Use of AI systems in developing a more sustainable animal husbandry and production

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Received: 20.04.2026.
Accepted: 18.06.2026.

Abstract: AI systems have become integral to many fundamental human activities, including industry, agriculture, healthcare, and scientific research. A comprehensive review of the literature on primary AI applications in animal husbandry and production has been conducted. Relevant sources were collected and evaluated using available AI research tools to assess the benefits and efficiency of these applications. The results obtained in the areas of animal health and welfare monitoring, precision feeding and nutrition optimisation, breeding programme development, sustainable farming, and the automation and robotics of farm operations were then reviewed. It can be concluded that efficiency benefits exist across all areas of animal production. However, as discussed here, problems, barriers, and challenges in implementing AI tools are also present. The study also aimed to introduce the most frequently used AI tools for reviewing the ever-growing literature, paying special attention to Elicit — an AI tool developed for research — to demonstrate an optimal research strategy; however, not been proven to be faultless in the selection of sources. Referentia and Verifing, advanced AI tools that extract references from any type of scientific paper and compare live titles with those cited in your paper to help identify outdated links, title mismatches, and inaccessible sources, were also tested and produced surprising results.

Keywords: AI systems, machine learning, precision livestock farming, sustainability, animal welfare

Introduction

Since its inception in the 1950s, the field of Artificial Intelligence (AI) has evolved rapidly, becoming deeply integrated into the fabric of everyday life, from healthcare to finance. The role of AI systems' applications is expanding significantly in fundamental areas that have a profound impact on our lives and future, from education to political decision-making (Crawford, 2023). AI agents are software programs that are capable of perceiving their environment, making autonomous decisions, and taking actions to achieve specific goals. Their prevalence is increasing in various domains, including scientific research (Tegmark, 2017; Winn, 2025). The global agricultural sector is currently facing significant challenges in meeting the food demands of a growing population, whilst also dealing with issues such as climate change, resource scarcity, and ethical concerns. In this high-stakes environment, animal husbandry and production are undergoing a profound transformation, driven by the integration of Artificial Intelligence (AI). This change signifies a fundamental shift in the role of the farmer, transitioning from a manual labourer to a data-driven manager and animal welfare expert. As Chingaryan et al. (2020), and Gebbers and Adamchuck (2021) demonstrate, detailed information regarding machine learning (ML) applications in crop and livestock systems is available, including disease detection, yield forecasting, and soil analysis. The primary domains of these applications are as follows:

Precision farming: Smart sensors and drones monitor soil moisture, temperature, and crop health in real time, and by satellite and aerial imagery, AI analyses data to detect disease, pests, or drought (Berckmans, 2017).

- Automated machinery: Autonomous tractors and harvesters, self-driving farm equipment, reduce labor costs. Robotic harvesting: AI-powered robots pick fruit.
- Crop and soil monitoring: AI-powered analytics predict optimal planting and harvest times. Disease detection: Cameras and machine learning identify plant diseases early.
- Livestock management: Facial recognition for cattle tracking, health, and behavior. Automated feeding systems: AI adjusts feed based on animal needs (Ruchay et al., 2024).
- Supply chain and yield prediction: AI forecasts crop yields to optimize market supply and tracks food from farm to table.

The objective of this review is to provide a synopsis of the extant knowledge on the utilization of AI in the domains of animal husbandry and production, having a wide variety of practices, including management, healthcare, breeding, and overall welfare. Moreover, the most used AI-helped tools for literature reviewing are also presented and critically discussed.

Material and Methods

Firstly, the most relevant literature was collected from standard online scientific literature sources (Google Scholar, Medline, ScienceDirect, PubMed, Scopus, Web of Science, Academia.edu, and ResearchGate). For this study, ChatGPT was also employed for experimentation. Furthermore, the study demonstrates the usefulness of research assistants and systematic literature search tools such as Consensus, Scinapse, Research Rabbit, and Elicit.

Elicit is a highly effective research assistant primarily designed for scientific and academic research. It can automate the most time-consuming aspects of searching academic databases, though it is not yet perfect. The methodology, source evaluation steps, inclusion criteria, and results are presented in detail in the 'MI-driven optimal feed plans' section, which provides an example of an optimal search strategy that would be challenging to implement without AI tools.

