Challenges in Integrating Robotics and AI in Animal Husbandry

Swati Dahiya, Neelam Rani, Anita Dalal, Deepika Sheoran

The integration of Artificial Intelligence (AI) and robotics into animal husbandry represents a revolutionary advancement in precision farming, promising to enhance productivity, welfare, and sustainability in livestock management. However, several critical challenges hinder widespread adoption. This chapter discusses the multidimensional constraints affecting the adoption and integration of AI and robotics in animal health systems. Chief among these are data accuracy and sensor calibration issues, which compromise reliability, especially in environments where recalibration or maintenance may not be easily performed. Sensor discomfort and hardware limitations further affect animal behaviour and the integrity of collected data. Privacy, data ownership, and cyber security are becoming vital concerns with increased digitization, particularly given the sensitive nature of biological and operational farm data. The ethical implications of AI-based surveillance and automation in animal care are also examined, including potential objectification of animals and the loss of farmer-animal relationships. High costs of intelligent sensor systems and limited scalability exacerbated by reliance on imported components pose economic hurdles for smallholders. Furthermore, difficulties in integrating these technologies with existing farm infrastructure, combined with gaps in farmer education and training, impede adoption. The chapter also highlights the need for robust regulatory frameworks, indigenous innovation, and inclusive technology dissemination. Finally, it explores emerging trends such as AI-powered predictive analytics and autonomous veterinary systems, envisioning a future where technology augments not replace humane and efficient livestock care. These innovations, if made accessible and ethically applied, could shape the future of sustainable, data-driven animal agriculture.

Keywords: *Animal husbandry, Artificial intelligence, Data privacy, Ethical concerns, Precision livestock farming, Robotics, Sensor calibration*

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Introduction

The growing integration of robotics and artificial intelligence in animal husbandry holds promise for improving livestock management, disease detection, and productivity. However, bringing these innovations into everyday farming is far from simple. Real-world conditions, such as infrastructure gaps, sensor inaccuracies, ethical concerns, and high costs, present substantial hurdles. Farmers, veterinarians, and developers must work together to align technology with on-the-ground realities. This chapter examines these pressing challenges, highlighting why a thoughtful, inclusive approach is essential for sustainable adoption. By understanding the barriers, we can better shape future solutions that are both effective and equitable.

Technological challenges and limitations

Technological challenges are central to the integration of AI and robotics in animal husbandry. Issues such as inaccurate sensor data, a lack of standard calibration, limited connectivity, and high device costs hinder the reliable application of these systems in field conditions. Moreover, algorithmic bias and data misinterpretation add further complexity to the deployment of these systems in diverse livestock environments.

- **Data accuracy and sensor calibration issues:** Accurate data collection is vital in animal health monitoring. Wearable sensors collect data on temperature, heart rate, and movement, but poor calibration can trigger false alarms or miss early signs of disease (Shajari et al., 2023). Current animal sensors lack simple recalibration protocols and often require technical expertise or specialized tools. Environmental factors such as dirt and moisture further reduce sensor performance. Remote areas often face connectivity issues, limiting access to real-time cloud-based systems.

- **Lessons from human glucose monitoring:** Human glucose monitoring systems offer valuable insights into sensor calibration, and they also aid in the successful management of diabetes in today's world. These devices allow for easy recalibration through user-friendly systems, such as entering a code or auto-coding when a new test strip is used (Ghosh et al., 2025). This approach ensures accuracy and minimizes user errors, and similar systems could be applied to animal health monitoring for more reliable and accessible devices. Through these technologies, computer-based monitoring not only facilitates timely interventions but also offers consistent and objective data that can support research, regulatory compliance, operational efficiency, and welfare certifications (Maroto-Molina et al., 2019; Chen et al., 2021). A nanotechnology-based array of sensors has been tailored for the detection of *Mycobacterium bovis*-infected cattle via breath, which allows real-time cattle monitoring (Peled et al., 2012).

- **Animal comfort and device intrusiveness:** Wearable and implantable devices may induce stress or discomfort in animals if not designed with ergonomics in mind (Nguyen & Choi, 2022). This necessitates further innovation toward non-invasive and animal-friendly sensor platforms (Green & Black, 2023).

- **Algorithmic reliability and data interpretation:** Machine learning algorithms must be trained on diverse datasets to avoid geographic or species-based bias. Inaccurate algorithms can misclassify health risks or overlook critical issues (Young & Brown, 2023; Taylor & Evans, 2024).

- **Training and education:** User education is essential for the effective use of sensor technologies in animal care. Just as diabetic patients are trained to use glucose monitors, animal handlers/ caretakers need guidance on operating, maintaining, and calibrating their sensors. These devices are crucial for monitoring health and environmental conditions, but their reliability depends on correct usage. Without proper training, errors in placement, calibration, or maintenance can lead to inaccurate data and delayed interventions. Simple guides and digital tutorials can help users understand sensor operation and troubleshooting. Regular refresher training ensures continued accuracy and updates animal handlers/ caretakers on new practices. Educated users are more confident and consistent, leading to better data and improved animal welfare (Ritz et al., 2019).

Privacy, security, and ethical challenges

The integration of AI introduces ethical debates on data ownership, animal autonomy, and surveillance. Animal data privacy, often overlooked, is increasingly relevant with the rise of digital farming (Neethirajan, 2023).

Data privacy and ownership: Farmers generate vast datasets through sensor use. Without clear ownership rights, data may be exploited by third parties. Transparent protocols are essential (Orts & Spigonardo, 2014; Sharma et al., 2024).

Cybersecurity threats: Cloud-based platforms are vulnerable to cyberattacks that may compromise animal health records or operational continuity (Gupta et al., 2020; Campoverde et al., 2024). Encryption, authentication, and verification layers are crucial.

Ethical objectification of animals: Excessive reliance on metrics can reduce animals to data points, neglecting their sentience and emotional needs (Neethirajan, 2023). Human-animal bonds and welfare-oriented farming must remain central.

Financial Challenges and Scalability Constraints

High development costs: Sensor development includes expensive components like microcontrollers and silicon chips. Costs remain a barrier, particularly in developing countries (Goedde, 2019; Dawkins, 2021). Advanced systems require substantial initial investments and maintenance, particularly challenging for small-scale farms (John et al., 2024).

Need for indigenous manufacturing: Public-private partnerships are essential for building local sensor ecosystems. Projects such as Moosense (Sarangi et al., 2014) and INAPH demonstrate successful local adaptation. Modular, open-source platforms can significantly reduce costs.

Scalability and data integration: Large-scale sensor systems face challenges in real-time processing and integration of GPS, RFID, and health metrics. Robust algorithms are required to ensure reliability and speed (Neethirajan, 2023).

Environmental and infrastructural challenges

Power and connectivity issues in rural farming areas: Rural regions often face inconsistent electricity supply and limited internet connectivity, which hampers the performance of cloud-based AI systems and real-time robotic monitoring. Dependence on wireless data transmission and 24/7 power access creates a digital divide that restricts smallholder farmers from adopting such technologies.

Sustainability and carbon footprint of AI and robotics: The manufacturing, deployment, and operation of robotics and AI devices involve high energy consumption and material use, contributing to environmental degradation. Data centres, training algorithms, and robotic hardware increase carbon emissions, prompting the need for energy-efficient designs and renewable-powered infrastructures.

Disposal and recycling of obsolete robotic components: Electronic waste from outdated or non-functional robotic systems poses serious environmental risks. Components such as batteries, microchips, and sensors contain hazardous substances that require responsible recycling mechanisms. However, formal e-waste management infrastructure is often lacking in agricultural communities, necessitating policy interventions and take-back programs.

Integration with existing farm management systems

Smallholder farmers often lack the infrastructure to implement AI technologies. Economic challenges, education gaps, and poor connectivity restrict their judicious use. High upfront costs, software subscriptions, and data plans limit accessibility (Chen et al., 2021). Modular tools designed for scalability can provide affordable entry points.

Lack of training and technical support: Farmers may lack the technical knowledge to maintain sensor systems (Misaki et al., 2018). Training programs, helplines, and visual tutorials are needed to support effective adoption.

Proposed solutions: To overcome these challenges, several solutions can be implemented:

- **Affordable, scalable solutions**: Manufacturers can create modular, low-cost sensor systems tailored to the size of a farm. These systems should be easy to install and operate, with basic features at an affordable price. Farmers should be able to scale up the technology as needed.

- **Training and education programs**: To bridge the knowledge gap, governments, NGOs, and tech providers can offer accessible training programs. These can include on-site workshops, digital tutorials, and peer-to-peer mentoring to help farmers learn how to use the technology.

- **Financial support**: Governments and financial institutions can provide subsidies, grants, or low-interest loans to help small farmers afford sensor technologies. This would make it easier for them to invest in digital tools without the upfront financial burden.

- **Community-based models**: Shared infrastructure, such as community-based sensor hubs, could help lower costs. Multiple farmers could share sensors and data, reducing individual expenses while fostering collaboration.

Future trends and innovations

As the realm of animal health monitoring continues to evolve, groundbreaking technologies are poised to revolutionize veterinary science and livestock management. The integration of artificial intelligence (AI), advanced bio-sensing materials, and autonomous systems promises to unlock new levels of precision, efficiency, and sustainability, shaping the future of animal health and welfare.

AI-powered predictive analytics in animal health: AI-driven predictive health analytics is reshaping disease management by analyzing complex biomarker data to predict individual health trajectories. This approach enables early interventions and customized treatment plans, marking a transformative shift in personalized healthcare (Kargbo, 2024). In veterinary science, these applications enhance disease management, leading to better health outcomes in animals (Alzubi, 2023; Sharun et al., 2024) and support precision medicine (Min et al., 2024).

Prospects for autonomous ai-driven veterinary systems: The concept of autonomous AI-driven veterinary systems represents the next frontier in animal healthcare. These systems would integrate AI, robotics, and automated diagnostics to handle routine health assessments, treatment administration, and even surgeries. AI and deep learning can eliminate the subjectivity in image interpretation, a common bias in diagnostics. While medical image analysis is well-developed in human healthcare, its use in veterinary practice, particularly in low- and middle-income regions, is still evolving (Bohr, 2020). Combining radiomics and AI has shown promise in applications like disease detection and prognosis, predicting surgical needs in colic-affected horses. Technologies like Johns Hopkins' STAR robot have outperformed humans in procedures such as bowel anastomosis in animals. AI-assisted surgeries enhance outcomes by planning optimal strategies, assessing risks, and providing real-time, data-driven guidance to improve precision and decision-making (Fraiwan, 2020).

Conclusion

AI and robotics hold promise for transforming animal husbandry through enhanced diagnostics, welfare, and productivity. However, technological, ethical, economic, and infrastructural challenges must be systematically addressed. Veterinarians benefit from precise diagnostic tools; farmers gain from improved disease management and productivity. Innovative tools also improve animal welfare. Stakeholders must build inclusive frameworks that promote equitable access to AI tools. Government support, regulatory clarity, and public-private partnerships are essential. With investments in digital infrastructure, algorithmic reliability, farmer education, and ethical oversight, AI can power a more humane, efficient, and sustainable animal farming future.

Conflicts of interest

The authors declare no conflicts of interest.

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