

Artificial Intelligence-Based Beef Cattle Farming Transformation: A Systematic Literature Review of Opportunities, Constraints, and Future Development Directions

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ABSTRACT

Smallholder beef cattle farming faces various challenges, including market access and limited digital literacy. This systematic literature review aims to identify opportunities for developing transformational smallholder beef cattle farming based on artificial intelligence and digital technology. A literature search was conducted in the Scopus database following the PRISMA process. Of the 605 initial articles, after limiting publication years to 2021–2026, English language, and open access, 451 articles were selected for screening. After title and abstract screening, 43 articles were included in the final synthesis, consisting of 23 core articles and 20 supporting articles. The review results indicate that technologies such as machine learning, the Internet of Things, sensors, smart collars, computer vision, remote sensing, blockchain, and decision support systems have the potential to improve productivity, feed efficiency, livestock health, and sustainability. However, their adoption remains limited by infrastructure, digital literacy, and institutional support. Therefore, AI development needs to be directed toward technologies that are affordable, simple, and focused on smallholder farmers.

Keywords: artificial intelligence; smallholder farming; beef cattle; precision livestock farming; systematic literature review.

1. INTRODUCTION

In small-scale beef cattle farming, management generally relies on local experience and knowledge, as well as informal market information (Zhang, 2025). This pattern allows farmers to adapt husbandry practices to local conditions, but at the same time, makes the production system highly dependent on individual judgment and vulnerable to uncertainty (Syarifuddin *et al.*, 2026). Smallholder beef cattle farmers must simultaneously manage all aspects, from feed availability and animal health to reproductive performance, growth monitoring, price fluctuations, and environmental pressures (Zurnawita, 2025). This is increasingly important because beef cattle farming is expected not only to increase household incomes and rural livelihoods but also to contribute to food security and the sustainability of livestock systems (Folarin *et al.*, 2025). Several recent studies have begun to examine the potential of artificial intelligence and related digital technologies to support more precise, timely, and data-driven

decision-making in smallholder beef cattle farming systems (Gresse and van Marle-Köster, 2024; Zhang, 2025).

Artificial intelligence-based livestock transformation should not be understood solely as the direct use of AI algorithms (Kapundu et al., 2026). The current technology ecosystem encompasses machine learning and the Internet of Things (IoT), mobile applications, and precision livestock farming (Rahmawati, Haryanto and Setiawan, 2025). These technologies enable livestock data to be transformed into usable information to support daily management decisions (Tang, 2024). One study (Umsura and Chaidee, 2024) discusses the importance of an IoT-based smart farming system developed to assist small-scale cattle farmers through feed monitoring and breeding analysis. A cloud-based platform and wireless sensor network enable more systematic collection and processing of livestock data. Furthermore, a deep reinforcement learning approach has been proposed as a support system for small-scale beef cattle farming by incorporating variables such as production costs, market prices, livestock health, land resources, financial capacity, risk preferences, and seasonal variations into farmer-level decision models (Zhang, 2025). These studies show that AI-based technology has the potential to shift smallholder beef cattle farming from experience-based management to data-based management.

A number of studies also show that AI and digital technology can answer various technical problems in cattle production, namely studies (Umsura and Chaidee, 2024; Ali, Atmaja and Herviyanto, 2025; Bhamashetti et al., 2025; Zhang, He and Guo, 2025). Computer vision and morphometric modeling have been used to estimate livestock live weight, thereby reducing reliance on physical weighing facilities that are often unavailable or too expensive for smallholder farmers, as described in studies (Ali, Atmaja and Herviyanto, 2025; Kinkpe, Emmanuel and Di, 2026). Other studies highlight livestock health and welfare monitoring through low-cost IoT-based health monitoring systems, smart collars, cattle stress sound detection, and computer vision-based parasite or livestock disorder risk detection (Rajapakse, Maduranga and Dissanayake, 2021; Zurnawita, 2025; Kusumarini, Janumurti and Nurhidayah, 2026). In addition, remote sensing and machine learning have been used to estimate grazing pressure and feed availability. This is particularly important for extensive and semi-intensive beef cattle systems, where feed availability is heavily influenced by land, climate, and seasonal dynamics (Caron, Rumiano and Wielgus, 2023; Wang, Huang and Tian, 2025).