To identify outdated links, mismatched titles, and inaccessible sources in the primary collection of 83 items, Verifing (https://verifing.com/) and Referentia (https://refvalidation.org/) were used. These tools identified that around two-thirds of the articles in the collection had mismatched titles. However, personally checking all items revealed that 10% of these were incorrectly identified as mismatched.

Key applications of artificial intelligence in animal husbandry and production

Artificial intelligence (AI) is rapidly transforming animal husbandry, shifting the focus from traditional, experience-based practices to a data-driven science. This revolution is key to meeting global food production demands while improving animal welfare and ensuring environmental sustainability. Among the most significant applications of AI are real-time monitoring of animal health and welfare, precision feeding, advanced breeding programs, environmental control, robotic automation, and sophisticated data analysis for informed decision-making (Iyiola-Tunji et al., 2024). A simplified model of AI methodology in farming is shown in Figure 1, created by GPT-4o.

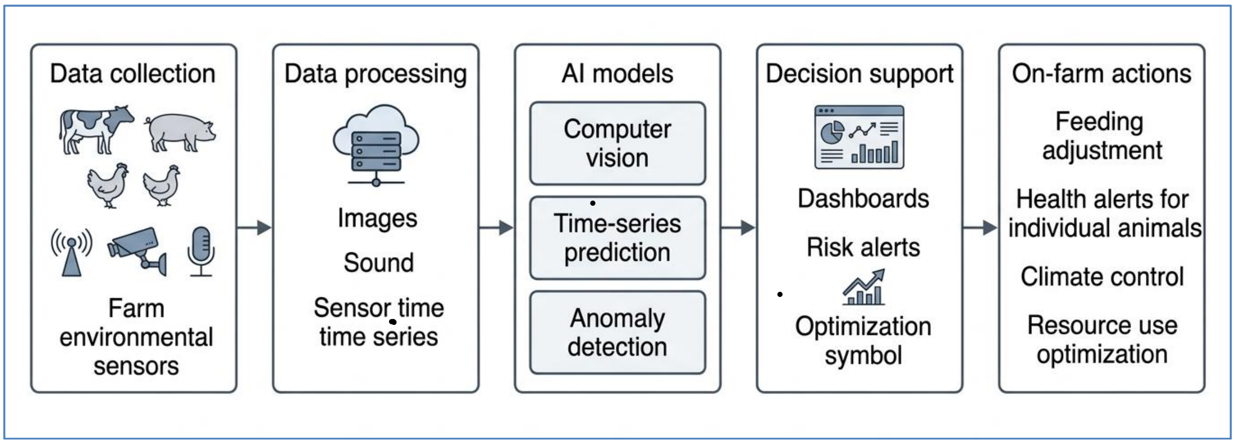

Figure 1 AI methodology in animal farming

The introduction of AI brings significant economic benefits, including cost reductions in veterinary care, labor, and feed waste; increased efficiency and productivity through higher yields; optimized resource use; and improved product quality. In addition to economic benefits, AI contributes to animal welfare through early problem detection and personalized care, and supports sustainability by minimizing environmental impacts. Although challenges such as high initial investment and a lack of digital literacy remain, continuous technological advances and supportive initiatives are paving the way for the widespread integration of AI, ensuring a promising, more flexible, profitable, and humane future for animal husbandry (Banhazi et al., 2012; Elbderi and Chestnov, 2021; Rosati, 2024).

Main Areas of Application of AI in Animal Husbandry

Advanced Animal Health and Welfare Monitoring

AI-based systems enable continuous, real-time monitoring of animal health, behavior, and welfare using sensors (accelerometers, gyroscopes, biosensors of temperature, heart rate, movement, sound) and cameras. Wearable technologies such as smart collars and ear tags monitor vital signs, location, and activity levels 24/7, transmitting data to farmers' devices. Computer vision systems monitor behavioral patterns (eating, drinking, movement, social interactions, posture) and can detect deviations from normal. Facial recognition technologies can also be used to track and analyze behavior, movement, and activity (Enzanno et al., 2021; Kumar et al., 2025).

