

# International Journal of Advanced Biochemistry Research



ISSN Print: 2617-4693  
ISSN Online: 2617-4707  
NAAS Rating (2026): 5.29  
IJABR 2026; SP-10(7): 27-35  
[www.biochemjournal.com](http://www.biochemjournal.com)  
Received: 21-04-2026  
Accepted: 24-05-2026

**Dr. Snehal Misal**  
Ph.D., Department of Animal Genetics and Breeding, ICAR-National Dairy Research Institute, Karnal, Haryana, India

**Dr. Hira Arif**  
Ph.D., Department of Animal Genetics and Breeding, ICAR-National Dairy Research Institute, Karnal, Haryana, India

**Dr. Bharatbhushan M**  
Assistant Professor & Head, Department of Livestock Farm Complex, Affiliation: Shri Bhaurao Deshpande Veterinary College Athani, KVAFSU, Bidar, India

**Dr. Sanjay Chaudhary**  
Professor, Officer Incharge, KVK, Govind Ballabh Pant University of Agriculture and Technology, Pantnagar, Uttarakhand, India

**Dr. NK Ribadiya**  
Assistant Professor, Junagadh Agricultural University, Junagadh, Gujarat, India

**Dr. Bagavathi M**  
District Animal Welfare Officer, Tamil Nadu Animal Welfare Board, Tenkasi, Tamil Nadu, India

**Dr. Chitralekha Deo**  
Veterinary Assistant Surgeon (VAS), Livestock Development Department Government of Chhattisgarh, India

**Dr. M Ramasamy**  
Assistant Professor, Department of Veterinary and Animal Sciences, ICAR-Krishi Vigyan Kendra, Virinjipuram, Vellore, Tamil Nadu, India

**Dr. Jayashree Pattar**  
Assistant Professor, Department of Animal Science, Dairy Unit, MARS, University of Agricultural Sciences Dharwad, Karnataka, India

**Corresponding Author:**  
**Dr. Hira Arif**  
Ph.D., Department of Animal Genetics and Breeding, ICAR-National Dairy Research Institute, Karnal, Haryana, India

## Precision livestock farming technologies: A review of sensors and data analytics

**Snehal Misal, Hira Arif, Bharatbhushan M, Sanjay Chaudhary, NK Ribadiya, Bagavathi M, Chitralekha Deo, M Ramasamy and Jayashree Pattar**

DOI: <https://www.doi.org/10.33545/26174693.2026.v10.i7Sa.8922>

### Abstract

Precision livestock farming (PLF) is revolutionizing conventional husbandry via the use of latest sensors and analytics to track each animal's performance and surroundings in real time. This detailed study covers the development of PLF from basic identification tags and feed scales to the present day systems using cameras, wearable IoT devices and artificial intelligence. We cover main sensor categories (wearable accelerometers, environmental monitors, RFID and bolus sensors, imaging and acoustic systems, etc.), specifying their goal measurements, performance parameters, application scenarios and pros/cons. We also review data analytics techniques (statistical models, machine learning, deep learning, computer vision, edge vs. cloud processing) utilized to turn sensor data into actionable insights. We review applications in animal health (early illness detection, vital sign monitoring), welfare (behaviour tracking, stress indicators), productivity (precise feeding, growth and reproduction management) and environmental sustainability (climate control, emissions tracking). Discussion of key obstacles such as high prices, data management, connection in remote locations and regulatory/ethical concerns and stakeholder specific mitigating solutions.

**Keywords:** Livestock, artificial intelligence, productivity, sustainability, cloud

### Introduction

Precision livestock farming is a change in animal husbandry from managing groups of animals to monitoring and controlling individual animals. PLF, using sensors and analytics, allows each animal to be governed by its individual state and requirements [1]. This "per-animal" method was recommended in the early 2000s and has been growing with Industry 4.0 and IoT advancements. The idea is to employ technology to make livestock production more efficient, sustainable and better for animal welfare. Early examples were electronic milk meters and automated feeders that monitored output and consumption at the individual level [2]. More contemporary systems include digital tags, cameras and networked devices to gather data about behaviour, physiology and surroundings. Meanwhile, data science developments enable the processing of massive data streams into insights for disease diagnosis, breeding, feeding optimization and more [3]. This study addresses state of the art in PLF technology, sensor modalities and data analytics, applications, implementation challenges and future developments. We first review important historical events that have formed PLF, then discuss sensor types and their properties and then address data analysis methodologies. Applications in health, welfare, productivity and environment are discussed. After examining practical obstacles and ethical considerations, we examine future directions [4]. This evaluation is an integrated, in-depth analysis on the impact of sensors and analytics on livestock farming and will be used as a resource for academics, industry stakeholders and policy makers.

The origins of precision livestock farming are based on the fundamental necessity to monitor production variables more precisely than via human observation [5]. In the 1970s and 1980s, electronic identification (EID) and automated weighing systems were introduced to check traceability and feed. More complex automated technology started to appear throughout time. For example, the first robotic milking systems were commercially accessible in the late 1990s to 2000 [6].

Meanwhile, in the 1990s, researchers such as Berckmans and colleagues developed the notion of on-line monitoring, utilizing sensors and models to assess animal wellbeing in real time. With the advent of inexpensive wireless sensor networks and RFID in the 2000s the PLF evolved to allow digital monitoring of individual animals and their outputs [7]. The 2010s were marked by the explosion of IoT devices and smartphones, which made connection widespread on farms. During this time, the farms started to frequently utilize accelerometer collars (e.g. for estrus detection) and infrared cameras (e.g. body condition) [8]. A further leap came in the early 2020s, when big data platforms and machine learning were integrated, enabling mining of patterns from continuous sensor feeds. Over the longer term, more advanced AI (including large language models and federated learning) will be embedded in PLF for decision support and sensor miniaturization and cost reduction will continue to democratize the technology even for small-scale producers in the 2020s and beyond [9].

## Sensor Technologies

### Wearable and Animal-Mounted Sensors

Wearable sensors are designed to collect data directly from the animal. The most common are accelerometers and inertial units (IMUs), usually in collars or ear tags, which measure motion and orientation in 3D [10]. These track activity levels, standing/lying behaviour, steps walked and sometimes posture. Specifications often include sampling rates on the order of 10-50 Hz and multi-axis measurement. Use-cases include estrus detection (showing elevated activity), lameness alerts (abnormal gait) and general activity monitoring [11]. Pros include continuous monitoring and relatively low cost per sensor, cons include data noise and the need for battery power. Another class is temperature sensors: typically infrared (contactless) sensors or implanted devices (rumen boluses) that log body/core temperature. These help detect fever or heat stress. Typical specs might be accuracies of  $\pm 0.1$ -1.0 °C. They can detect onset of infection or estrus (which raises temperature), but may miss localized issues (e.g. foot injury) [12, 13].