AI-based technologies are increasingly connected to the livestock value chain through blockchain, IoT, and supply chain data systems. These technologies can strengthen livestock identification, disease control, and market access. In the smallholder beef cattle system, which involves multiple actors, including farmers, collectors, and slaughterhouses, its effectiveness depends heavily on the availability of good data, the knowledge of farmers, and their trust in digital systems (Nguhiu-Mwangi, 2023; Kapundu et al., 2026).

The adoption of AI-based technologies among smallholder farmers remains limited. Several studies have shown that barriers to adoption are not only technical but also socio-

economic and institutional. Limited internet connectivity, high investment costs, low digital literacy, and uncertain economic returns can hinder technology adoption, even when farmers already own smartphones or have access to basic digital devices (Huang, Zhipeng and Xu, 2024; Ghali, Ben Arfa and Justinia, 2025; Sila, Kayusi and Atuheire, 2025). Studies on the adoption of mobile applications by farmers also show that perceived ease of use and perceived usefulness significantly influence farmers' intentions to use digital technology. This suggests that technology design needs to be farmer-centered, simple, affordable, and clearly linked to practical benefits, rather than simply sophisticated.

The context of smallholder farmers is crucial for understanding the true potential of AI in beef cattle farming. Technologies developed in intensive dairy, poultry, pig, or large-scale cattle farming systems cannot be automatically transferred to smallholder beef cattle farming systems. Smallholder farmers typically keep limited livestock, combine livestock farming with crop farming or non-farm activities, and rely on family labor (Valerio et al., 2024). The value of AI-based technology should be determined not only by algorithm accuracy but also by affordability and compatibility with local practices. As with other livestock innovations, implementation barriers can arise at different stages: before adoption, when farmers assess the usefulness and feasibility of the technology, and during the transition phase, when farmers attempt to integrate the technology into daily management. This will undoubtedly face several challenges and diverse opportunities (Ghali, Ben Arfa and Justinia, 2025).

This review aims to identify opportunities, constraints, and future development directions for AI-based transformation of smallholder beef cattle farming. The first section of the review maps key AI and digital technologies that have been implemented or proposed in beef cattle and related smallholder livestock systems. The second section identifies the key opportunities these technologies offer for productivity, feed efficiency, animal health, and sustainability. The third section examines barriers to adoption, including affordability and farmer skills. Finally, the review proposes research, policy, and knowledge transfer strategies to support the development of AI systems that are technically robust, economically viable, and adaptable to local contexts.

2. METHODS

This systematic literature review was conducted to identify and synthesize literature on the transformation of smallholder beef cattle farming based on artificial intelligence and related digital technologies. The literature search was conducted in the Scopus database because this database has extensive coverage of internationally reputable scientific articles, particularly in the fields of livestock and digital technology. Data was exported from Scopus on June 23, 2026, as recorded in the abstract export file used in the article selection process.

The search was conducted by combining three main keyword groups. The first group represents technology, including artificial intelligence, machine learning, deep learning, computer vision, precision livestock farming, smart farming, digital livestock, Internet of

Things, sensors, remote sensing, big data, decision support systems, blockchain, and digital technology. The second group represents livestock topics, including beef, cattle, bovine, livestock, beef production, cattle farming, and cattle fattening. The third group represents the context of smallholder farmers, including smallholder, small-scale, small farm, family farm, rural farm, traditional farm, developing countries, low-resource, and resource-poor.

The search strings used are as follows:

((("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "computer vision" OR "precision livestock farming" OR "smart farming" OR "digital farming" OR "digital livestock" OR "internet of things" OR IoT OR sensor* OR "remote sensing" OR "big data" OR "decision support system*" OR automation OR "predictive model*" OR "digital technolog*") AND ("beef cattle" OR "cattle farming" OR cattle OR bovine OR livestock OR "meat production" OR "beef production") AND (smallholder* OR "small holder*" OR "small-scale" OR "small scale" OR "family farm*" OR "small farm*" OR "traditional farm*" OR "rural farm*" OR "resource-poor" OR "low-resource" OR "developing countr*" OR "emerging econom*"))

An initial restriction was then applied to the Scopus search results. The articles considered were those published between 2021 and 2026, written in English, and open access. The 2021-2026 restriction was used to capture the latest developments in AI, IoT, and precision livestock farming, as digital technology in livestock farming is rapidly evolving during this period.

Inclusion and Exclusion Criteria

Articles were included if they met at least one technology criterion and had a clear connection to cattle, beef cattle, livestock, or smallholder farming systems. Inclusion criteria included: articles discussing AI or related digital technologies; articles related to cattle, beef cattle, livestock, or ruminant systems; articles within the context of smallholder, small-scale, rural, low-resource, or developing countries; articles discussing technological opportunities for productivity, livestock health, feed efficiency, animal welfare, traceability, grazing management, or sustainability; articles discussing barriers to technology adoption; and articles providing directions for future research, policy, or technology development.

Articles were excluded if they did not align with the review focus. Exclusion criteria included: articles that used the term AI for artificial insemination instead of artificial intelligence; articles that only discussed plants, soil, irrigation, hydroponics, or crop farming without any connection to livestock; articles that focused solely on dairy cattle without any relevance to technology transfer to beef cattle; articles that discussed non-beef commodities such as poultry, pigs, fish, or goats without any methodological contribution that could be transferred to smallholder beef cattle systems; articles that were too technical but unrelated to livestock management, such as microfluidic devices, human health, or the use of bovine blood only as a laboratory test material; and articles that were too general about smart agriculture

without any contribution to the opportunities, constraints, or direction of AI development in smallholder livestock farming.

The selection process was carried out in stages following the PRISMA flow as shown in Diagram 1. The initial Scopus search yielded 605 records. After applying the 2021–2026 publication year, English language, and open access filters, 154 records were excluded. This left 451 records for the title and abstract screening stage. During the title and abstract screening stage, each article was assessed based on its suitability to the review focus, namely the transformation of smallholder beef cattle farming based on AI and digital technology. Articles that were unrelated to livestock, did not discuss digital technology, focused solely on crop farming, used AI for artificial insemination, or did not contribute to the discussion of opportunities, constraints, and future directions were excluded. Of the 451 records screened, 341 were excluded at this stage. A total of 110 records were then retained for the eligibility assessment stage. This group consisted of 23 core articles and 87 borderline articles. Core articles are articles that directly address AI, IoT, sensors, computer vision, decision support systems, remote sensing, blockchain, or precision livestock farming in the context of cattle, beef cattle, smallholder livestock, or small-scale livestock systems. Borderline articles are articles that do not focus solely on smallholder beef cattle but still have potential transferable relevance to technology or future digital livestock systems.

During the eligibility assessment stage, 87 borderline articles were reassessed based on their transferability to smallholder beef cattle farming. Of these 87 articles, 67 were excluded because their contribution to the research questions was deemed limited. Twenty articles were retained as supporting articles because they provided important information on barriers to technology adoption, livestock monitoring systems, wearable technology, digital traceability, remote sensing, grazing management, sustainability, and future livestock innovations. Thus, the final number of articles included in the synthesis was 43, consisting of 23 core articles and 20 supporting articles.

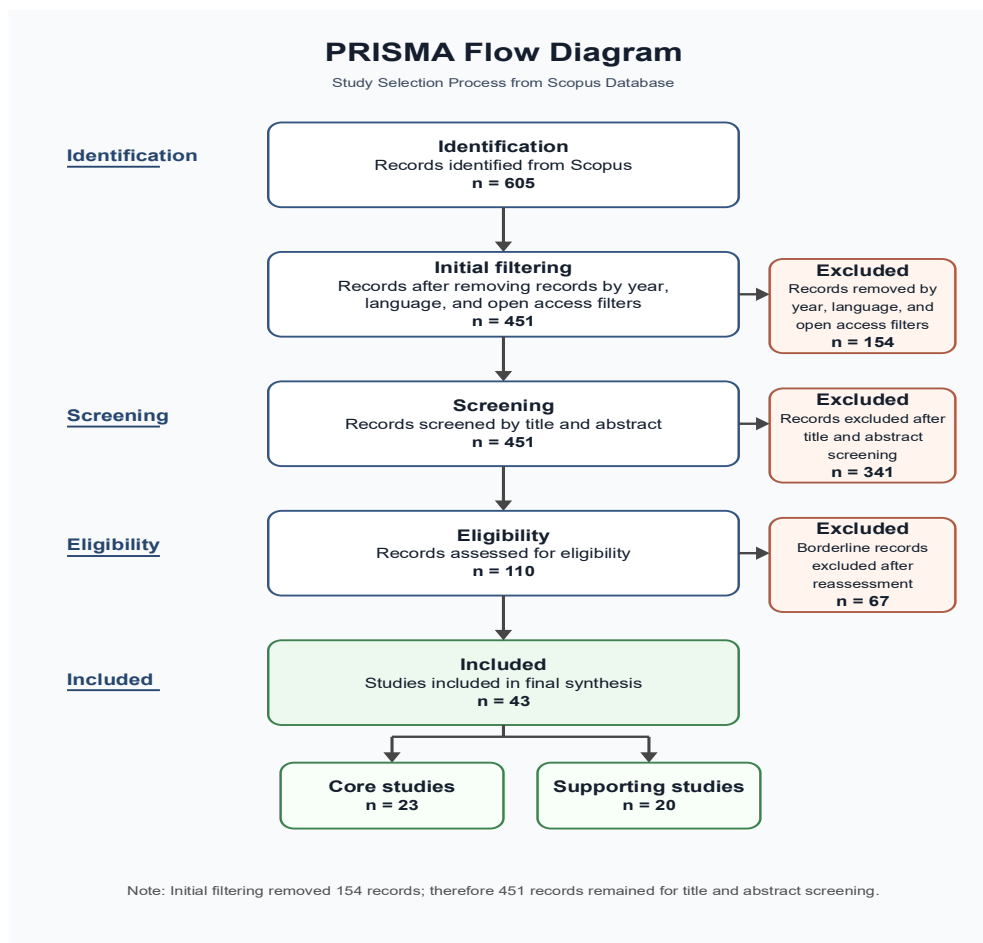


Diagram 1. PRISMA FLOW DIAGRAM

To clarify the position of the 43 articles in the synthesis, the articles that passed the selection were divided into two categories. The first category is core studies, namely articles that have a direct relationship to the main topic. Articles in this category discuss AI or digital technology in the context of cattle, beef cattle, smallholder livestock, or small-scale farming. This article is the main basis for answering research questions about the form of technology, opportunities, obstacles and directions for the development of AI in smallholder beef cattle farming.

The second category is supporting studies, namely articles that do not completely focus on smallholder beef cattle farming, but provide transferable evidence. Articles in this category are retained because they discuss technology or issues that are relevant to smallholder livestock, such as digital livestock monitoring, wearable sensors, smart collars, remote sensing, grazing management, blockchain traceability, livestock productivity, digital engagement, adoption barriers, and sustainability. Thus, the supporting articles are not positioned as direct evidence of the application of AI to smallholder beef cattle farming, but as contextual evidence to understand the opportunities, obstacles and future directions of digital transformation in smallholder livestock systems.

Thematic Synthesis

The synthesis was conducted narratively and thematically because the included articles had diverse research designs, regional contexts, technology types, and units of analysis. Therefore, a quantitative meta-analysis was not performed. The selected articles were grouped into several main themes: AI-based decision support systems; IoT, sensors, smart collars, and livestock health monitoring; computer vision and body weight estimation; remote sensing for grazing, feed, and land carrying capacity; blockchain, biometrics, and supply chain traceability; technology adoption, digital literacy, and institutional barriers; sustainability, emissions, and climate-smart livestock; and robotics, automation, and future smart livestock systems.

Thematic synthesis was conducted by comparing each article's contribution to four research questions. First, what technologies have been implemented or proposed in smallholder beef cattle and related livestock systems? Second, what opportunities do these technologies offer for productivity, livestock health, feed efficiency, traceability, animal welfare, and sustainability? Third, what obstacles limit technology adoption by smallholder farmers? Fourth, what research directions, policies, and knowledge transfer are needed to support the AI-based transformation of smallholder beef cattle farming.

Ensuring Transparency and Method Limitations

To maintain transparency, the entire selection process was conducted by recording the number of articles at each PRISMA stage, the primary reasons for exclusion, and the relevance categories of the articles retained. Borderline articles were not immediately included as core articles but were reassessed based on their contribution to the context of smallholder beef cattle farming. This approach is important because the literature on AI specifically addressing smallholder beef cattle farming is still limited and scattered across various related livestock systems.

Cattle farming is still limited and scattered across various adjacent livestock systems.

A limitation of this method is the use of only one database, Scopus, so relevant articles indexed only in Web of Science, PubMed, IEEE Xplore, or Google Scholar may not be covered. Furthermore, the restriction to open access and English-language articles may exclude some relevant studies that are not publicly available or published in other languages. However, these restrictions are implemented to ensure that all articles are fully searchable, readable, and verifiable during the synthesis process.

3. RESULTS AND DISCUSSION

Table 1 describes the literature search process, which yielded 605 records from the Scopus database. After applying filters for publication year 2021-2026, English language, and open access, 451 records were retained for title and abstract screening. During the screening stage, 341 records were excluded for not aligning with the review's focus, primarily because they did not discuss livestock, focused only on crops or general agriculture, used the term AI for artificial insemination, were not related to digital technology, or did not contribute to the

theme of opportunities, constraints, and future directions for AI in smallholder beef cattle farming.

A total of 110 records were then assessed for eligibility. This group consisted of 23 core articles and 87 borderline articles. Borderline articles were reassessed based on their relevance to smallholder beef cattle farming systems. Of the 87 borderline articles, 67 were excluded, while 20 were retained as supporting articles. Thus, 43 articles were included in the final synthesis, consisting of 23 core studies and 20 supporting studies. This flow follows the PRISMA reporting pattern as the example article presents the number of articles at each stage of search, screening, eligibility, and included studies.

Table 1. PRISMA Protocol Stages

PRISMA Stage	Information	Number of Articles
Identification	Records identified from Scopus	605
Initial filtering	Records removed by year, language, and open access filters	154
Screening	Records screened by title and abstract	451
Screening exclusion	Records excluded after title and abstract screening	341
Eligibility	Records assessed for eligibility	110
Eligibility exclusion	Borderline records excluded after reassessment	67
Included	Studies included in final synthesis	43
Included detail	Core studies	23
Included detail	Supporting studies	20

These results indicate that although the initial search yielded a relatively large number of articles, only a small fraction were truly relevant to the focus of AI-driven transformation in smallholder beef cattle farming. Narrowing the search from 451 articles to 43 articles demonstrates that the literature on AI for smallholder beef cattle farming remains fragmented and spread across several topics such as IoT, sensors, computer vision, remote sensing, traceability, precision livestock farming, and technology adoption among smallholder farmers.

General Characteristics of Included Studies

Of the 43 included articles, the majority were published between 2024 and 2026, indicating that the topics of AI, IoT, and precision livestock farming in smallholder livestock systems are very new areas of study. The highest number of articles was found in 2025, followed by 2026 and 2024. This reinforces the rationale for limiting the research to 2021–

2026, as the rapid development of AI technology in livestock farming is occurring rapidly, and many recent studies appeared after 2024.

Table 2. Study Characteristics

Publication Year	Number of Articles	Information
2021	3	<i>Early use of IoT, sensors, and smart livestock in the context of livestock farming</i>
2022	1	<i>Remote sensing and resource feeds are starting to emerge in the smallholder context.</i>
2023	4	<i>Digital engagement, livestock detection, and remote sensing studies are starting to develop.</i>
2024	6	<i>Enhanced studies on IoT, smart farming, smart collars, and technology adoption</i>
2025	16	<i>Top publications related to AI, computer vision, traceability, and decision support</i>
2026	13	<i>New studies on PLF, smart monitoring, and AI integration emerge</i>
Total	43	<i>23 core studies dan 20 supporting studies</i>

Based on the relevance categories in Table 3, 23 articles are directly related to cattle farming, beef cattle, smallholder livestock, or small-scale livestock systems. Meanwhile, the other 20 articles have supporting relevance because they discuss technologies or issues that can be transferred to the context of smallholder beef cattle, such as smart collars, digital traceability, remote sensing, digital engagement, and barriers to technology adoption.

Table 3. Distribution of articles by relevance category

Article Categories	Amount	Function in Synthesis
Core studies	23	Key evidence on AI, IoT, sensors, computer vision, remote sensing, or PLF in cattle/beef cattle/smallholder livestock
Supporting studies	20	Transferable supporting evidence to explain opportunities, constraints and future directions
Total	43	Thematic synthesis basis

Geographically, the included articles span the contexts of Asia, Africa, Europe, South America, and global studies. Indonesia emerged as a key context, with several articles

discussing local cattle, small-scale livestock farmers, smart tags, sensors, remote sensing, and livestock health detection. Thailand also stands out for its studies on IoT for small-scale cattle farmers and the application of computer vision in precision livestock farming. Furthermore, several articles from Africa, Sub-Saharan Africa, Botswana, Zambia, Zimbabwe, Malawi, and South Africa provide important contributions to understanding AI and digital livestock in the context of developing countries, low-resource systems, and smallholder systems.

The co-occurrence visualization of the 43 studies in Figure 1 shows that artificial intelligence serves as a central node connecting various key topics in the literature, particularly beef cattle, the Internet of Things, precision livestock farming, machine learning, and health monitoring. This demonstrates that AI-based transformation of beef cattle farming is not only related to algorithms, but also to the integration of sensor technology, IoT, monitoring systems, and predictive analytics. The emergence of the topic of adoption barriers indicates that the literature also pays attention to the obstacles to technology implementation, particularly in the context of small-scale livestock farming. Thus, this bibliometric map reinforces that the focus of SLR covers three main dimensions, namely technological opportunities, technical applications in cattle production, and barriers to adoption among smallholder farmers.

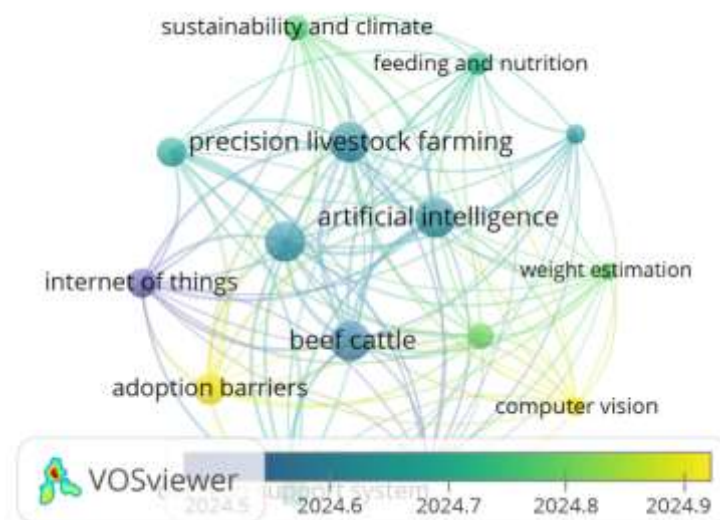


Figure 1. Analisis Bibliometrik Topic

Types of AI and Digital Technologies Identified

Table 4, the synthesis results, shows that the technologies emerging in the 43 articles can be grouped into several main categories. The most dominant technologies are IoT, sensors, wearable devices, and smart collars, followed by AI/machine learning/decision support, remote sensing/GIS, computer vision, robotics/automation, and blockchain/traceability. These findings demonstrate that AI transformation in smallholder beef cattle farming does not exist as a standalone algorithm, but rather as a technological ecosystem connecting sensors, data, digital platforms, predictive models, and management decisions.

Table 4. Technology groups found in 43 articles

Technology Group	Examples of Technology	Application Focus	Study Example
AI and decision support	Deep reinforcement learning, machine learning, predictive model, SHAP, LIME	Decision making, risk prediction, management priorities	(Zhang, He and Guo, 2025; Kinkpe, Emmanuel and Di, 2026)
IoT, sensor, and wearable	Sensor suhu, aktivitas, smart collar, cloud, WSN, LoRaWAN	Monitoring of health, behavior, location, feed, early warning	(Rajapakse, Maduranga and Dissanayake, 2021; Umsura and Chaidee, 2024; Zurnawita, 2025)
Computer vision	YOLO, DeepLabCut, image processing, smartphone-based measurement	Weight estimation, behavior detection, parasite detection, livestock detection	(FAO, 2025; Kinkpe, Emmanuel and Di, 2026; Kusumarini, Janumurti and Nurhidayah, 2026)
Remote sensing and GIS	Satellite imagery, vegetation index, grazing pressure mapping, carrying capacity	Land carrying capacity, feed, grazing, environmental risks	(Caron, Rumiano and Wielgus, 2023; Wang, Huang and Tian, 2025)
Blockchain and traceability	Blockchain, biometric identification, facial recognition, digital recording	Livestock identification, food safety, supply chain, record keeping	(Gresse and van Marle-Köster, 2024)
Robotics and automation	Feeding robot, robot-assisted herding, automated monitoring	Labor efficiency, feeding, livestock management	(Bae <i>et al.</i> , 2024; Rahmawati, Haryanto and Setiawan, 2025)
Sustainability and climate-smart livestock	Methane prediction, emission monitoring, climate adaptation, PLF	Emission mitigation, resource efficiency, climate adaptation	(Komacllo and Gonsalves, 2024; Sila, Kayusi and Atuheire, 2025)

Several key articles demonstrate technology applications closely aligned with the needs of small-scale cattle farmers. For example, a study (Umsura and Chaidee, 2024) describes IoT in Thailand developing a smart farming system for beef cattle management in Chiang Rai, with features for monitoring feed consumption, growth, breeding analysis, and cost estimation via WSN and a cloud platform. The study found a strong correlation between feed quantity and

weight gain and stated that this system can improve the accuracy of small-scale cattle farmers' decisions.

A study (Zhang, 2025) used deep reinforcement learning to develop a decision support system for small-scale beef cattle farming. The model incorporated variables such as production costs and market prices as the basis for decision-making. These findings demonstrate that AI can be used not only to detect livestock conditions but also to support strategic decisions regarding resource allocation and production resilience.

AI Opportunities in Smallholder Beef Cattle Farming

Table 5 explain synthesis results indicate that the main opportunities for AI and digital technology in smallholder beef cattle farming can be grouped into six areas: increased productivity, feed efficiency, health monitoring, weight estimation, grazing management, and supply chain transparency.

Table 5. Key opportunities for AI and digital technology in smallholder beef cattle farming

Opportunity Areas	Forms of Technology Contribution	Implications for Smallholder Farmers
Productivity	Growth prediction, feed optimization, livestock performance monitoring	Helping farmers determine maintenance strategies and sales timing
Feed efficiency	Feed consumption sensors, WSN, cloud analytics, feed management	Reduce feed waste and increase PBBH
Weight estimation	Computer vision, smartphone image, morphometric analysis	Reduces the need for physical scales and simplifies transactions
Livestock health	IoT health monitoring, smart collar, temperature sensor, abnormal behavior detection	Early warning of disease and faster treatment
Welfare and behavior	DeepLabCut, behavior recognition, distress sound detection	Monitoring stress, estrus, activity and welfare of livestock
Grazing and natural feed	Remote sensing, GIS, carrying capacity model	Determining land carrying capacity and overgrazing risk
Traceability and supply chain	Blockchain, biometrik, digital recording, facial recognition	Improving record-keeping, transparency and security of cattle trade

The most immediate opportunity for smallholder cattle farmers is computer vision-based weight estimation. In small-scale beef cattle farming systems, limited scales often require

visual weight assessments. This can be disadvantageous for farmers, weakening their bargaining position when transacting with traders. Studies on image-based weight estimation models demonstrate that mobile technology and computer vision can provide low-cost, real-time weight estimation, potentially improving transaction fairness and strengthening farmer decision-making. (Bai et al., 2025) an abstract in Scopus data, also demonstrates that the mobile phone-based LaWE model can estimate cattle weight with over 97% accuracy and is intended to support smallholder cattle farmers.

The second opportunity is health monitoring and early disease warnings. Sensor-based IoT systems can monitor cattle body temperature, heart rate, activity levels, and behavior in real time. Such systems are relevant for smallholder farmers because traditional monitoring methods often rely on manual observation and delay the detection of early signs of disease. In one abstract, a low-cost IoT-based cattle health monitoring system was designed with wearable sensors, a cloud server, and a mobile application to provide early warnings and action recommendations for farmers (Gandal et al., 2026).

The third opportunity is feed and grazing management. Remote sensing and machine learning can be used to map grazing pressure and land carrying capacity. A study (Fernández et al., 2025) in the South American Dry Chaco showed that accounting for grazing systems and production intensity can alter estimates of carrying capacity and land degradation levels. This finding is important for semi-intensive and extensive beef cattle farms because ignoring variations in production systems can lead to bias in assessing grazing pressure and land degradation.

Barriers to AI Implementation at the Decision and Transition Stages

Table 6 shows the barriers at the decision and transition stages, and the barriers to AI adoption in smallholder beef cattle farming can also be grouped into two stages. The first stage is the decision stage, when farmers decide whether the technology is feasible. The second stage is the transition stage, when farmers begin to integrate the technology into their daily husbandry practices. This distinction is important because the barriers before adoption and during implementation often differ.

Table 6. Constraints to AI Implementation in Smallholder Cattle Farms

Obstacle Stage	Types of Obstacles	Form of Obstacle	Implication
Decision stage	Knowledge barriers	Farmers do not yet understand the benefits of technology	Low adoption intention despite technology availability
Decision stage	Economic barriers	The cost of tools, sensors, internet and maintenance is considered expensive.	The technology is deemed financially unviable

Obstacle Stage	Types of Obstacles	Form of Obstacle	Implication
Decision stage	Barriers to trust	Farmers are skeptical about data accuracy and information security.	Data is not used in decisions
Decision stage	Barriers to relevance	The technology is considered suitable for large farms, not small farmers.	Rejection before trial
Transition stage	Technical obstacles	Internet connection, electricity, broken sensors, difficult to use applications	Inconsistent use
Transition stage	Managerial barriers	Data is available but not translated into practical action	Technology becomes a passive tool, not a decision support
Transition stage	Institutional barriers	Lack of outreach, training, and policy support	Unsustainable adoption
Transition stage	Interoperability barriers	Data from sensors, applications, and markets is not integrated	Fragmented digital systems

Barriers at the decision stage primarily relate to farmers' perceptions of usability, ease of use, cost, and risk (Bustamante, Capote and González, 2026). Several articles indicate that digital technology is not simply available; it must also be perceived as useful and easy to use by farmers. Studies on the adoption of digital applications among smallholder farmers emphasize that intention to use an application is influenced by trust, connectivity, digital knowledge, and perceived usefulness. This means that technology design must be based on farmers' real-world problems, not just the system's technical capabilities.

Barriers at the transition stage are more related to daily use. Unstable sensors, complex applications, weak internet connections, and lack of support can prevent technology adoption, even if farmers are initially interested. This aligns with a study (Devi et al., 2026) of PLF in smallholder and extensive systems, which showed that many PLF solutions still have a low level of technology readiness, hampered by infrastructure, sensor reliability, system compatibility, and training requirements.

Tabel 7, differences Between Core Articles and Supporting Articles in the Synthesis

The synthesis results show that the 23 core articles primarily provide direct evidence on technology applications in cattle, beef cattle, or smallholder livestock systems. These articles serve as the primary basis for answering questions about which technologies have been implemented, what opportunities they offer, and how they can support smallholder livestock management.

In contrast, the 20 supporting articles provide transfer evidence that broadens understanding of barriers to adoption, livestock digitization, traceability, sustainability, and future directions. Supporting articles are important because specific literature on AI in smallholder beef cattle is still limited. By carefully including supporting articles, this review can capture technologies and strategies that have not been widely tested in smallholder beef cattle but have potential for application through local adaptation.

Table 7. The role of core studies and supporting studies in synthesis

Article Group	Main Features	Functions in Results and Discussion
Core studies	Direct focus on cattle, beef cattle, smallholder livestock, AI, IoT, sensors, computer vision, remote sensing, or PLF	Serves as primary evidence to answer RQ1 and RQ2
Supporting studies	Not always specific to beef cattle, but relevant technologically, adoptively, institutionally, or sustainably.	Supports discussion of constraints and future directions
Transferable evidence	Evidence from dairy, general livestock, grazing systems, PLF, or digital agriculture	Used in a limited manner and described as proof of transfer
Excluded evidence	Not relevant to livestock, digital AI, or smallholder context	Not used in synthesis

This approach makes the synthesis methodologically more robust because it does not force all articles to be considered direct evidence. