technologies [9]. Farmers in rural areas may also be placed at a disadvantage due to broadband access [56].

Barriers and potential failures to take advantage of the '3B's' namely the biometric biosensors, big data and blockchain technologies in livestock farming by the smallholder farmers in developing countries include political, social, economic, and organizational factors. Knowledge diffusion, policy advocacy, entrepreneurship, weak interaction among value chain actors is some of the hindrances in the adoption of the technologies in livestock sector [77]. Engaging and promoting livestock entrepreneurs, strengthening the supply chains, boosting payment for ecosystem services are some of the ways to overcome the barriers in technology adoption in the animal farming. Unlocking the potential of new tools and technologies in livestock farming requires social architecture (value propositions, governance models, data stewardship, etc.,) as well as technical architecture (interoperability, semantic web, ontologies, etc.) [78].

To implement PLF on farms, the information, communication, and telecommunications (ICT) industry must address the abovementioned acceptability and accessibility issues, as well as push to create easy-to-use software and data visualization. Achievement of these goals will be key to widespread use of PLF by farmers and veterinarians [56]. The use of cell phones to receive real-time alerts of on-farm issues is currently being implemented on some farms as easy-to-use technology [8]. A comprehensive behavioral approach together with extensive experimental research in livestock systems is possible through the integration of sensors, IoT, blockchain.

The application of Digital Technologies in Livestock Systems will help to investigate thoroughly and fully understand the dynamics and impact of climate change on farm animal ecology. Innovative means and best practices are of paramount importance for effectively tackling emerging transboundary livestock infectious animal diseases, and especially zoonosis (transfer to humans). Digitalization can offer solutions, such as predictive tools for livestock disease prevention, mitigation, and preparedness for pandemic crises.

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 [54]. However, most of the studies and literature on PLF technologies originates from North America and Europe. Farms in developing countries, have unique challenges that cannot be addressed with data and information from North American and European farms. A more globally relevant

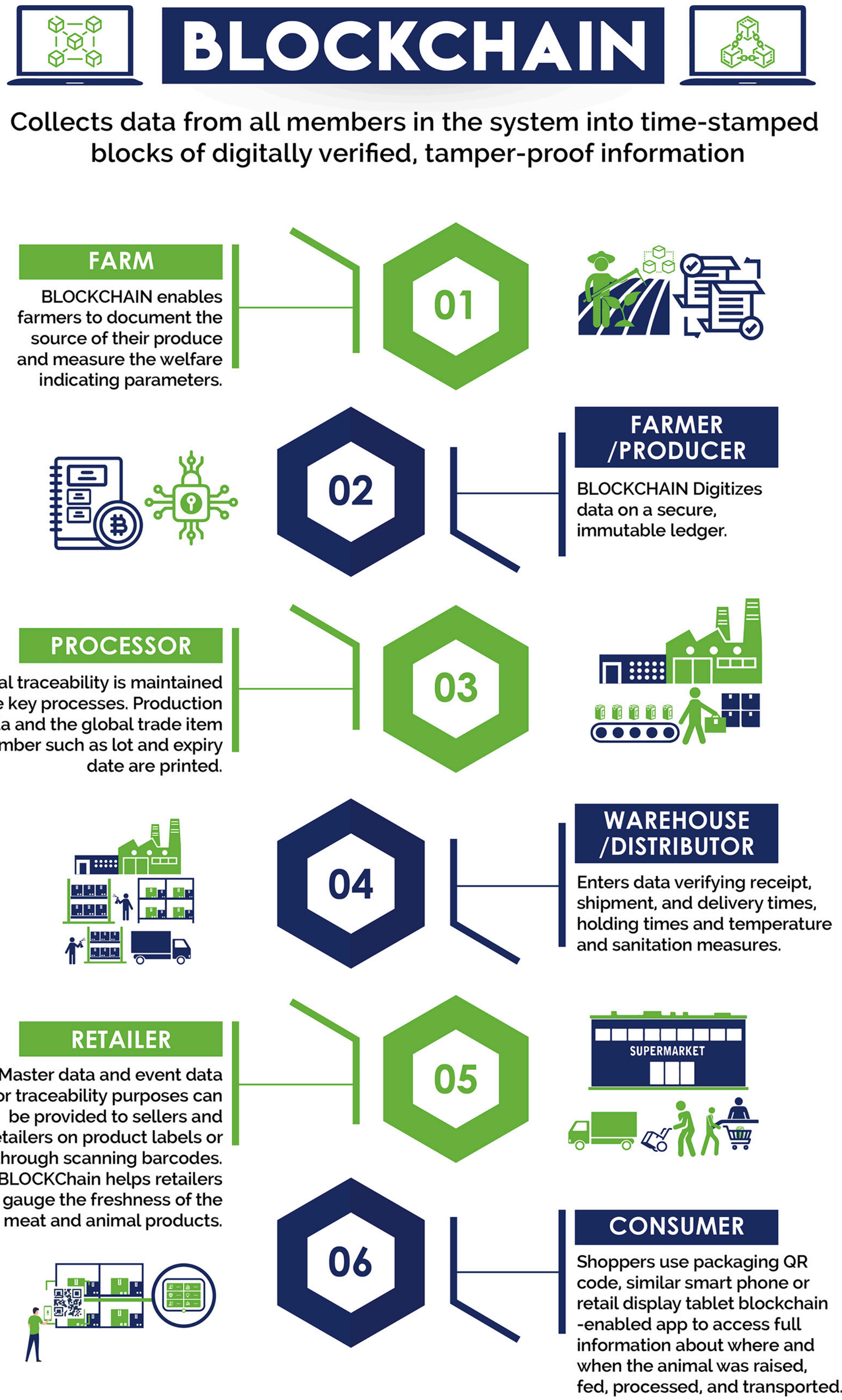

Figure 3. Prairies to Plate: Livestock supply chain depicting origin, storage, and flow of information as the animal products move from the farm and through processing and distribution channels to consumers. Blockchain platform enhances the supply chain visibility, product traceability and build consumer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

Table 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

approach to PLF technologies development therefore is mandated.

6. Conclusions

This critical review paper focused on PLF technologies, that help farmers increase production while addressing consumer concerns, namely biometric and biological sensors, big data, and blockchain technology. Digitalization 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. For example, digitalization of livestock farming offers ways to test and demonstrate systemic innovations in support of the European Green Deal Farm-to-Fork Strategy [79]. Several of the most promising PLFs include biometric and biological sensors, big data, and blockchain technologies. Sensors 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 analytics convert sensor data into meaningful and actionable outputs for farmers. Blockchain technology renders livestock agriculture more transparent and traceable, increasing consumer trust and improving food safety. Of course, no major advances in livestock agriculture come without potential drawbacks, and these require to be identified and addressed. 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. Social and economic transformations contributing to a digitally inclusive and healthy society, as promised through innovation in digitalization solutions for livestock farming, demands participation and involvement from citizens through co-creation of the technology development and validation.

Funding

This research work did not receive any external funding.

Author Contributions

SN conceived the approach, developed, and wrote the paper. BK reviewed the work and provided critical comments. Edited by both SN and BK.

Declaration of Competing Interest

The authors declare no competing interests.

References

[1] FAO (Food and Agriculture Organization of the United Nations), World Livestock 2011 – Livestock in Food Security. Rome. http://reliefweb.int/sites/reliefweb.int/files/resources/Full%20Report_421.pdf, 2011.
[2] UN (United Nations) Department of Economic and Social Affairs, Population Division, World population prospects. https://www.un.org/development/desa/publications/world-population-prospects-2019-highlights.html, 2019.