Early and predictive disease detection

AI can predict disease outbreaks, identify potential host reservoirs, and detect emerging disease threats, enabling rapid intervention. Examples include foot-and-mouth disease, early detection of avian influenza, and bluetongue disease. Specific applications include the detection of mastitis in dairy cows by analyzing udder temperature, swelling, color, milk somatic cell count, and historical herd data, as well as early detection of lameness in horses. AI also analyzes genetic pedigrees to predict and diagnose disorders based on historical data. The shift from reactive disease management to proactive prediction and early intervention enabled by AI is fundamentally changing the cost-benefit analysis of animal health. This transformation moves away from costly, herd-level treatments towards targeted, individual care, which reduces antibiotic use and results in more resistant animal populations. Predictive capabilities enable livestock farmers to respond more quickly to infectious diseases, spend less on veterinarians and antibiotics, and avoid costly and not always healthy herd-level preventive treatments. This not only brings economic benefits but also contributes to the fight against antibiotic resistance, with wider public health benefits.

Epidemiological risk mapping and optimization of disease control strategies

AI can model disease spread, predict economic impacts, and identify the most cost-effective interventions. Examples include identifying avian influenza risk zones based on wild bird migration routes and weather data, and tracking infection chains for diseases such as bluetongue using big data and Radio Frequency Identification (RFID). The FAO and OIE also use such AI-based epidemiological risk maps. AI can classify potential host reservoirs of zoonotic diseases by analyzing the sharing of pathogens between farmers (Muley et al., 2025; Ye et al., 2025).

Precision Feeding and Nutrition Optimization

Personalized feed rationing

MI-controlled precision feeding ensures that individual animals are fed on time, in the right quantities, and according to their individual needs. It uses physiological data (e.g., weight, age, health status, production stage) and scientific calculations to determine feed requirements and dynamically adjust them during different growth stages. RFID tags and smart collars identify individual animals at feeding stations, dispensing precisely measured rations.

Maximizing feed conversion ratio (FCR) and minimizing waste

AI models optimize FCR, reducing feed waste by up to 25% and promoting more efficient feed utilization. This reduces costs and improves digestion. One key point is that AI can help identify protein alternatives for animal nutrition.

Automated monitoring of feed intake patterns

Continuous recording of feed consumption enables immediate response to anomalies, such as when an animal or group is not eating, which may indicate a feeder malfunction, water shortage, or disease. Sensors in the feeders can detect and prevent both overfeeding and underfeeding.

MI-driven optimal feed plans

Machine learning algorithms analyze millions of data points to predict feed efficiency or detect early signs of disease, continuously improving recommendations. Data analytics is transforming feed formulation by optimizing nutritional content in real time for maximum animal performance, adjusting the composition based on growth rates, milk production, and health markers. The integration of AI in precision feeding represents a paradigm shift from herd-level average nutrition to individual metabolic optimization. This transforms feed from a bulk commodity to precisely managed input that directly influences animal health, productivity, and economic performance while reducing the environmental footprint. Traditional feeding is often based on group averages, but AI enables "individual adaptation," "personalized feed rationing," and "feed adjustment to individual needs without having to measure each animal individually." This individualized approach, driven by real-time data and machine learning, leads directly to "reduced waste, increased utilization and production efficiency, reduced waste and promoted efficient feed utilization, and reduced operating costs and environmental impacts. This process represents the holistic optimization of critical inputs.

Selected results of searching this topic using Elicit

Precision animal feeding using artificial intelligence methods has been applied across diverse species and production systems. In studies with sows, machine learning techniques such as k-shape clustering and regression models yielded reductions in nitrogen/phosphorus excretion (up to 28–42%) and lowered feed costs (up to 12% or 3.4€ per gestation). Likewise, precision systems for growing pigs and dairy cows demonstrated improved feed efficiency and dosing accuracy—one comparison showing a reduction of mean absolute percentage error from 3.84% to 0.52%—and enhanced prediction performance, with the coefficient of determination increasing from 0.80 to 0.93. Computer vision- and deep learning–based approaches in aquaculture and beef cattle achieved accuracies of 95–99.8% in detection, segmentation, and ration prediction. AI-driven precision feeding systems optimize nutrient delivery across diverse animal species, achieving significant reductions in feed costs (up to 12%) and nutrient excretion (up to 42%) while improving feed efficiency and prediction accuracy (95-99.8%). Key outcomes reported include:

1. Consistent reductions in nutrient excretion and feed costs in multiple studies.
2. High accuracy in predicting feeding behavior and nutrient requirements across species.
3. Effective use of diverse AI techniques—including regression, decision support systems, and deep learning models—to tailor feeding regimens in species ranging from pigs and dairy cows to fish and calves.

These results support the conclusion that AI-driven precision feeding systems can optimize nutrient delivery and improve economic and performance outcomes in animal production.

Using the research question titled ”Precision Animal Feeding and Nutrition Optimization with AI methods”, a cross-search of 126 million academic papers from the Semantic Scholar corpus was conducted, from which the 500 papers most relevant to the query were retrieved. Characteristics of the included studies are summarized in Table 1.

Table 1. Characteristics of some of the studies included in the search carried out by Elicit*

Study	Animal species	AI/ML technology used	Feeding system type	Primary outcomes measured
Durand et al., 2021	Sows (gestating)	ML: logistic regression, least absolute shrinkage, etc.	Sensor based, automated feeders	Nutrient intake/ excretion, prediction accuracy, feed cost
Gauthier et al., 2022	Lactating sows	ML: k-shape regression	Decision support system, smart feeders	Litter growth, feed cost, N/P excretion
Domingos et al., 2024	Sows (gestating)	Mathematical model	Precision feeder	Litter weight, feed intake, maternal index
Su et al., 2025	Lactating sows	ML: random forest, gradient boosting decision tree	Data-driven, farm based	Weaning performance, milk composition
Dagel et al., 2022	Heifer caves	Precision supplementation	SmartFeed, SmartScale	Feed use, daily gain
Dong, 2024	Dairy cows	Amplitude iterative pruning (deep convolutional neural network)	Smart, automated	Detection rate, milk production

Study	Animal species	AI/ML technology used	Feeding system type	Primary outcomes measured
King et al., 2024	Dairy cows	Deep learning (YOLOv8)	Vision-based	Feeding behavior tracking
Brambilla et al., 2025	Dairy cows, bulls	Computer vision, (optical sensor)	Mixing wagon, automatic feeding	Fibre length, total mixed ration consistency
Hossam et al., 2024	Tilapia	ML: (YOLOv8), computer vision, Internet of Things	Automated, sensor based	Production, fish size/count accuracy
Huang and Vadloori, 2024	Fish (aquaculture)	Deep learning (feature fusion attention U-net optimization)	Automated, video-based	Segmentation/ optimization accuracy
Son and Yeong, 2024	Pollock salmon	Convolutional neural network, gated recurrent unit	Automated, sensor-based	Growth, ration prediction accuracy

*Rows written in red later proved to have mismatched identification.

Revolutionary Breeding Programs and Genetic Selection

This subject was widely discussed from different points of view (Meuwissen et al., 2001; Gonzalez-Recio et al, 2014; Montesinos-López et al., 2021; Van Klompenberg et al., 2022). MI-driven technologies provide a data-driven approach to animal breeding, refining techniques, minimizing errors, and maximizing reproductive success. They accelerate genetic progress by enabling more accurate selection and intensive use of genetically superior parents. The artificial insemination process has also been revolutionized by AI algorithms. AI monitors the reproductive cycles of animals by analyzing visual indicators (e.g., estrus signs based on images/videos) and other data (e.g., step counter data, inclinometer, temperature). This allows farmers to predict fertility cycles, select the optimal timing for insemination, choose effective breeding techniques, and reduce errors, leading to higher pregnancy rates and improved reproductive efficiency. AI-based genomic tools analyze whole-genome data to identify both obvious and hidden genetic similarities, revealing inbreeding risks that traditional pedigree analysis may not detect. Runs of Homozygosity (ROH) are used to accurately measure an animal's true inbreeding level. AI helps track recent genetic relationships and identify inbreeding risks early, maintaining genetic diversity while enabling rapid genetic progress. AI integrates genetic information with epigenetics, gene expression, and environmental factors to continuously refine predictions for traits such as milk yield, udder health, and temperament.

AI's contribution to breeding goes beyond mere efficiency gains; it redefines the foundations of genetic improvement by enabling the selection of complex, previously unmeasurable traits (e.g., methane emissions, heat stress tolerance, welfare indicators) and providing unprecedented precision in the management of genetic diversity. This ensures long-term herd resilience and sustainability in the face of environmental and market pressures. Traditional breeding has primarily focused on production traits. Still, AI enables the selection of "previously difficult-to-measure traits" and "genetic improvement beyond traditional production traits, including welfare indicators, environmental impacts, and resilience." The ability to identify "hidden breeding potential" and optimize breeding strategies based on vast, integrated data (genomics, epigenomics, environment) means that AI not only accelerates existing processes but fundamentally changes *what* can be selected and *how* genetic progress can be achieved, leading to more robust and adaptive animal populations in the face of growing challenges. Some special aspects of this field were discussed by Chakraborty et al., 2022; Hamadani and Ganai, 2022; Emsen et al., 2025.

Environmental Regulation and Sustainable Farming

Artificial intelligence contributes to environmentally sustainable animal farming by using machine learning, sensors, and connected devices to optimize resources, reduce emissions, and enable sustainable intensification across farming systems. It supports sustainable animal farming by enabling four key practices:

Precision monitoring and resource optimization:

- Studies using sensors and Internet-of-Things platforms report real-time tracking of animal health, feed intake, and water use, leading to targeted interventions, reduced feed waste, and lower emission levels.

Predictive analytics for environmental management:

- Papers employing machine learning and big data show that forecasting animal health issues and environmental risks can help mitigate pollutants such as ammonia and greenhouse gases. These systems also hint at indirect benefits like reduced antibiotic use.

Automation systems for sustainable operations:

- Reports on robotics, drones, and blockchain note improved feeding, climate control, and waste management that enhance operational efficiency and traceability in dairy, poultry, and pig production.

Integrated data platforms for holistic assessment:

- Multiple studies describe the importance of fusing animal health, environmental, and production data through cloud-based systems to support informed, comprehensive sustainability decisions. Evidence from reviews and one field trial suggests that AI technologies, especially machine learning, sensors, and connected devices, contribute to resource optimization, emission reduction, and sustainable intensification in various farming systems.

A more thorough delineation of the area is outlined in the works of Tullo et al., 2019; Collins et al., 2022; Franzo et al., 2023; Kaur et al., 2023.

Automation and Robotics in Daily Farm Operations

Automated feeding systems

Automated feeding systems manage feed preparation, mixing, and distribution, often using mixing and dispensing robots. These systems provide customized nutrition for each animal based on individual needs, reducing feed waste by up to 25%. Mobile mixers and feed pushers ensure 24/7 availability of fresh feed without disturbing the animals.

Robotic milking systems

These systems have revolutionized milk production by enabling cows to be milked 24 hours a day without human intervention. Milking robots learn and adapt to the unique characteristics of each cow (milk production, udder shape, teat location), optimizing routines and increasing milk production by up to 15%. They also monitor milk quality (HACCP) and cow health, detecting potential infections (Kaur et al., 2023).

Robots can take care of barn cleaning and waste management. Drones can monitor large herds and assess pastures. Virtual fencing using GPS and special collars to define and adjust pasture boundaries reduces the need for physical fencing and extra infrastructure. AI-enhanced security monitoring by advanced computer vision algorithms detects unusual activity on the farm, such as unauthorised vehicles, intruders, or suspicious activity, increasing security. The use of AI-driven robotics and automation in farming is good for two things. It helps to solve the problem of not having enough people to do the work, and it makes the lives of animals better. It also makes farming much more efficient. All of this means that the way humans and animals interact on modern farms is completely different to how it used to be. Technology, using AI, takes over repetitive, physically demanding jobs and gives humans more important jobs like supervising and making important decisions. Therefore, it is entirely reasonable to refer to this stage of development as 'Industry 4.0' and 'Precision Livestock Farming' (PLF), as proposed by Morrone et al. (2022).