**Position and movement trackers** such as GPS collars or tags measure animal location (accuracy ~3-10 m) and can record grazing patterns or detect escape. Pros are precise location data, cons are higher cost and battery drain. Pedometers (pressure-sensitive leg bands or mats) count steps or weight distribution, useful for gait analysis [14]. Vital sign monitors (e.g. heart rate belts, respiratory sensors) are emerging, e.g. chest-band sensors can estimate heart/pulse and breathing from body movements, aiding stress detection. Rumen boluses are swallowable capsules that reside in the stomach, they can measure internal temperature, pH and motion. These have limited life (battery) but provide internal physiological data, important for health and estrus monitoring [14].

### Environmental and Production Sensors

External sensors monitor the animal's immediate environment.

Temperature/humidity sensors track barn climate to ensure thermal comfort, typical specs (range 0-50 °C,  $\pm 0.5$  °C, humidity  $\pm 2\%$ ). These feed into ventilation and heating control [15].

Gas sensors measure ammonia, CO<sub>2</sub> and other air quality metrics in livestock housing to gauge ventilation needs [16]. Light and sound level meters gauge conditions for welfare (e.g. too noisy or dark barn stresses animals) [17].

Feed and water intake sensors measure consumption. For example, scales or load cells under feed bunks record feed disappearance per animal or group, flow meters on water lines quantify individual or overall drinking rates [18]. These measure intake with precisions like  $\pm 1$ -5% of volume or mass. High intake can indicate good health, while sudden drops may flag illness. Pros include direct insights into nutrition, cons include installation complexity and calibration needs. Automatic weight scales (walk-over-weighing platforms) allow animals to be weighed as they pass, typical accuracy might be  $\pm 2\%$ . They provide periodic body-weight trends without manual restraint [19, 20].

Identification and counting sensors (e.g. RFID readers at gates, photoelectric beams) allow tracking of animals through systems (milking parlour entry, sorting gates) and counting. These indirectly measure presence/time of resource usage. Pros: non-intrusive, cons: limited to discrete checkpoints [21].

RGB cameras capture video or images of animals and pens. With computer vision, they can count animals, detect abnormal behavior, estimate body condition score, or monitor aggression. Cameras vary from simple static units to pan-tilt types, resolutions from VGA (640×480) to HD or higher [22].

Thermal (infrared) cameras capture surface temperature patterns, identifying hotspots (e.g. inflamed udder for mastitis, hoof heat for lameness) or heat stress. They typically have thermal resolution of  $<0.1$  °C and range of tens of meters [23].

Depth cameras (stereo or time-of-flight, e.g. structured light sensors) create 3D data of an animal's shape, used to estimate weight or body condition from volume. These often require short-range (~0-10 m) and can work in dark [24].

Hyperspectral or multispectral cameras (less common in livestock, more in crop sensing) could measure subtle features (e.g. reflectance indicating bruising or illness), but are mostly experimental. Pros of imaging include non-contact, the ability to monitor many animals at once and rich data. Limitations include sensitivity to lighting, occlusion (animals crowding) and heavy data processing requirements [25].

### Acoustic and Other Sensors

Microphones and acoustic arrays detect sounds like coughing, sneezing, vocalizations, or grinding teeth. In pigs or poultry, cough detection can indicate respiratory disease, in cattle, bellowing patterns or coughing count. These sensors pick up audible range or even infrasound. Algorithms process sound signatures to identify events [26]. Pros: can monitor continuously over wide areas, cons: background noise interference and processing needs. Other specialized sensors include wearable bio-sensors (e.g. sweat or saliva analyzers for hormone or metabolite detection), though these are mostly in development. Additionally, drones or UAVs equipped with cameras or thermal sensors are used to survey large grazing areas or detect stray animals, though these are not permanently mounted systems [27].

**Table 1:** Sensor types in precision livestock farming, with measured variables, typical specifications, common applications [28, 29, 30, 31, 32]

| Sensor Type                  | Measured Variables                       | Typical Specs                 | Common Use-Cases                                      |
|------------------------------|------------------------------------------|-------------------------------|-------------------------------------------------------|
| Accelerometer/IMU (wearable) | Body movement (activity, steps, posture) | 3-axis, ~10-50 Hz sampling    | Activity monitoring, estrus detection, lameness       |
| Gyroscope (IMU)              | Angular motion/orientation               | 3-axis, ~50 Hz                | Posture analysis, refine motion tracking              |
| RFID Ear Tag (ID)            | Animal ID (passive)                      | Range ~1 m (passive)          | Tracking entries/exits, feed station logging          |
| Smart Ear Tag/Collar         | Combined (ID, temp, activity etc.)       | Battery-powered, multi-sensor | Health monitoring (temp, behavior), location          |
| Bolus Sensor                 | Rumen temp, pH, motility                 | Internal capsule, battery     | Detect fever, estrus (temp rise), rumen health        |
| GPS Tracker                  | Location (lat/long, speed)               | GPS module, ~3-10 m accuracy  | Grazing behavior, virtual fencing                     |
| Weigh Scale (platform)       | Body weight                              | Accuracy±1-2%, ~1 ton cap.    | Routine weighing in exit lanes or stalls              |
| Feed Scale/Intake Sensor     | Feed mass flow or weight                 | Flow meter or load cell       | Measure individual/group feed intake, feed conversion |
| Water Flow Meter             | Water volume usage                       | Flow rate sensor, ±2-5%       | Track drinking patterns, detect dehydration or leak   |
| Infrared Thermometer         | Surface body temperature                 | Range ~0-50 °C, ±0.5 °C       | Fever screening, heat stress alerts                   |

### Data Analytics and Methods

Collecting data from sensors is only one half of the story. Turning that data into useful information takes a whole set of analytic approaches. PLF data analysis ranges from classical statistics to current artificial intelligence [33]. Methods may be roughly grouped as follows:

**Descriptive and Statistical Analysis:** The analyses are elementary, using statistical techniques to describe data (means, trends, variance) and test hypotheses (regressions, ANOVAs). Charting average daily increase or herd milk supply over time helps spot strange things. Control chart (e.g. Shewhart, CUSUM) is used to determine when a parameter (e.g. milk conductivity) is outside of its usual boundaries and an alarm is sent [34, 35]. The strengths of the statistical approaches include interpretability and cheap processing requirements, the constraints are difficulties modelling complicated and nonlinear interactions and the necessity for established parametric assumptions. Standard methods include linear regression, threshold rules and time series decomposition [36].

