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Review Article

Digital Transformation of Livestock Farming for Sustainable Development

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Abstract:
With the increasing global population, livestock farming must adapt to respond to the growing demands for food while increasing productivity more efficiently. At the same time, worries about animal welfare, environmental sustainability, and public health must be addressed. The objective of this article is to present an overview of recent developments in using biometric devices, big data, and blockchain technology to digitize animal husbandry in Precision Livestock Farming (PLF). Biometric sensors are devices that monitor the health and behavior of an individual animal. Farmers may use this information for doing population-level analysis. Big data analytics systems use statistical algorithms to analyze large and complex data sets, identifying relevant trending patterns and providing guidance on decisions for farmers. These systems analyze and combine data from biometric sensors. Blockchain technology with sensors makes it safe and easy to track animal products from the farm to the table. This is an effective way to monitor disease outbreaks, prevent economic losses, and mitigate food-related health pandemics. The adoption of PLF technologies throughout the livestock sector can help to achieve sustainable development.

Keywords: livestock; digitalization; technology; sustainability

1. Introduction

The predicted worldwide human population is expected to exceed 9 billion by 2050, representing an increase of nearly 2 billion compared to the current population. The population expansion will predominantly take place in developing countries. The rise in population and accelerated development in these nations will lead to a surge in the demand for animal products (Raihan & Himu, 2023). Livestock production in developing countries offers reliable food sources, employment, and prospects for enhanced revenue. A significant portion of the demand for animal products will be satisfied through domestic production. Nevertheless, despite the increasing population and the rising need for animal protein, consumers are displaying heightened apprehension regarding the adverse effects of livestock production on the environment, public health, and animal welfare (Ochs et al., 2018). As water and land resources are becoming insufficient, livestock farmers will have to find ways to increase productivity while using their limited resources in a sustainable manner (Baldi & Gottardo, 2017).

Furthermore, there is a significant shift in societal views, particularly among consumers, which intensifies the need for responsible research and innovation to address urgent issues in livestock production using circular and sustainable approaches (Himu & Raihan, 2023). The process of digitalization will contribute to the advancement of theseobjectives.

Utilizing digital technologies in livestock farming will provide a comprehensive investigation and complete comprehension of the dynamics and consequences of climate change on farm animal ecology (Raihan, 2023a). Effective management of new transboundary livestock infectious animal diseases, particularly zoonosis (transmission to humans), relies heavily on the implementation of innovative strategies and best practices. Digitalization can provide solutions, such as prediction tools for preventing, mitigating, and preparing for animal diseases and pandemic emergencies (Raihan, 2023b).

In order to satisfy the increasing need for animal protein while also addressing issues regarding environmental sustainability, public health, and animal welfare, farmers and animal scientists may increasingly depend on Precision Livestock Farming (PLF) technologies to digitize the practice of livestock agriculture. This research study explores the utilization of PLF technologies, including biometric sensors, big data, and blockchain technology, to enhance livestock production, specifically in terms of enhancing animal health and well-being. Figure 1 presents the utilization of PLF technologies in livestock production.

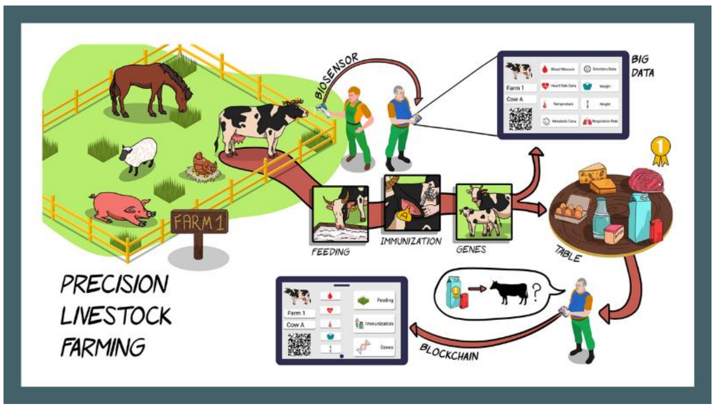

Figure 1: The utilization of PLF technologies in livestock production (Neethirajan & Kemp, 2021).