[3] D.S. Ochs, C.A. Wolf, N.J. Widmar, C. Bir, Consumer perceptions of egg-laying hen housing systems, Poult. Sci. 97 (10) (2018) 3390–3396, https://doi.org/10.3382/ps/pey205.
[4] A. Baldi, D. Gottardo, Livestock Production to Feed the Planet: Animal Protein: A Forecast of Global Demand over the Next Years, Rel.: Beyond Anthropocentrism 5 (2017) 65, https://doi.org/10.7358/rela-2017-001-bald.
[5] A. Helwatkar, D. Riordan, J. Walsh, September. Sensor technology for animal health monitoring, in: 8th international conference on sensing technology, Liverpool, 2014, pp. 266–271.
[6] U. Bernabucci, Climate change: impact on livestock and how can we adapt, Animal Frontiers: the Review Magazine of Anim. Agri. 9(1) (2019) 3.
[7] P.K. Thornton, Livestock production: recent trends, future prospects, Philos. Trans. R. Soc. B. 365 (1554) (2010) 2853–2867, https://doi.org/10.1098/rstb.2010.0134.
[8] S. Neethirajan, Recent advances in wearable sensors for animal health management, Sens Biosensing Res. 12 (2017) 15–29, https://doi.org/10.1016/j.sbsr.2016.11.004.
[9] L. Klerkx, E. Jakku, P. Labarthe, A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda, Njas-Wagen. J. Life Sc. 90 (2019) 100315, doi:10.1016/j.njas.2019.100315.
[10] M. Benjamin, S. Yik, Precision livestock farming in swine welfare: a review for swine practitioners, Animals 9 (4) (2019) 133, https://doi.org/10.3390/ani9040133.
[11] S. Neethirajan, K.V. Ragavan, X. Weng, Agro-defense: Biosensors for food from healthy crops and animals, Trends Food Sci. Technol. 73 (2018) 25–44, https://doi.org/10.1016/j.tifs.2017.12.005.
[12] T. Norton, C. Chen, M.L.V. Larsen, D. Berckmans, Precision livestock farming: building 'digital representations' to bring the animals closer to the farmer, Animal 13 (12) (2019) 3009–3017, https://doi.org/10.1017/S175173111900199X.
[13] M. Jorquera-Chavez, S. Fuentes, F.R. Dunshea, E.C. Jongman, R.D. Warner, Computer vision and remote sensing to assess physiological responses of cattle to pre-slaughter stress, and its impact on beef quality: A review, Meat. Sci. 156 (2019) 11–22, https://doi.org/10.1016/j.meatsci.2019.05.007.
[14] E.D. Ellen, M. Van Der Sluis, J. Siegford, O. Guzhva, M.J. Toscano, J. Bennewitz, L. E. Van Der Zande, J.A. Van Der Eijk, E.N. de Haas, T. Norton, D. Piette, Review of sensor technologies in animal breeding: Phenotyping behaviors of laying hens to select against feather pecking, Animals 9 (3) (2019) 108, https://doi.org/10.3390/ani9030108.
[15] J.E. Koltes, D.A. Koltes, B.E. Mote, J. Tucker, D.S. Hubbell III, Automated collection of heat stress data in livestock: new technologies and opportunities, Transl. Anim. Sci. 2 (3) (2018) 319–323, https://doi.org/10.1093/tas/txy061.
[16] B. Martinez, J.K. Reaser, A. Dehgan, B. Zamft, D. Baisch, C. McCormick, A. J. Giordano, R. Aicher, S. Selbe, Technology innovation: advancing capacities for the early detection of and rapid response to invasive species, Biol. Invasions 22 (1) (2020) 75–100, https://doi.org/10.1007/s10530-019-02146-y.
[17] P. Joosen, T. Norton, J. Marchant-Forde, D. Berckmans, Animal welfare monitoring by real-time physiological signals, Precision Livestock Farming'19 (2019) 337–344.
[18] L. Nie, D. Berckmans, C. Wang, B. Li, Is Continuous Heart Rate Monitoring of Livestock a Dream or Is It Realistic? A Review, Sensors 20 (8) (2020) 2291, https://doi.org/10.3390/s20082291.
[19] A. Mahdavian, S. Minaei, C. Yang, F. Almasganj, S. Rahimi, P.M. Marchetto, Ability evaluation of a voice activity detection algorithm in bioacoustics: A case study on poultry calls, Comput. Electron. Agric. 168 (2020) 105100, https://doi.org/10.1016/j.compag.2019.105100.
[20] M. Marsot, J. Mei, X. Shan, L. Ye, P. Feng, X. Yan, C. Li, Y. Zhao, An adaptive pig face recognition approach using Convolutional Neural Networks, Comput. Electron. Agric. 173 (2020) 105386, https://doi.org/10.1016/j.compag.2020.105386.