**Machine Learning (ML):** The proliferation of data has increased the importance of ML techniques in PLF. Supervised learning techniques such as decision trees, random forests, support vector machines (SVMs) and gradient boosting can classify or predict outcomes based on labelled data samples [37]. For example, data from the accelerometer and activity may be used to train an ML model to identify estrus vs. non-estrus or diagnose mastitis. Unsupervised approaches (k-means clustering, principal component analysis) may locate patterns or outliers without labels [38]. This is important for anomaly identification (e.g. seeing calves acting differently). The pros of ML include its flexibility and capacity to understand complicated patterns. Cons of ML: Need of huge quality datasets and the danger of overfitting Common algorithms: Random Forest, SVM, k-NN, K-means and PCA Deep [39].

**Learning and Computer Vision:** High resolution imaging is used with deep neural networks especially convolutional neural networks (CNNs) for visual tasks such as object identification (e.g. counting animals in a pen), behaviour recognition (e.g. laying vs standing vs eating) or health indicators (e.g. identifying lame cows from video) [40]. Recurrent neural networks (RNNs) and long-short-term memory (LSTM) networks are used for sequential data processing (e.g. time-series of activity or eating habits) for

predicting events such as the beginning of sickness. Deep learning is good at unstructured data but needs a lot of labelled data and computing. Algorithms include CNN architectures like ResNet and YOLO for detection, RNN/LSTM for temporal data and autoencoders for anomaly detection [41].

**Signal processing:** Some data is considered as signals. For example, sound (microphone data) may be examined using Fourier transforms or wavelet analysis to produce properties of sound. Chewing patterns may be identified by data processing using vibrational sensors (e.g. jaw motion sensors). Feature extraction (MFCCs for sound, spectral characteristics, etc.) is commonly a pre-step to ML classification. The benefit is that it captures information in the frequency domain but demands skill in signal methods [42].

**Edge & Cloud Computing:** Data Analytics may be performed either on the device or in centralized servers. Edge computing is when you execute less complex algorithms on local hardware (e.g. microcontrollers or embedded processors on farm gateways) to pre-process data or detect local events (e.g., a threshold alarm). This cuts down on data transfer requirements and latency. But it is limited by hardware capacity [43]. Cloud-based analytics means data is sent to a distant server for storage and analysis. The cloud can run big-data frameworks (Hadoop, Spark) and deep learning training. Its pros include almost infinite computing and simple integration of heterogeneous data sources, disadvantages are connection reliance, data security problems and possible delay. Hybrid fog/edge-cloud systems are increasingly pushing certain analytics to the edge (real-time detection) while more complicated modelling happens in the cloud [44].

**Data Integration and Fusion:** The PLF generally involves several data streams (e.g. behavior, production, environment). These may be combined to increase accuracy, using techniques such as Kalman filtering or Bayesian fusion. For example, the position obtained from RFID can be merged with data from the accelerometer to corroborate the activity. Ensemble learning is used to increase the robustness of predictions, which is a combination of many ML models [45].

**Decision Support and AI:** Many PLF platforms contain expert systems or rule-based modules in addition to

algorithms that transform insights into actionable recommendations (e.g., notifications to farmers). Some systems may include knowledge of the domain (i.e., fever thresholds, known estrus patterns) to understand outputs. Emerging options include large language models (LLMs) or generative AI, for example, a PLF system may employ an

LLM fine-tuned on animal health literature to interpret complicated data patterns in human language, or to recommend therapies in farmers’ terminology. These AI agents could also assist consolidate disparate data sources (weather, market prices) for wider decision support <sup>[46]</sup>.

**Table 2:** Data analytics methods for PLF, with input data types, typical outputs, strengths and limitations and common algorithms <sup>[47, 48, 49, 50, 51, 52]</sup>

| Method/Approach                 | Input Data Types                                 | Typical Outputs                                  | Typical Algorithms/Tools           |
|---------------------------------|--------------------------------------------------|--------------------------------------------------|------------------------------------|
| Statistical Analysis            | Numeric sensor data (time-series)                | Trend plots, summary stats, flags                | Regression, control charts, ANOVA  |
| Time Series Modeling            | Continuous measurements (weight, intake)         | Forecasts, anomaly detection                     | ARIMA, Kalman filters, moving avg  |
| Descriptive Thresholds          | Real-time sensor readings                        | Alert if threshold exceeded                      | Simple threshold rules             |
| Supervised Machine Learning     | Labeled datasets (sensor + outcome)              | Classification/prediction (e.g. estrus, disease) | Random Forest, SVM, Logistic Regr. |
| Unsupervised Learning           | Unlabeled sensor data                            | Clusters, anomaly scores                         | K-means, PCA, DBSCAN               |
| Neural Networks (Deep Learning) | High-dimensional inputs (images, video, sensors) | Complex predictions/classification               | CNN, RNN/LSTM, Autoencoders        |
| Computer Vision                 | Camera images/videos                             | Object counts, pose/behavior classification      | YOLO, Mask R-CNN, optical flow     |
| Signal Processing               | Audio/vibration signals                          | Frequency-domain features, event detection       | FFT, wavelet transform, MFCC       |
| Edge Analytics                  | On-sensor or near-sensor data                    | Local alerts, aggregated metrics                 | TinyML models, threshold checks    |

**Applications of PLF**

Precision livestock technologies span many applications, which we categorize here under animal health, welfare, productivity and environmental sustainability.

**Health Monitoring and Disease Prevention**

An early aim of PLF is to diagnose illness in a timely manner. Continuous monitoring may detect subtle signals of sickness before overt symptoms. For example, changes in food or drinking behaviors identified by intake sensors sometimes occur before clinical disease <sup>[53]</sup>. Accelerometer data showing restless or sluggish behaviour may suggest fever or lameness. Regular temperature checks, either using ear tags or infrared sensors, might detect fevers that a farmer would not notice. Computer vision can recognize aberrant stride or posture indicating lameness and thermal cameras may detect localized heat from inflammation (e.g. mastitis) <sup>[54]</sup>. If a microphone detects a person coughing or sneezing more often then it acoustically raises an alarm about a respiratory condition. Basically, PLF offers an automated triage, animals that deviate from their typical baseline trigger an alarm, enabling farmers or veterinarians to act early, frequently lowering the need for medications and improving outcomes <sup>[55]</sup>. PLF systems are very useful in preventive health as well as diagnosis. Environmental sensors control barn conditions (temperature, ammonia levels) at appropriate levels to reduce stress and danger of diseases. Hygiene (e.g. leak detection which contaminates water) and proper nourishment are assured via automated water and feed monitoring. GPS surveillance of free-range herds may tell if animals are straying into dangerous areas (ticks, predators) <sup>[56]</sup>. Good records help with breeding and immunizations. Immunizations can be targeted and screening can be focused. The outcome is a more proactive approach to managing herd health. Studies have indicated that farms that employ PLF health tools may decrease illness incidence and the usage of antibiotics, however the precise results will depend on the size and management of the farm <sup>[57]</sup>.

**Animal Welfare and Behaviour**

PLF is well suited to welfare monitoring since many welfare indicators are behavioural or subtle. Sensors provide continuous monitoring without the effect of human presence on behaviour. Collars may include accelerometers to measure lying time and activity levels for example <sup>[58]</sup>. Sudden changes (e.g. less lying, more standing) might indicate discomfort or pain. Cameras may identify aggressiveness, crowding or fall risks. Microphones can record stress-related vocalizations. Thermal or noise conditions are monitored by environmental sensors to see whether they are within comfort zones <sup>[59]</sup>. Together these statistics allow for an impartial assessment of wellbeing. For example, a PLF system may identify when barn temperature increases and broiler chicks are clustering in corners (using cameras) triggering ventilation. In pigs, more biting sounds or movement may indicate bad circumstances in a confinement <sup>[60]</sup>. Some of the automated welfare scoring algorithms are still in the research phase, but they are capable to measure gait impairment or weight distribution as a measure of lameness. Importantly, welfare-focused PLF does more than merely detect issues but also offers fixes (e.g. change light or feeding schedules) <sup>[61]</sup>. The challenge with welfare is to ensure technology does not depersonalize care. Although automated monitoring minimizes the need for continuous human observation, the PLF is best used as a complement to, rather than a replacement for, attentive care. “Farmers say that reliable alerts on welfare issues help them get back to them quicker,” Overall, PLF may enhance wellbeing by providing a responsive habitat, according to the condition of each animal <sup>[62]</sup>.

**Productivity and Efficiency**

- The economic promise of PLF is to boost productivity- to obtain more output for every unit of input. Precision feeding is one significant use. Sensors measure individual intake and growth and enable meals to be adjusted to requirements <sup>[63]</sup>. For instance, automatic feeders may tailor the feed for each animal depending

on weight and milk supply, maximizing nutrition. Research has demonstrated that precision feeding may save feed waste and minimize feed costs by ensuring that each animal receives precisely the right amount. Real time surveillance of body weight (scales or camera based estimations) is useful in managing growth trajectories, vital in beef and lamb production<sup>[64]</sup>.

- Dairy PLF systems are used for managing milk production. Electronic milk meters record every cow per milking and allow examination of production curves. These technologies, along with mastitis detection sensors (conductivity, somatic cell counts using inline analyzers) allow an early treatment and hence reduce the loss of milk. Reproductive efficiency is also a beneficiary<sup>[65]</sup>. Activity sensors are extensively employed to detect estrus. A cow in heat will wander more. Electronic identification of this enables for timely insemination enhancing conception rates and shortening calving intervals. Monitoring systems for calving and feeding activities may provide early warning signs of postpartum problems (ketosis, metritis), hence boosting the recovery and future production of the dairy cow<sup>[66]</sup>.
- PLF for growing animals (pigs, poultry) may feature automatic weight control and feed intake monitoring for optimum feed conversion. Smart feeders that measure the amount of feed provided and denied may compute feed conversion rate per pen. Dieticians may use this knowledge to fine-tune diets<sup>[67]</sup>. Farmers also employ data analytics to mimic breeding and marketing situations. The bottom line of productivity increases is frequently larger yields (milk, meat, eggs) and cheaper cost of production, however the advantages must be greater than the technological expenses to be profitable<sup>[68, 69]</sup>.

### Environmental Sustainability

- Increasing desire to reduce the environmental harm caused by contemporary cattle farming. The PLF has several uses. Precision feeding reduces nitrogen excretion by matching the meal to the precise needs of the animal and, therefore, reducing overfeeding of protein. Management of greenhouse gases may be achieved by monitoring emissions, e.g., using methane sensors or models, which can be fed intake data<sup>[70]</sup>. For example, if a cow's diet can be changed to reduce the quantity of methane generated, an alert may be issued. Sensors in the surroundings also optimise energy use, with automated temperature management switching on ventilation or heating only when sensors detect a need for it, which in turn lowers power consumption and improves air efficiency<sup>[71]</sup>.
- A further worry is the use of GPS and satellite imagery to monitor grazing intensity in pasture management. Drones fitted with cameras might be used to evaluate the health of pastures so as to avoid overgrazing<sup>[72]</sup>. To help prevent nutrient runoff, PLF systems can monitor the production of manure and time its distribution to fields appropriately. Water sensors improve the efficiency of water consumption and may also uncover leaks at an earlier stage. All these aspects contribute to a higher resource efficiency, a lower carbon and nitrogen footprint and to the compliance with the environmental regulations<sup>[73]</sup>.

- Integration of environmental data with industrial data may result in a complete approach to sustainability. For example, the carbon footprint of a farm per liter of milk may be estimated by linking sensors for milk production with models of greenhouse gas emissions<sup>[74]</sup>. Tracking feed efficiency and waste in real time makes it feasible to make changes more rapidly. Therefore, PLF supports the productivity and sustainability objectives: more environmentally friendly farms tend to be more productive<sup>[75]</sup>.

### Implementation Challenges

Despite the potential of PLF, deploying it at scale faces hurdles. These challenges can be technical, economic, or social.

- **Technical Integration:** Existing infrastructure on most farms and new sensors and software must be able to interface with it. Device compatibility (various manufacturers/protocols) remains a problem. Wireless access might be unstable in barns or isolated pastures, making it difficult to get real-time data flow. The power supply of the sensors (battery life vs. frequency of data collecting) is a design trade-off<sup>[76]</sup>. Calibrating sensors in tough agricultural conditions (dust, humidity, animal interference) is not straightforward. Large quantities of data demand strong IT infrastructure. Many small farms lack experienced IT help. User interfaces have to sift through complicated data to provide clear warnings-bad design can result in farmers being bombarded with false positives or misleading graphs, which may lead to mistrust of the system<sup>[77]</sup>. These challenges may be addressed by technical robustness (waterproof, durable sensors), defined protocols (e.g. ISO standards for animal data) and smart software design. Reliability of connection and interoperability is of significant importance<sup>[78]</sup>.
- **Economic Barriers** PLF systems are expensive to implement. Automated barns or robotic milking may cost hundreds of thousands of dollars, which may be acceptable on big dairies but not on small farms. Even tiny sensors and software subscriptions are a huge expenditure to a farmer with low margins<sup>[79]</sup>. The return on investment is not always instantaneous. It may take months for productivity increases to be seen. It is hard to put a price on the economic benefits of improved wellbeing or reduced use of antibiotics. Many farmers are reluctant to invest in innovation that hasn't been demonstrated. To offset this, there is a need for strong value propositions. Cost may be dispersed via subsidies, leasing schemes or cooperative ownership (farmers sharing a service)<sup>[80]</sup>.
- **Farmer adoption and skills:** The adoption of technology is often dependent on the mindset of the farmer. Older farmers or those who are set in their ways may be resistant to change or be afraid of new equipment. Digital illiteracy is a barrier to accessing data dashboards or understanding analytics<sup>[81]</sup>. Cost is a major priority as financial risk is a significant barrier to adoption. Part of it is cultural opposition (to conventional livestock husbandry). Confidence building requires training and extended services. Peer to peer learning (farmers witnessing neighbours thrive with PLF) may enhance adoption. "Involving farmers early on in the design of the system will mean the technology

will solve real problems and have an interface that can be used. This problem has a medium priority. Social elements are dynamic, yet important for continued usage <sup>[82]</sup>.