2. Current trends in livestock farming:

Over the past decade, major improvements have been made in various areas such as automated feeding systems, milking robots, waste management, and optimizing production efficiency through the use of instruments, animal breeding, genetics, and nutrition. Despite this progress, there are still major obstacles that exist. Intensive livestock management is important to satisfy the growing need for animal products. However, the compact and congested conditions of livestock houses create challenges for farmers in monitoring the health and well-being of the animals (Helwatkar et al., 2014). The increasing effects of climate change will increase the vulnerability of livestock animals to diseases, heat stress, and other health risks (Bernabucci, 2019; Raihan, 2023c). Consequently, there will be an increased need to quickly identify health problems and disease outbreaks, understand how diseases spread, and implement preventive actions to mitigate significant economic damages (Thornton, 2010; Raihan, 2023d). The increasing concerns over animal welfare, transparency, and environmental sustainability (Raihan, 2023e), along with these issues, have resulted in a rising interest in the digitalization of livestock agriculture using PLF technologies (Klerkx et al., 2019).

The PLF technologies apply process engineering techniques to automate livestock agriculture. This allows farmers to efficiently monitor the well-being and health of large animal populations, quickly identify problems with specific animals, and even predict possible problems by analyzing past data (Benjamin & Yik, 2019). Recent developments in PLF technologies include various uses. Such as the monitoring of cow behavior, the detection of vocalizations such as screams in pigs, the monitoring of coughs in various animals to identify respiratory illnesses, and the detection of bovine pregnancy by changes in body temperature. PLF technologies may help farmers in monitoring infectious diseases in livestock agriculture, hence increasing food safety and availability. Implementing PLF technology will eventually improve animal well-being and minimize food safety problems while increasing resource utilization (Norton et al., 2019).

3. Challenges to traditional livestock business:

The primary obstacles in effectively monitoring animal welfare are three fundamental elements: cost, reliability, and timing of observations. The majority of existing strategies are defined as being time-consuming, requiring a significant amount of labor, and hence, being expensive (Jorquera-Chavez et al., 2019). Livestock farmers frequently depend on stockpeople's observations to identify health and welfare issues. However, numerous commercial facilities have a significant imbalance between the number of stockpeople and the number of animals. For instance, on a commercial pig farm, the ratio of stockpersons to pigs is often 1:300 (Benjamin & Yik, 2019). Even the most attentive and highly skilled stockpeople may fail to notice animals in a critical state. Third-party auditing programs provide detailed assessments of animal care, but they are frequently expensive and time-consuming.

Implementing PLF technologies, namely biometric sensors, would enable farmers to monitor the well-being of animals in real time with accuracy, objectivity, and regularity. This would facilitate the early detection of problems and the timely implementation of preventive actions to avoid serious failures. PLF technologies provide non-intrusive sampling, enabling farmers and researchers to gather accurate measurements that can be utilized to solve welfare issues (Jorquera-Chavez et al., 2019). PLF technologies have the potential to reduce the use of resources. By adopting a proactive and customized approach to animal health, the reliance on drugs, especially antibiotics, might be significantly reduced.

Consumers' growing concern with the sustainability (Raihan, 2024) and welfare of animal products has led to an increased need for transparency from livestock farmers. Blockchain technology enables farmers to establish transparency with consumers about the food, without putting additional time requirements on the farmers. The time saved in this context might be more effectively utilized to oversee matters about animal welfare, public safety, and environmental sustainability (Benjamin & Yik, 2019).