Challenges and Future Prospects

The integration of artificial intelligence into animal farming, often referred to as 'precision livestock farming' (PLF), is transforming the industry. Leveraging technologies such as computer vision, sound analysis, and machine learning, AI has the potential to boost productivity, improve animal welfare, and enhance sustainability. However, this transformation also has significant challenges, described below.

1. Data scarcity and quality: AI models are notoriously data-hungry. It is difficult and expensive to acquire large, high-quality, well-annotated datasets for various livestock species, breeds, and production environments. Biased or incomplete data can lead to models that fail to generalise across different farms, resulting in inaccurate predictions (Shumaly et al., 2025).
2. Technical infrastructure and cost: Implementing AI requires robust infrastructure, including sensors, high-speed internet, and computing power. The initial capital investment required is often beyond the means of many small- and medium-scale farmers, which could widen the technology gap within the industry.
3. Algorithm interpretation and trust: Many complex AI models, particularly deep learning networks, operate as 'black boxes', where the reasoning behind a decision is not transparent. In order for farmers and veterinarians to trust and act upon an AI's alert (e.g., an early disease warning), they require explanations that they can understand, rather than just outputs.
4. Integration and user-friendliness: A tool is only useful if it can be seamlessly integrated into daily farm routines. Complex systems that require significant

technical expertise to operate and maintain are unlikely to be adopted. The technology must be designed with the end user, the farmer, in mind (Berckmans, 2022).

Despite these challenges, the future of AI in animal farming is bright, driven by several promising trends:

1. Early disease detection and prevention: The future lies in predictive rather than reactive health management. AI can analyse combined data streams (e.g., video for lameness, infrared thermography for fever, and microphones for coughing) to identify subclinical illness long before it is visible to the human eye. This enables targeted intervention and reduces the use of antibiotics.
2. Welfare-Centric Management: AI will move beyond productivity metrics to provide holistic welfare assessments. By continuously monitoring behaviours such as social interaction, resting patterns, and the expression of natural instincts, AI systems can serve as an 'animal-centric' dashboard, enabling farmers to validate and enhance welfare standards (Benjamin & Yik, 2019).
3. Automation of Complex Tasks: Advances in robotics coupled with AI will automate labour-intensive tasks such as sorting animals, cleaning, and assisted milking or feeding. This will mitigate labour shortages and improve consistency.
4. Sustainability Optimisation: AI will play a key role in optimising the use of resources and reducing the environmental footprint of farming. This includes precision feeding to minimise waste, managing manure, and monitoring methane emissions. This will contribute directly to creating more sustainable food systems (Astill et al., 2020).

To sum up, AI tools have the potential to make the animal farming sector more efficient, ethical, and sustainable. However, the path forward requires a collaborative effort among researchers, engineers, and farmers to overcome current challenges related to data, cost, and trust. By developing robust, interpretable, and user-centric solutions, we can ensure that technology and animal husbandry work together for the benefit of all in the future.

Conclusions

AI represents a paradigm shift in animal production, offering substantial efficiency, welfare, and sustainability benefits. These advantages can be seen in every area of animal production, from farming practices and animal health and welfare monitoring to precision feeding and nutrition, breeding programs and genetic selection, and the automation and robotics used in everyday farming.

However, successfully implementing AI tools requires overcoming economic barriers, ensuring farmer education, and upholding ethical standards. Rather than replacing farmer expertise, technology should complement it, forming a partnership between human experience and machine intelligence.

As AI continues to evolve, its role in feeding a growing global population while minimizing environmental impact will likely become increasingly critical. The challenge lies in making these technologies accessible and practical for farms of all sizes, while ensuring that they genuinely improve outcomes for animals, farmers, and the environment. AI tools developed for gathering and evaluating information sources, and for reviewing and checking these sources for mismatches, are efficient but not yet faultless. Personally, one-by-one checking still seems to be necessary for the time being.

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