[21] A.V. Viscardi, M. Hunniford, P. Lawlis, M. Leach, P.V. Turner, Development of a piglet grimace scale to evaluate piglet pain using facial expressions following castration and tail docking: a pilot study, Front. Vet. Sci. 4 (2017) 51, https://doi.org/10.3389/fvets.2017.00051.
[22] B.R. Müller, V.S. Soriano, J.C.B. Bellio, C.F.M. Molento, Facial expression of pain in Nellore and crossbred beef cattle, J. Vet. Behav. 34 (2019) 60–65, https://doi.org/10.1016/j.jveb.2019.07.007.
[23] I. Camerlink, E. Coulange, M. Farish, E.M. Baxter, S.P. Turner, Facial expression as a potential measure of both intent and emotion, Sci. Rep. 8 (1) (2018) 1–9, https://doi.org/10.1038/s41598-018-35905-3.
[24] N.A. Mungroo, S. Neethirajan, Biosensors for the detection of antibiotics in poultry industry—a review, Biosensors 4 (4) (2014) 472–493, https://doi.org/10.3390/bios4040472.
[25] S.R. Ahmed, É. Nagy, S. Neethirajan, Self-assembled star-shaped chiroplasmonic gold nanoparticles for an ultrasensitive chiro-immunosensor for viruses, RSC Adv. 7 (65) (2017) 40849–40857, https://doi.org/10.1039/C7RA07175B.
[26] S.R. Ahmed, J. Mogus, R. Chand, E. Nagy, S. Neethirajan, Optoelectronic fowl adenovirus detection based on local electric field enhancement on graphene quantum dots and gold nanobundle hybrid, Biosens. Bioelectron. 103 (2018) 45–53, https://doi.org/10.1016/j.bios.2017.12.028.
[27] X. Weng, S. Neethirajan, Immunosensor based on antibody-functionalized MoS 2 for rapid detection of avian coronavirus on cotton thread, IEEE Sens. J. 18 (11) (2018) 4358–4363, https://doi.org/10.1109/JSEN.2018.2829084.
[28] R. Chand, Y.L. Wang, D. Kelton, S. Neethirajan, Isothermal DNA amplification with functionalized graphene and nanoparticle assisted electroanalysis for rapid detection of Johne's disease, Sens. Actuators B Chem. 261 (2018) 31–37, https://doi.org/10.1016/j.snb.2018.01.140.
[29] S.K. Tuteja, S. Neethirajan, Exploration of two-dimensional bio-functionalized phosphorene nanosheets (black phosphorous) for label free haptoglobin electro-immunosensing applications, Nanotech. 29 (13) (2018) 135101, https://doi.org/10.1088/1361-6528/aaab15.
[30] V. Röttgen, P.C. Schön, F. Becker, A. Tuchscherer, C. Wrenzycki, S. Düpjan, B. Puppe, Automatic recording of individual oestrus vocalisation in group-housed dairy cattle: development of a cattle call monitor, animal 14 (1) (2020) 198–205, https://doi.org/10.1017/S1751731119001733.
[31] S.K. Tuteja, S. Neethirajan, A highly efficient 2D exfoliated metal dichalcogenide for the on-farm rapid monitoring of non-esterified fatty acids, Chem. Commun. 53 (2017) 100002, https://doi.org/10.1039/C7CC04894G.
[32] X. Weng, L. Chen, S. Neethirajan, T. Duffield, Development of quantum dots-based biosensor towards on-farm detection of subclinical ketosis, Biosens. Bioelectron. 72 (2015) 140–147, https://doi.org/10.1016/j.bios.2015.05.008.
[33] S.K. Tuteja, T. Duffield, S. Neethirajan, Liquid exfoliation of 2D MoS 2 nanosheets and their utilization as a label-free electrochemical immunoassay for subclinical ketosis, Nanoscale 9 (30) (2017) 10886–10896, https://doi.org/10.1039/C7NR04307D.
[34] M. Veerapandian, R. Hunter, S. Neethirajan, Ruthenium dye sensitized graphene oxide electrode for on-farm rapid detection of beta-hydroxybutyrate, Sens. Actuators B Chem. 228 (2016) 180–184, https://doi.org/10.1016/j.snb.2016.01.028.
[35] S.K. Tuteja, T. Duffield, S. Neethirajan, Graphene-based multiplexed disposable electrochemical biosensor for rapid on-farm monitoring of NEFA and βHBA dairy biomarkers, J. Mater. Chem. B. 5 (33) (2017) 6930–6940, https://doi.org/10.1039/C7TB01382E.