- **Data Management and Privacy:** PLF systems produce sensitive data: agricultural production records, health incidents, genetic or financial information. Questions of data ownership (who owns the data, the farmer or the vendor?), privacy and security come up. Data saved in the cloud can be subject to breaches <sup>[83]</sup>. There are also competitive intelligence issues with the use of big data (aggregated data across farms). Clear data regulations and encryption is what we need to deal with this. Federated learning (data remain on-farm) is a potential technological solution for privacy protection. There may be regulations that end up regulating agricultural data. Medium-high priority issue: if not solved, farmers may not share data and/or use technology <sup>[84]</sup>.
- **Infrastructure and Scalability:** In certain areas, particularly in poor nations, the essential infrastructure (electricity, Internet) is missing, which makes high-tech PLF not practicable. And even in rural pastures in nations, there is no guarantee of cell phone reception. We require scalable solutions (solar-powered, low-bandwidth communication protocols). This is a medium priority. As global livestock production increases in developing nations, solutions need to be tailored to lower-resource settings <sup>[85]</sup>.
- **Technological Maturity:** Finally, several PLF technologies are still in their infancy. For instance, vision systems for pigs or automated sheep scanners offer intriguing research outcomes but are not commercially viable. Widespread implementation will have to wait till proved reliable in different agriculture situations. The move from lab to farm is facilitated by prioritizing iterative testing, field trials and modular enhancements <sup>[86]</sup>.

### Ethical and Privacy Considerations

**Data Privacy:** PLF farms of the future will create extensive data on each animal (health records, performance) and on farm operations. This data is significant not just to the farmers but also to technological businesses or other parties. Who owns this information? For instance, if a service looks at patterns in herd health, is the raw data available to the farmer or locked away in a vendor's cloud? Data may be stolen or abused <sup>[87]</sup>. Farmers may be reluctant to use cloud-based analytics if they are concerned about losing control of sensitive information (e.g., how their farm is doing compared to rivals). Must have comprehensive cybersecurity (encrypted data transfer and storage, secure authentication). Privacy should be built-in by design (edge computing, data anonymization, tight user agreements). Other legal and regulatory compliance (e.g. data protection requirements) may also apply. Farmers need clear agreements on what data is collected and how it is used and eventually the right to delete or export their data <sup>[88]</sup>.

**Ethics of animal welfare:** PLF wants to promote wellbeing, but we need to examine the intrusion of sensors and automation. Continuous monitoring ensures the animals are always being watched, however you may consider if this might stress the animals, on welfare grounds. Most sensors (tags, collars) are generally low-profile although attention

must be made in design (lightweight, comfortable attachments). Concern occurs when data compels output beyond natural boundaries or when farmers depend more on technology than observation <sup>[89]</sup>. The human-animal link is crucial and some worry that seeing of animals simply via data might lessen empathy or lead to their being treated as just industrial units. Note that PLF should enhance caretaking, removing routine chores from farmers to enable them to focus on attentive care and spot problems early to mitigate them <sup>[90]</sup>.

**Ethical Farming Practices:** A further concern is that PLF may enable more intensive systems with a superficial claim to sustainability. PLF could be used to drive animals harder (overfeeding for faster growth) and conceal welfare problems behind hi-tech management. Thus laws or codes of conduct may be required to ensure that efficiency does not undermine basic welfare standards. Transparent certification (e.g. labelling that animals were monitored with PLF for welfare compliance) should comfort customers <sup>[91]</sup>.

**Socioeconomic Impacts:** Labour Automation in animal production can reduce some labour (e.g. milking robots replace milkers). There are societal implications for farm labourers and rural communities. Negative effects may be compensated by training and redeployment of labour (e.g. from manual to data processing). Producers should consider the wider community from an ethical standpoint in their planning <sup>[92]</sup>.

### Conclusion

Precision livestock farming is an intersection of biology, engineering and data science, which aims to improve efficiency, sustainability and animal welfare in livestock production. The PLF has grown over the last decades from basic electronic tags and scales to complex networks of sensors and artificial intelligence. Today, farms have wearable activity trackers, sophisticated imaging systems, networks of environmental sensors and strong analytics to spot issues early and customize management to each animal. This review has explored the PLF technology landscape. We reviewed the whole gamut of sensors accelerometers, temperature boluses, cameras, microphones describing their operations and duties. We examined analytics tools from classical statistics to contemporary machine learning and deep learning and emphasized the significance of both edge and cloud computing for handling the flood of data. In practice, PLF systems are being used to protect animal health (e.g. early illness warnings), improve welfare (monitoring comfort and behaviour), increase production (precise feeding and breeding) and minimize environmental impact (optimised resource usage and emission tracking). Ethical and privacy issues (from ensuring animal welfare to protecting farm data) need to be addressed, legislated and regulated. Going ahead, cooperation between animal biologists, engineers, computer scientists and social specialists will be vital to solve these difficulties. It's equally important to engage farmers at all stages to ensure the technology is practical and really helps in actual farm situations. In the future, developing technologies are expected to be integrated, providing even greater possibilities. We expect more advanced AI (including language-based interfaces), more robots and cheaper sensors to put PLF within the reach of all manufacturers. If these

inventions are motivated by sustainability and ethics, then PLF may become an important tool in the world issue of producing more animal protein with less resources. In conclusion, precision livestock farming is a promising approach to make livestock production more intelligent and responsible. With advancing technology, the challenge will be to ensuring innovation is matched by practicality, affordability and care for animals and communities.