4. Biometric sensing:

Biometric sensors monitor the behavioral and physiological characteristics of livestock, enabling farmers to assess the health and well-being of an animal over some time. Currently, there is a diverse range of biometric sensors available, which can be categorized as either non-invasive or invasive. Adaptable non-invasive sensors for barn monitoring include surveillance cameras and sensors added to feeding systems for monitoring animal weight and feed consumption. Non-invasive sensors include several sensors that can be easily attached to animals, including pedometers, GPS (global positioning system), and MEMS (micro-electromechanical) based activity sensors. These sensors are utilized for monitoring and tracking animal behavior (Helwatkar et al., 2014). Less frequently explored in livestock, invasive sensors are typically ingested or implanted in an animal. These sensors are beneficial for monitoring internal physiological indicators in dairy cows, such as rumen health, body temperature, and vaginal pressure (Helwatkar et al., 2014).

The livestock business has implemented biometric sensor technologies to efficiently monitor a larger number of animals without requiring more time or staff. This allows the industry to get accurate and unbiased measurements of animal health and wellbeing (Helwatkar et al., 2014). The sensors gather data which is ultimately saved in databases and analyzed by algorithms - sets of instructions or calculations that are conducted sequentially to address specific problems. Livestock biometric sensors utilize advanced algorithms to analyze raw sensor data and generate biologically significant information. This includes metrics such as the duration of various behaviors exhibited by animals on a given day, as well as variations in activity levels over specific time intervals (Benjamin & Yik, 2019). These sensors may additionally monitor behaviors within specified criteria and notify farmers when an animal's behavior differs from normal levels, enabling them to inspect the animal and take appropriate action to enhance its health and well-being. The combination of biometric sensors with big data analytics, artificial intelligence, and bioinformatics technologies, such as those used for genomics, has the potential to detect animals with desirable characteristics and help with their selection for breeding programs (Ellen et al., 2019).

There is a predicted increase in the use of biometric sensors in the livestock farming and animal health industries throughout the next decade. These advantages come from their ability to provide real-time results, high accuracy, and the capacity to gather huge amounts of data. Acquiring information about animal wellbeing at the earliest possible stage enables quick action and often reduces the need for additional treatments. Thermal infrared (TIR) imaging can be used as an alternative to invasive thermometers that involve restriction and control of animals, to monitor their body temperatures. Thermal infrared imaging (TIR) of the eye region and overall skin temperature can be used to monitor stress levels and identify diseases sooner than previous methods, typically by 4-6 days (Koltes et al., 2018). This allows for timely treatment and reduces the risk of disease spreading across groups of animals, such as flocks or herds (Martinez et al., 2020). The main non-invasive sensors employed for monitoring livestock animals include thermometers, accelerometers, radio-frequency identification (RFID) tags, microphones, and cameras. These devices enable farmers to observe and monitor the temperature, activity levels, sound levels in the barn (such as vocalizations, sneezing, and coughing), and specific behaviors (such as aggression in pigs) (Benjamin & Yik, 2019).

Thermometers, in conjunction with physiological sensors such as TIR and heart rate monitors, can measure stress levels in animals before they are slaughtered. These measurements can then be compared with meat quality indicators to improve the uniformity and excellence of consumer products (Jorquera-Chavez et al., 2019). By using biometric sensors, researchers can immediately identify fluctuations in heart rate about both positive (eustress) and negative stressors. They can also compare individual responses among animals and monitor how heart rate changes over time as a result of various stresses. During an experiment with pigs, the presence of a negative stressor resulted in a temporary increase in heart rate for one minute after exposure to a loud noise. Providing a positive stressor, such as a towel to play with, resulted in an increased heart rate that lasted for two minutes. Conventional or indirect indicators of welfare may lack the ability to identify these complex variations (Joosen et al., 2019). Heart rate monitors are valuable tools for measuring both overall health and metabolic energy generation. Biometric sensors, such as photoplethysmographic sensors, can be easily attached to ear tags or other body areas to provide continuous monitoring of livestock heart rates (Nie et al., 2020).