[36] H. Jang, S.R. Ahmed, S. Neethirajan, GryphSens: A smartphone-based portable diagnostic reader for the rapid detection of progesterone in milk, Sensors 17 (5) (2017) 1079, https://doi.org/10.3390/s17051079.
[37] J. Werner, C. Umstatter, L. Leso, E. Kennedy, A. Geoghegan, L. Shalloo, M. Schick, B. O'Brien, Evaluation and application potential of an accelerometer-based collar device for measuring grazing behavior of dairy cows, Animal 13 (9) (2019) 2070–2079, https://doi.org/10.1017/S1751731118003658.
[38] L.R. Williams, S.T. Moore, G.J. Bishop-Hurley, D.L. Swain, A sensor-based solution to monitor grazing cattle drinking behaviour and water intake, Comput. Electron. Agric. 168 (2020) 105141, https://doi.org/10.1016/j.compag.2019.105141.
[39] R. Munoz-Tamayo, J.R. Agudelo, R.J. Dewhurst, G. Miller, T. Vernon, H. Kettle, A parsimonious software sensor for estimating the individual dynamic pattern of methane emissions from cattle, animal. 13 (6) (2019) 1180–1187, https://doi.org/10.1017/S1751731118002550.
[40] H. Buller, H. Blokhuis, P. Jensen, L. Keeling, Towards farm animal welfare and sustainability, Animals 8 (6) (2018) 81, https://doi.org/10.3390/ani8060081.
[41] M. Friel, H.P. Kunc, K. Griffin, L. Asher, L.M. Collins, Positive and negative contexts predict duration of pig vocalisations, Sci. rep. 9 (1) (2019) 1–7, https://doi.org/10.1038/s41598-019-38514-w.
[42] K. Wurtz, I. Camerlink, R.B. D'Eath, A.P. Fernández, T. Norton, J. Steibel, J. Siegford, Recording behaviour of indoor-housed farm animals automatically using machine vision technology: A systematic review, PloS one 14 (12) (2019), e0226669, https://doi.org/10.1371/journal.pone.0226669.
[43] E.A. Andrianov, A.N. Sudakov, A.A. Andrianov, N.Y. Skolznev, Non-invasive monitoring of avian embryo heart rate, J. Anim. Behav. Biometeorol. 7 (3) (2019) 119–122, https://doi.org/10.31893/2318-1265jabb.v7n3p119-122.
[44] A. Phuphanin, L. Sampanporn, B. Sutapun, Smartphone-Based Device for Non-Invasive Heart-Rate Measurement of Chicken Embryos, Sensors 19 (22) (2019) 4843, https://doi.org/10.3390/s19224843.
[45] V. Bloch, N. Barchilon, I. Halachmi, S. Druyan, Automatic broiler temperature measuring by thermal camera, Biosyst. Eng. (2019), https://doi.org/10.1016/j.biosystemseng.2019.08.011.
[46] A. Khaliduzzaman, S. Fujitani, A. Kashimori, T. Suzuki, Y. Ogawa, N. Kondo, A non-invasive diagnosis technique of chick embryonic cardiac arrhythmia using near infrared light, Comput. Electron. Agric. 158 (2019) 326–334, https://doi.org/10.1016/j.compag.2019.02.014.
[47] X. Du, L. Carpentier, G. Teng, M. Liu, C. Wang, T. Norton, Assessment of laying hens' thermal comfort using sound technology, Sensors 20 (2) (2020) 473, https://doi.org/10.3390/s20020473.
[48] X. Du, F. Lao, G. Teng, A sound source localisation analytical method for monitoring the abnormal night vocalisations of poultry, Sensors 18 (9) (2018) 2906, https://doi.org/10.3390/s18092906.
[49] A. Nasirahmadi, J. Gonzalez, B. Sturm, O. Hensel, U. Knierim, Pecking activity detection in group-housed turkeys using acoustic data and a deep learning technique, Biosyst. Eng. 194 (2020) 40–48, https://doi.org/10.1016/j.biosystemseng.2020.03.015.
[50] L. Carpentier, E. Vranken, D. Berckmans, J. Paeshuyse, T. Norton, Development of sound-based poultry health monitoring tool for automated sneeze detection, Comput. Electron. Agric. 162 (2019) 573–581, https://doi.org/10.1016/j.compag.2019.05.013.
[51] L. Liu, B. Li, R. Zhao, W. Yao, M. Shen, J. Yang, A Novel Method for Broiler Abnormal Sound Detection Using WMFCC and HMM, J. Sensors 2985478 (2020), https://doi.org/10.1155/2020/2985478.
[52] N. Li, Z. Ren, D. Li, L. Zeng, Automated techniques for monitoring the behaviour and welfare of broilers and laying hens: towards the goal of precision livestock farming, Animal 14 (3) (2020) 617–625, https://doi.org/10.1017/S1751731119002155.

[53] X. Du, T. Guanghui, F. Lao, X. Du, Fusion of depth image and sound analysis for monitoring poultry behaviors, ISAEW (2017) 421–427.
[54] S. Wolfert, L. Ge, C. Verdouw, M.J. Bogaardt, Big data in smart farming–a review, Agric. Syst. 153 (2017) 69–80, https://doi.org/10.1016/j.agsy.2017.01.023.
[55] G. Morota, R.V. Ventura, F.F. Silva, M. Koyama, S.C. Fernando, Big data analytics and precision animal agriculture symposium: machine learning and data mining advance predictive big data analysis in precision animal agriculture, J. Anim. Sci. 96 (4) (2018) 1540–1550, https://doi.org/10.1093/jas/sky014.
[56] J.E. Koltes, J.B. Cole, R. Clemmens, R.N. Dilger, L.M. Kramer, J.K. Lunney, M.E. McCue, S.D. McKay, R.G. Mateescu, B.M. Murdoch, R. Reuter, A vision for development and utilization of high-throughput phenotyping and big data analytics in livestock, Front. Genet. 10 (2019) 1197, doi:10.3389%2Ffgene.2019.01197.
[57] C. Piñeiro, J. Morales, M. Rodríguez, M. Aparicio, E.G. Manzanilla, Y. Koketsu, Big (pig) data and the internet of the swine things: a new paradigm in the industry, Anim. Front. 9 (2) (2019) 6–15, https://doi.org/10.1093/af/vfz002.
[58] Y. Sasaki, Detection and prediction of risk factors associated with production losses using production records on commercial pig farms. Food Agricultural Policy Platform Article (2019). Accessed on June 7, 2020 on: http://ap.fftc.agnet.org/ap_db.php?id=1066.
[59] K. VanderWaal, R.B. Morrison, C. Neuhauser, C. Vilalta, A.M. Perez, Translating big data into smart data for veterinary epidemiology, Front. Vet. Sci. 4 (2017) 110, https://doi.org/10.3389/fvets.2017.00110.
[60] M. Ebrahimi, M. Mohammadi-Dehcheshmeh, E. Ebrahimie, K.R. Petrovski, Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: Deep Learning and Gradient-Boosted Trees outperform other models, Comput. Biol. Med. 114 (2019) 103456, https://doi.org/10.1016/j.compbiomed.2019.103456.
[61] M. Taneja, J. Byabazaire, N. Jalodia, A. Davy, C. Olariu, P. Malone, Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle, Comput. Electron. Agric. 171 (2020) 105286, https://doi.org/10.1016/j.compag.2020.105286.
[62] D. Warner, E. Vasseur, D.M. Lefebvre, R. Lacroix, A machine learning based decision aid for lameness in dairy herds using farm-based records, Comput. Electron. Agric. 169 (2020) 105193, https://doi.org/10.1016/j.compag.2019.105193.
[63] V.C.F. Aiken, J.R.R. Dórea, J.S. Acedo, F.G. de Sousa, F.G. Dias, G.J. de Magalhães Rosa, Record linkage for farm-level data analytics: Comparison of deterministic, stochastic and machine learning methods, Comput. Electron. Agric. 163 (2019) 104857, doi:10.1016/j.compag.2019.104857.
[64] R. da Rosa Righi, G. Goldschmidt, R. Kunst, C. Deon, C.A. da Costa, Towards combining data prediction and internet of things to manage milk production on dairy cows, Comput. Electron. Agric. 169 (2020) 105156, doi:10.1016/j.compag.2019.105156.
[65] M. Gulyaeva, F. Huettmann, A. Shestopalov, M. Okamatsu, K. Matsuno, D.H. Chu, Y. Sakoda, A. Glushchenko, E. Milton, E. Bortz, Data mining and model-predicting a global disease reservoir for low-pathogenic Avian Influenza (A) in the wider pacific rim using big data sets, Sci. rep. 10 (1) (2020) 1–11, https://doi.org/10.1038/s41598-020-73664-2.