## References

- Nielsen MB, Meyer AS, Arnau J. The Next Food Revolution Is Here: Recombinant Microbial Production of Milk and Egg Proteins by Precision Fermentation. *Annu Rev Food Sci Technol*. 2024;15:173-187.
- Banach JL, van der Berg JP, Kleter G, van Bokhorst-van de Veen H, Bastiaan-Net S, Pouvreau L, *et al*. Alternative Proteins for Meat and Dairy Replacers: Food Safety and Future Trends. *Crit Rev Food Sci Nutr*. 2023;63:11063-11080.
- Gil M, Rudy M, Duma-Kocan P, Stanisławczyk R, Krajewska A, Dziki D, *et al*. Sustainability of Alternatives to Animal Protein Sources, a Comprehensive Review. *Sustainability*. 2024;16:7701.
- Chelotti JO, Martinez-Rau LS, Ferrero M, Vignolo LD, Galli JR, Planisich AM, *et al*. Livestock Feeding Behaviour: A Review on Automated Systems for Ruminant Monitoring. *Biosyst Eng*. 2024;246:150-177.
- Bernabucci G, Evangelista C, Girotti P, Viola P, Spina R, Ronchi B, *et al*. Precision Livestock Farming: An Overview on the Application in Extensive Systems. *Ital J Anim Sci*. 2025;24:859-884.
- Schillings J, Bennett R, Rose DC. Exploring the Potential of Precision Livestock Farming Technologies to Help Address Farm Animal Welfare. *Front Anim Sci*. 2021;2:639678.
- Jiang B, Tang W, Cui L, Deng X. Precision Livestock Farming Research: A Global Scientometric Review. *Animals*. 2023;13:2096.
- Nsabiyeze A, Zhang M, Li J, Zhao Q, Zhang X. Precision Livestock Farming for Climate-Resilient Livestock Management: A Review of Real-Time Monitoring and Decision Support Systems. *J Clean Prod*. 2025;524:146454.
- Trabachini A, Moreira MdR, Harada ÉdS, Amorim MdN, Silva-Miranda KO *da*. Precision Livestock Farming Applied to Swine Farms—A Systematic Literature Review. *Animals*. 2025;15:2138.
- Papakonstantinou GI, Voulgarakis N, Terzidou G, Fotos L, Giamouri E, Papatsiros VG. Precision Livestock Farming Technology: Applications and Challenges of Animal Welfare and Climate Change. *Agriculture*. 2024;14:620.
- Gómez Y, Stygar AH, Boumans IJMM, Bokkers EAM, Pedersen LJ, Niemi JK, *et al*. A Systematic Review on Validated Precision Livestock Farming Technologies for Pig Production and Its Potential to Assess Animal Welfare. *Front Vet Sci*. 2021;8:660565.
- Aquilani C, Confessore A, Bozzi R, Sirtori F, Pugliese C. Review: Precision Livestock Farming Technologies in Pasture-Based Livestock Systems. *Animal*. 2022;16:100429.
- Zhang M, Wang X, Feng H, Huang Q, Xiao X, Zhang X. Wearable Internet of Things Enabled Precision Livestock Farming in Smart Farms: A Review of Technical Solutions for Precise Perception, Biocompatibility and Sustainability Monitoring. *J Clean Prod*. 2021;312:127712.
- Stygar AH, Gómez Y, Berteselli GV, Dalla Costa E, Canali E, Niemi JK, *et al*. A Systematic Review on Commercially Available and Validated Sensor Technologies for Welfare Assessment of Dairy Cattle. *Front Vet Sci*. 2021;8:634338.
- Li N, Ren Z, Li D, Zeng L. Review: Automated Techniques for Monitoring the Behaviour and Welfare of Broilers and Laying Hens: Towards the Goal of Precision Livestock Farming. *Animal*. 2020;14:617-625.
- Van Hertem T, Rooijakkers L, Berckmans D, Fernández AP, Norton T, Vranken E. Appropriate Data Visualisation Is Key to Precision Livestock Farming Acceptance. *Comput Electron Agric*. 2017;138:1-10.
- Rutten CJ, Velthuis AGJ, Steeneveld W, Hogeveen H. Invited Review: Sensors to Support Health Management on Dairy Farms. *J Dairy Sci*. 2013;96:1928-1952.
- Neethirajan S. The Role of Sensors, Big Data and Machine Learning in Modern Animal Farming. *Sens Bio-Sens Res*. 2020;29:100367.
- King MTM, LeBlanc SJ, Pajor EA, DeVries TJ. Cow-Level Associations of Lameness, Behavior and Milk Yield of Cows Milked in Automated Systems. *J Dairy Sci*. 2017;100:4818-4828.
- Nasirahmadi A, Edwards SA, Sturm B. Implementation of Machine Vision for Detecting Behaviour of Cattle and Pigs. *Livest Sci*. 2017;202:25-38.
- Neethirajan S, Kemp B. Digital Livestock Farming. *Sens Bio-Sens Res*. 2021;32:100408.
- Morota G, Ventura RV, Silva FF, Koyama M, Fernando SC. 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*. 2018;96:1540-1550.
- Halachmi I, Guarino M, Bewley J, Pastell M. Smart Animal Agriculture: Application of Real-Time Sensors to Improve Animal Well-Being and Production. *Annu Rev Anim Biosci*. 2019;7:403-425.
- Benaissa S, Tuytens FAM, Plets D, De Pessemier T, Trogh J, Tanghe E, *et al*. On the Use of On-Cow Accelerometers for the Classification of Behaviours in Dairy Barns. *Res Vet Sci*. 2019;125:425-433.
- Wolfger B, Timsit E, Pajor EA, Cook N, Barkema HW, Orsel K. Accuracy of an Ear Tag-Attached Accelerometer to Monitor Rumination and Feeding Behavior in Feedlot Cattle. *J Anim Sci*. 2015;93:3164-3168.
- Schirmann K, Chapinal N, Weary DM, Heuwieser W, Von Keyserlingk MAG. Rumination and Its Relationship to Feeding and Lying Behavior in Holstein Dairy Cows. *J Dairy Sci*. 2012;95:3212-3217.
- Matthews SG, Miller AL, Plötz T, Kyriazakis I. Automated Tracking to Measure Behavioural Changes in Pigs for Health and Welfare Monitoring. *Sci Rep*. 2017;7:17582.
- Qi F, Zhao X, Shi Z, Li H, Zhao W. Environmental Factor Detection and Analysis Technologies in Livestock and Poultry Houses: A Review. *Agriculture*. 2023;13:1489.