Livestock farmers are increasingly using RFID devices, which can be attached to ear tags and collars or placed under the skin, to monitor a diverse range of behaviors including overall activity, feeding, and drinking. Utilizing microphones, acoustic analysis enables monitoring of vocalizations and coughing, providing early detection of welfare concerns for farmers. Microphones possess the benefit of effortless and discreet installation in barns to monitor sizable animal populations (Mahdavian et al., 2020). Similarly, cameras may be easily placed in barns and utilized to record a diverse range of practical information. Video image algorithms can identify changes in animals' posture, which may act as an indication of lameness and other health issues (Jorquera-Chavez et al., 2019). Camera image analysis enables the monitoring of animal weight, movement, water consumption, individual identification, and aggression (Norton et al., 2019).

Automated animal welfare monitoring is increasingly focused on the development of facial detection technology. Facial recognition technologies utilize machine learning algorithms to identify specific features on an animal's face, enabling the identification of individuals or the monitoring of changes associated with emotional states (Marsot et al., 2020). A group of animal welfare researchers are now working on the development of "grimace scales" for animals. These scales aim to help stockpeople effectively monitor the emotional states of animals, specifically focusing on pain (Viscardi et al., 2017). Livestock animals often undergo distressing operations such as dehorning, tail docking, and castration (Viscardi et al., 2017; Müller et al., 2019). Facial expression analysis can accurately identify behavioral intent in animals. Pigs that display aggression show noticeable facial variations compared to those that decrease or avoid violence (Camerlink et al., 2018). Facial detection has been suggested as a more economical substitute for RFID tags in identifying individual animals (Marsot et al., 2020).

Biometric sensors play a crucial role in mitigating the effects and transmission of diseases. These sensors are capable of monitoring temperature fluctuations, behavioral patterns, sound levels, and physiological indicators such as pH levels, metabolic activity, pathogens, and the detection of toxins or antibiotics within the body. The overutilization of antibiotics in cattle farming is presently a significant issue with severe consequences for human health (Himu & Raihan, 2023). The ability to detect the presence of antibiotics enables farmers to provide treatment to animals for illnesses, while simultaneously ensuring the production of safe and nutritious animal products for the world population. Biosensing technologies can be employed to identify harmful infections, including avian influenza, coronavirus, and Johne's disease. Johne's disease is a harmful bacterial illness in ruminants that can lead to significant financial losses for farmers. Biometric sensors are capable of detecting indicators associated with inflammation, enabling the monitoring of diseases on a large scale. For example, thermal infrared imaging (TIR) can be used to identify foot diseases by analyzing images of feet (Jorquera-Chavez et al., 2019). Figure 2 presents the applications of biosensors in livestock production.

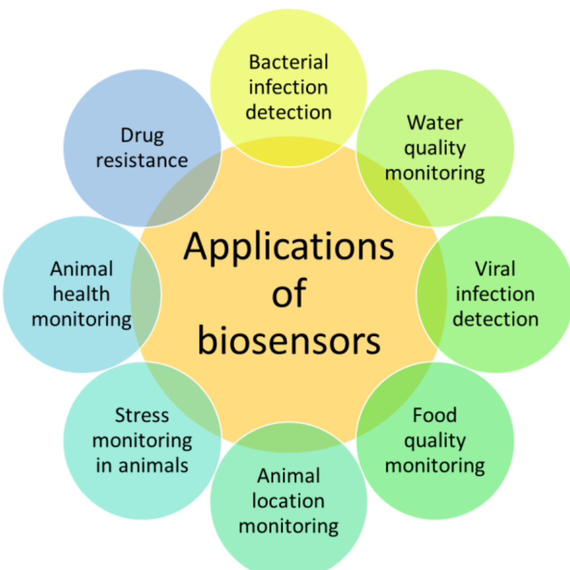

Figure 2: Applications of biosensors in livestock production.