[66] C.T. Lu, J.R. Tsay, T.C. Tu, Application of Common Information Platform to Foster Data-Driven Agriculture in Taiwan, Food Agri. Policy Plat. Art. (2020), Accessed on June 7, 2020 on: http://ap.fftc.agnet.org/ap_db.php?id=1073.
[67] V.K. Chattu, A. Nanda, S.K. Chattu, S.M. Kadri, A.W. Knight, The emerging role of blockchain technology applications in routine disease surveillance systems to strengthen global health security, BDCC 3 (2) (2019) 25, https://doi.org/10.3390/bdcc3020025.
[68] V.V. Picchi, E.F. de Castro, F.C. Marino, S.L. Ribeiro, ICBTA, Increasing the Confidence of the Brazilian Livestock Production Chain using Blockchain, 2019, pp. 93–98, https://doi.org/10.1145/3376044.3376058.
[69] J. Lin, Z. Shen, A. Zhang, Y. Chai, Blockchain and IoT based food traceability for smart agriculture, in: Proceedings of the 3rd Int. Con. on Crowd Sci. and Eng, 2018, pp. 1–6.
[70] A. Dyda, P.Y. Nguyen, A. Chughtai, C.R. MacIntyre, Changing epidemiology of Salmonella outbreaks associated with cucumbers and other fruits and vegetables, Global Biosecurity, in: 1(3), 2020, https://doi.org/10.31646/gbio.49.
[71] G.A. Motta, B. Tekinerdogan, I.N. Athanasiadis, Blockchain Applications in the Agri-Food Domain: The First Wave, Front. Blockchain. 3 (2020) 6, https://doi.org/10.3389/fbloc.2020.00006.
[72] World Health Organization, Food Safety. https://www.who.int/news-room/fact-sheets/detail/food-safety, 2020 (Accessed 6th June, 2020).
[73] R.S. Alonso, I. Sittón-Candanedo, Ó. García, J. Prieto, S. Rodríguez-González, An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario, Ad Hoc Netw. 98 (2020) 102047, https://doi.org/10.1016/j.adhoc.2019.102047.
[74] M.O. Vaintrub, H. Levit, M. Chincarini, I. Fusaro, M. Giammarco, G. Vignola, Precision livestock farming, automats and new technologies: possible applications in extensive dairy sheep farming, Animal (2020), https://doi.org/10.1016/j.animal.2020.100143, 100143.
[75] X. Chuanzhong, W. Pei, Z. Lina, M. Yanhua, L. Yanqiu, Compressive sensing in wireless sensor network for poultry acoustic monitoring, Int, J. Agric. Biol. Eng. 10 (2) (2017) 94–102, https://doi.org/10.3965/J.IJABE.20171002.2148.
[76] F. Papst, O. Saukh, K. Römer, F. Grandl, I. Jakovljevic, F. Steininger, M. Mayerhofer, J. Duda, C. Egger-Danner, Embracing Opportunities of Livestock Big Data Integration with Privacy Constraints, In Proceedings of the 9th International Conference on the Internet of Things (2019) 1–4.
[77] E. Kebebe, Bridging technology adoption gaps in livestock sector in Ethiopia: A innovation system perspective, Tech. Soc. 57 (2019) 30–37, https://doi.org/10.1016/j.techsoc.2018.12.002.
[78] J.M. Antle, J.W. Jones, C.E. Rosenzweig, Next generation agricultural system data, models and knowledge products: Introduction, Agri. Sys. 155 (2017) 186–190, https://doi.org/10.1016/j.agsy.2016.09.003.
[79] Farm to Fork Strategy – for a fair, healthy and environmentally-friendly food system, https://ec.europa.eu/food/farm2fork_en (Accessed 9th December 2020).