29. Miles DM, Branton SL, Lott BD. Atmospheric Ammonia Is Detrimental to the Performance of Modern Commercial Broilers. *Poult Sci.* 2004;83:1650-1654.
30. Xin H, Gates RS, Green AR, Mitloehner FM, Moore PA, Wathes CM. Environmental Impacts and Sustainability of Egg Production Systems. *Poult Sci.* 2011;90:263-277.
31. Mautone A, Finzi A. Air Quality Monitoring in Piggeries through an IoT Gas and Environmental Sensors Device. In: *Precision Livestock Farming 2024*. Milan, Italy: Università degli Studi di Milano; 2024. p. 1728-1736.
32. Bist RB, Wang D, Chai L, Xiong Y. Precision Farming Technologies for Monitoring Livestock and Poultry. *AgriEngineering.* 2026;8:64.
33. Zhang Q, Yang Y, Liu G, Ning Y, Li J. Dairy Cow Mastitis Detection by Thermal Infrared Images Based on CLE-UNet. *Animals.* 2023;13:2211.
34. Guo Y, Chai L, Aggrey SE, Oladeinde A, Johnson J, Zock G. A Machine Vision-Based Method for Monitoring Broiler Chicken Floor Distribution. *Sensors.* 2020;20:3179.
35. Korelidou V, Simitzis P, Massouras T, Gelasakis AI. Infrared Thermography as a Diagnostic Tool for the Assessment of Mastitis in Dairy Ruminants. *Animals.* 2024;14:2691.
36. Niloofar P, Francis DP, Lazarova-Molnar S, Vulpe A, Vochin MC, Suci G, *et al.* Data-Driven Decision Support in Livestock Farming for Improved Animal Health, Welfare and Greenhouse Gas Emissions: Overview and Challenges. *Comput Electron Agric.* 2021;190:106406.
37. de Oliveira FM, Ferraz GAES, andre ALG, Santana LS, Norton T, Ferraz PFP. Digital and Precision Technologies in Dairy Cattle Farming: A Bibliometric Analysis. *Animals.* 2024;14:1832.
38. Curti PdF, Selli A, Pinto DL, Merlos-Ruiz A, Balieiro JcDc, Ventura RV. Applications of Livestock Monitoring Devices and Machine Learning Algorithms in Animal Production and Reproduction: An Overview. *Anim Reprod.* 2023;20:e20230077.
39. Kavlak AT, Pastell M, Uimari P. Disease Detection in Pigs Based on Feeding Behaviour Traits Using Machine Learning. *Biosyst Eng.* 2023;226:132-143.
40. Berckmans D. General introduction to precision livestock farming. *Anim Front.* 2017;7:6-11.
41. Zhou L, Hao L, Xiong Y, Qin H, Bao A, Chen Z. Research Progress of Robotic Technologies and Applications in Smart Pig Farms. *Agriculture.* 2026;16:334.
42. John AJ, Clark CEF, Freeman MJ, Kerrisk KL, Garcia SC, Halachmi I. Review: Milking Robot Utilization, a Successful Precision Livestock Farming Evolution. *Animal.* 2016;10:1484-1492.
43. Zhang Y, Sun W, Yang J, Wu W, Miao H, Zhang S. An Approach for Autonomous Feeding Robot Path Planning in Poultry Smart Farm. *Animals.* 2022;12:3089.
44. Yang D, Cui D, Ying Y. Development and Trends of Chicken Farming Robots in Chicken Farming Tasks: A Review. *Comput Electron Agric.* 2024;221:108916.
45. Distante D, Albanello C, Zaffar H, Faralli S, Amalfitano D. Artificial Intelligence Applied to Precision Livestock Farming: A Tertiary Study. *Smart Agric Technol.* 2025;11:100889.
46. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big Data in Smart Farming—A Review. *Agric Syst.* 2017;153:69-80.
47. Klerkx L, Jakku E, Labarthe P. A Review of Social Science on Digital Agriculture, Smart Farming and Agriculture 4.0: New Contributions and a Future Research Agenda. *NJAS Wagening J Life Sci.* 2019;90-91:1-16.
48. Liu N, Qi J, An X, Wang Y. A Review on Information Technologies Applicable to Precision Dairy Farming: Focus on Behavior, Health Monitoring and the Precise Feeding of Dairy Cows. *Agriculture.* 2023;13:1858.
49. Pomar C, Remus A. Fundamentals, Limitations and Pitfalls on the Development and Application of Precision Nutrition Techniques for Precision Livestock Farming. *Animal.* 2023;17:100763.
50. Tzanidakis C, Tzamaloukas O, Simitzis P, Panagakis P. Precision Livestock Farming Applications (PLF) for Grazing Animals. *Agriculture.* 2023;13:288.
51. Paixão G, Mata F, Cerqueira J, Araújo JP. Weather and Seasonal Effects in Behavioural Patterns for Grazing Cattle. *Appl Anim Behav Sci.* 2026;298:106935.
52. Merkelytė I, Šiukščius A, Nainienė R. The Role of Sensor Technologies in Estrus Detection in Beef Cattle: A Review of Current Applications. *Animals.* 2025;15:2313.
53. Santos CA\*, da\*, Landim NMD, de Araújo HX, Paim TdP. Automated Systems for Estrous and Calving Detection in Dairy Cattle. *AgriEngineering.* 2022;4:475-482.
54. Sakar ÇM, Ergin M, Altay Y. Comparative Analysis of Machine Learning Algorithms for Estrous Detection in Dairy Cows Using Sensor-Based Behavioral Data across Seasons. *Trop Anim Health Prod.* 2025;57:479.
55. Simoni A, König F, Weimar K, Hancock A, Wunderlich C, Klawitter M, *et al.* Evaluation of Sensor-Based Health Monitoring in Dairy Cows: Exploiting Rumination Times for Health Alerts around Parturition. *J Dairy Sci.* 2024;107:6052-6064.
56. Paudyal S. Using Rumination Time to Manage Health and Reproduction in Dairy Cattle: A Review. *Vet Q.* 2021;41:292-300.
57. Gusterer E, Kanz P, Krieger S, Schweinzer V, Süß D, Lidauer L, *et al.* Sensor Technology to Support Herd Health Monitoring: Using Rumination Duration and Activity Measures as Unspecific Variables for the Early Detection of Dairy Cows with Health Deviations. *Theriogenology.* 2020;157:61-69.
58. Teixeira VA, Lana AMQ, Bresolin T, Tomich TR, Souza GM, Furlong J, *et al.* Using Rumination and Activity Data for Early Detection of Anaplasmosis Disease in Dairy Heifer Calves. *J Dairy Sci.* 2022;105:4421-4433.
59. Neculai-Valeanu AS, Arition AM, Radu C, Porosnicu I, Sanduleanu C, Amariții G. From Herd Health to Public Health: Digital Tools for Combating Antibiotic Resistance in Dairy Farms. *Antibiotics.* 2024;13:634.
60. Tse C, Barkema HW, DeVries TJ, Rushen J, Pajor EA. Impact of Automatic Milking Systems on Dairy Cattle Producers' Reports of Milking Labour Management, Milk Production and Milk Quality. *Animal.* 2018;12:2649-2656.

61. Cogato A, Brščić M, Guo H, Marinello F, Pezzuolo A. Challenges and Tendencies of Automatic Milking Systems (AMS): A 20-Years Systematic Review of Literature and Patents. *Animals*. 2021;11:356.
62. Ozella L, Brotto Rebuli K, Forte C, Giacobini M. A Literature Review of Modeling Approaches Applied to Data Collected in Automatic Milking Systems. *Animals*. 2023;13:1916.
63. Beauchemin KA, Ungerfeld EM, Eckard RJ, Wang M. Fifty Years of Research on Rumen Methanogenesis: Lessons Learned and Future Challenges for Mitigation. *Animal*. 2020;14:s2-s16.
64. Kurras F, Jakob M. Smart Dairy Farming—The Potential of the Automatic Monitoring of Dairy Cows' Behaviour Using a 360-Degree Camera. *Animals*. 2024;14:640.
65. Ferguson HJ, Davison C, Lima J, Haskell MJ, Dewhurst RJ, Michie C, *et al.* Use of Animal-Mounted Accelerometers to Identify Positive Welfare in Dairy Cattle. *Dairy Sci Manag*. 2025;2:15.
66. Mellor DJ, Beausoleil NJ. Extending the 'Five Domains' Model for Animal Welfare Assessment to Incorporate Positive Welfare States. *Anim Welf*. 2015;24:241-253.
67. Werkheiser I. Technology and Responsibility: A Discussion of Underexamined Risks and Concerns in Precision Livestock Farming. *Anim Front*. 2020;10:51-57.
68. Bos JM, Bovenkerk B, Feindt PH, Van Dam YK. The Quantified Animal: Precision Livestock Farming and the Ethical Implications of Objectification. *Food Ethics*. 2018;2:77-92.
69. Pinillos RG, Appleby MC, Manteca X, Scott-Park F, Smith C, Velarde A. One Welfare—a Platform for Improving Human and Animal Welfare. *Vet Rec*. 2016;179:412-413.
70. Banhazi TM, Babinszky L, Halas V, Tschärke M. Precision Livestock Farming: Precision Feeding Technologies and Sustainable Livestock Production. *Int J Agric Biol Eng*. 2012;5:54-61.
71. Cardot V, Le Roux Y, Jurjanz S. Drinking Behavior of Lactating Dairy Cows and Prediction of Their Water Intake. *J Dairy Sci*. 2008;91:2257-2264.
72. Halachmi I, Guarino M. Precision Livestock Farming: A 'per Animal' Approach Using Advanced Monitoring Technologies. *Animal*. 2016;10:1482-1483.
73. Mottet A, de Haan C, Falcucci A, Tempio G, Opio C, Gerber P. Livestock: On Our Plates or Eating at Our Table? A New Analysis of the Feed/Food Debate. *Glob Food Sec*. 2017;14:1-8.
74. Llonch P, Haskell MJ, Dewhurst RJ, Turner SP. Current Available Strategies to Mitigate Greenhouse Gas Emissions in Livestock Systems: An Animal Welfare Perspective. *Animal*. 2017;11:274-284.
75. Pardo G, Moral R, Aguilera E, Del Prado A. Gaseous Emissions from Management of Solid Waste: A Systematic Review. *Glob Change Biol*. 2015;21:1313-1327.
76. Tullo E, Finzi A, Guarino M. Review: Environmental Impact of Livestock Farming and Precision Livestock Farming as a Mitigation Strategy. *Sci Total Environ*. 2019;650, 2751-2760.
77. Lovarelli D, Bacenetti J, Guarino M. A Review on Dairy Cattle Farming: Is Precision Livestock Farming the Compromise for an Environmental, Economic and Social Sustainable Production? *J Clean Prod*. 2020;262:121409.
78. Palma-Molina P, Hennessy T, O'Connor AH, Onakuse S, O'Leary N, Moran B, *et al.* Factors Associated with Intensity of Technology Adoption and with the Adoption of 4 Clusters of Precision Livestock Farming Technologies in Irish Pasture-Based Dairy Systems. *J Dairy Sci*. 2023;106:2498-2509.
79. Selvaggi R, Lusk JL, Pappalardo G. Eliciting Dairy Farmers' Willingness to Pay for Digital Devices for Precision Livestock Farming. *J Rural Stud*. 2025;119:103772.
80. Kaur J, Hazrati Fard SM, Amiri-Zarandi M, Dara R. Protecting Farmers' Data Privacy and Confidentiality: Recommendations and Considerations. *Front Sustain Food Syst*. 2022;6:903230.
81. Kleen JL, Guatteo R. Precision Livestock Farming: What Does It Contain and What Are the Perspectives? *Animals*. 2023;13:779.
82. Fountas S, Carli G, Sørensen CG, Tsiropoulos Z, Cavalaris C, Vatsanidou A, *et al.* Farm Management Information Systems: Current Situation and Future Perspectives. *Comput Electron Agric*. 2015;115:40-50.
83. Rimpika, Anushi, Manasa S, Anusha KN, Sharma S, Thakur A, *et al.* An Overview of Precision Farming. *Int J Environ Clim Change*. 2023;13(12):441-456.
84. Menezes GL, Mazon G, Ferreira REP, Cabrera VE, Dorea JRR. Artificial Intelligence for Livestock: A Narrative Review of the Applications of Computer Vision Systems and Large Language Models for Animal Farming. *Anim Front*. 2024;14:42-53.
85. Liakos KK, Busato P, Moshou D, Pearson S, Bochtis D. Machine Learning in Agriculture: A Review. *Sensors*. 2018;18:2674.
86. Terence S, Immaculate J, Raj A, Nadarajan J. Systematic Review on Internet of Things in Smart Livestock Management Systems. *Sustainability*. 2024;16:4073.
87. Monteiro A, Santos S, Gonçalves P. Precision Agriculture for Crop and Livestock Farming—Brief Review. *Animals*. 2021;11:2345.
88. Elliott KC, Werkheiser I. A Framework for Transparency in Precision Livestock Farming. *Animals*. 2023;13:3358.
89. Ayre M, Mc Collum V, Waters W, Samson P, Curro A, Nettle R, *et al.* Supporting and Practising Digital Innovation with Advisers in Smart Farming. *NJAS Wagening J Life Sci*. 2019;90-91:100302.
90. Rotz S, Duncan E, Small M, Botschner J, Dara R, Mosby I, *et al.* The Politics of Digital Agricultural Technologies: A Preliminary Review. *Sociol Rural*. 2019;59:203-229.
91. Krishnamoorthi A, Salam NK, Kalaiselvi D, KB C, Kumar S, Kumar V, *et al.* Digital sequencing information in agricultural crops: A comprehensive review. *International Journal*. 2024;8(8):1404-1412.
92. Herrero M, Thornton PK, Mason-D'Croz D, Palmer J, Bodirsky BL, Pradhan P, *et al.* Articulating the Effect of Food Systems Innovation on the Sustainable Development Goals. *Lancet Planet Health*. 2021;5:e50-e62.