5. Big data analytics and machine learning:

The utilization of biometric sensors and biosensors in monitoring the well-being and condition of livestock generates huge amounts of data that need processing and analysis to produce useful information for animal management. This has resulted in progress in the field of big data analytics, which involves obtaining and examining extensive and intricate datasets (Wolfert et al., 2017; Raihan, 2023f). Big data refers to data sets that are defined by a vast number of rows and columns, making it difficult to visually examine the data. Additionally, these data sets often contain numerous variables or predictors, which makes them complex and inappropriate for typical statistical procedures (Morota et al., 2018). 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 (Wolfert et al., 2017; Koltes et al., 2019).

The PLF technologies utilize advanced data analytics and modeling to provide managers with accurate information regarding dietary requirements, reproductive conditions, and decreasing productivity patterns, which may suggest potential concerns related to animal health and welfare. Big data models analyze data collected from sensors to detect abnormalities that may impact 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 (Koltes et al., 2019). The data from sensors can be categorized into two types: animal-oriented data, which focuses on the characteristics of the animals (phenotype), and environment-oriented data, which focuses on the characteristics of the surroundings. It is important to monitor both of these data types at the same time as they both affect the health and productivity of animals. The utilization of animal and environmental data in the digitalization of livestock agriculture has the potential to enhance various aspects such as health management, nutrition, genetics, reproduction, welfare, biosecurity, and greenhouse gas emissions (Piñeiro et al., 2019).

Analysis of data can be categorized into two main types: exploratory and predictive. Exploratory methods analyze data from past events to identify relevant aspects, whereas predictive models utilize data to forecast future occurrences based on specific criteria (Sasaki, 2019). Accurate use of data analysis is essential when working with large data sets. The presence of diverse data requires considering of several factors in the scenarios, and it is necessary to remove irrelevant information to clean the data (Koltes et al., 2019). Farmers may use predictive techniques to forecast future outcomes and adopt a proactive management approach (Wolfert et al., 2017). Big data technology may help in disease transmission monitoring by building contact networks and identifying populations at high risk (VanderWaal et al., 2017).

Machine learning (ML) is a branch of artificial intelligence that uses algorithms to make statistical predictions and inferences (Morota et al., 2018; Raihan, 2023g). Data mining is a process that involves training databases to recognize patterns to provide information (Raihan, 2023h). The ML is a new field in PLF that uses large datasets to develop computer algorithms. These algorithms may continually acquire information from sensor data and increase their performance without the involvement of a human data analyst (Benjamin & Yik, 2019).

The ML techniques are widely used in animal genetics research to make predictions about phenotypes using genotypic data, detect anomalies in a population, and do genotype imputation. The ML is also used to identify mastitis in dairy farms using automated milking technology, estimate body weight by image analysis, and monitor the health of the microbiome (Morota et al., 2018). The ML and big data analytics possess the capacity to enhance the welfare and productivity of dairy cattle. These disorders, lameness, and mastitis, are significant welfare concerns in dairy cattle and can have a negative impact on milk production.

Monitoring and predicting the possibility of these conditions is crucial. (Ebrahimi et al., 2019; Taneja et al., 2020; Warner et al., 2020).

Big data analytics approaches can be used to gather and combine data from several farms, aiming to enhance the efficiency of production processes and systems (Aiken et al., 2019). The importance of big data is dependent on the automation, accessibility, and accuracy of the provided data. To ensure the quality of the data, it is important to include error checking and quality control measures (VanderWaal et al., 2017). To effectively use PLF on farms, it will be essential to create software, establish quality control mechanisms, develop database systems, and use statistical methods to effectively summarize and visualize the data. Additionally, it will be essential to select the most suitable data models for this purpose (Koltes et al., 2019). Privacy and security pose significant challenges when dealing with large-scale data collected from farms (Wolfert et al., 2017). As a result, the gathering of data on farms is presently not fully utilized due to farmers' priority for maintaining privacy.

By utilizing data collected from biometric and biological sensors, advanced data analysis can be applied to develop digital farming service systems that have the potential to improve animal production capacity, productivity, and livestock welfare. The MooCare predictive model has been created to help dairy producers in dairy farming management using Internet of Things (IoT) sensors and big data. This model predicts milk output (Righi et al., 2020). Gulyaeva et al. (2020) created methods based on large data sets to identify and predict chicken diseases. The digital data collected from the animals' wearable sensors and livestock husbandry sensing platforms can be used to generate a digital fingerprint. This fingerprint can then be utilized in predictive and adaptive decision-making methods. The three factors, namely Footprint, Fingerprint, and Forecast will not only guide livestock producers in managing animal production but also help in the development of integrated application systems for livestock value, supply, and food chains (Tsay et al., 2019). Figure 3 presents the sensor-based big data applications in precision livestock production.

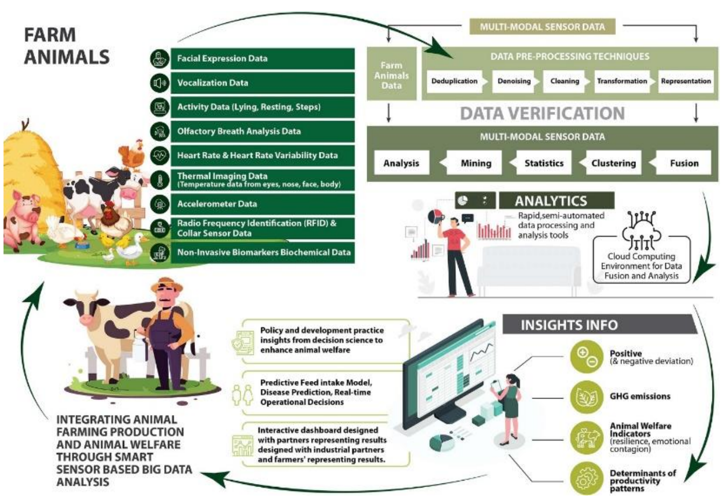

Figure 3: Sensor-based big data applications in precision livestock production (Neethirajan & Kemp, 2021).

6. Blockchain:

A blockchain is a protected database of activities that is decentralized or distributed, with each transaction generating a node. The nodes are arranged into records, referred to as "blocks", through an agreement among participating organizations. These blocks are interconnected and have unique hash codes, creating a chain. Whenever a new transaction occurs, a node is immediately generated containing relevant information about that transaction, which is then added to the blockchain (Chattu et al., 2019). The fundamental characteristics of blockchain technology are distributed, transparent, immutable, and democratic. In the field of livestock husbandry, it is necessary to give a separate identification to each animal on the farm. This separate identification will stay with the animal for its entire lifespan, gathering information about the farm(s) it stayed in, the method of transportation employed to transfer the animal from the farm(s) to the slaughterhouse, the veterinarian responsible for examining the animal at the slaughterhouse, the assessment of quality after slaughter, the transportation of the meat product, and ultimately, details about the packaging and selling of the product.

Blockchain technology offers numerous benefits to livestock farming, such as decentralized and automated transactions that may improve the efficiency of auditing systems for certification and regulatory agencies. It also enables easy system integration and maintains organized records of all transactions related to an animal's route from farm to table. Moreover, it improves traceability and transparency within the livestock agriculture sector (Picchi et al., 2019). In recent times, there has been an increasing absence of trust between farmers and customers as a result of the rising need for transparency in farm products. Blockchain technology has the potential to increase trust by offering consumers clear and comprehensive information about the entire lifespan of an animal.

The implementation of blockchain technology has the potential to be extremely helpful in the identification and monitoring of outbreaks of animal diseases, including H1N1 swine flu, Foot-and-Mouth and Mad Cow diseases, Avian influenza, and the recent increase in salmonella infections. Consumers are becoming more aware of the environmental and ethical aspects of livestock production (Raihan, 2023i). They are also demanding transparency about the methods used to raise animals. Food safety is an important concern for consumers. According to the World Health Organization, every year, 1 in 10 people suffer from food-related illnesses, resulting in over 420,000 deaths annually (WHO, 2020). Blockchain technology has the potential to increase the ability to monitor and locate the origin of harmful foods, hence improving the traceability and responsibility for problematic activities in livestock farming (Lin et al., 2018). One important benefit of blockchain technology is that information is distributed among a network of users rather than being controlled and held by a single individual or group. If there is an outbreak of a disease affecting livestock, farmers from all over the world would be able to input and access disease data safely. This would enable them to actively contribute towards controlling the outbreak or prepare themselves for an outbreak that they predict may affect their farm (Chattu et al., 2019).

With the increasing globalization of food chains and systems (Raihan, 2023j), animal products have to follow multiple animal welfare and sustainability regulations and standards. Regulators and third-party inspectors want easy access to regulatory documentation, which can be challenging when this material exists in physical form or restricted databases (Motta et al., 2020). As of 2020, the livestock farm industry is still lacking in digitalization compared to other industries, indicating significant potential for progress (Motta et al., 2020). The implementation of blockchain technology in animal agriculture has the potential to address the aforementioned concerns related to disease outbreaks and food safety.

Figure 4 illustrates the simplified operational framework of the system as it delivers services to various users. The primary focus of the quarantine department is to ensure the verification of vaccine quarantines and the thorough checking of health data. Meanwhile, the agricultural regulatory department is focused on specific requirements of the farming process. The environmental protection agency expresses concern about environmental difficulties (Raihan, 2023k) that arise throughout the breeding process, including the disposal of breeding waste. Nevertheless, the primary focus for farmers is on getting animal breeding information. Slaughterhouses require a system that helps in the management of livestock slaughter, and distributors require access to the slaughter information. Insurance agencies demand detailed information about the health status of the permitted livestock, whereas financial institutions focus on gathering information about farmers' assets and livestock breeding practices to make accurate risk assessments.

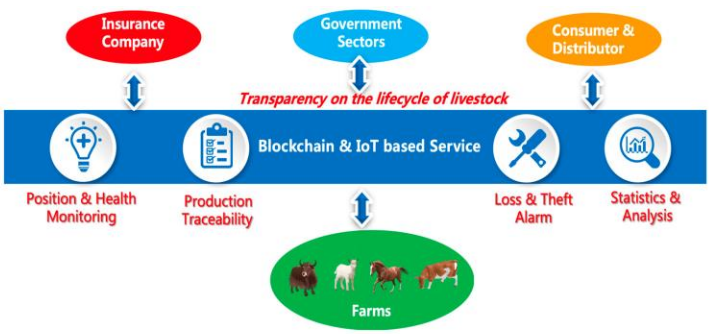

Figure 4: The simplified business model of livestock insurance (Shen et al., 2023).

Despite its numerous advantages, blockchain technology is now in the preliminary phases of progress for extensive use in the food business, with only a limited number of research examining its effects on livestock farming (Picchi et al., 2019). Bioengineers and data scientists can contribute significantly to the development of specific criteria for selecting the most effective blockchain solution for specific industries in cattle production.

7. Conclusion:

This review article focuses on PLF technologies, which aim to enhance livestock production while tackling customer worries. The technologies explored in this research include biometric sensors, big data analysis, and blockchain technology. The implementation of PLF technologies can tackle consumers' increasing concerns regarding animal welfare, environmental sustainability, and public health. Additionally, it can also help in meeting the rising demand for animal products due to the expanding human population. Biometric sensors enable farmers to gather instant data on the well-being and condition of animals, helping them implement proactive management measures that ensure sustainable and secure food production. Big data analysis converts sensor data into meaningful and useful results for farms. The implementation of blockchain technology enhances the transparency and traceability of animal agriculture, hence increasing customer trust while improving food safety. However, the use of PLF technology on animal farms is currently in its developing stage, and several challenges must be overcome before these technologies gain popularity among farmers and consumers globally. The achievement of a digitally inclusive and healthy society, which is made possible by innovative digitalization techniques for livestock farming, requires active participation and engagement from citizens in the collaboration and approval of technological development.

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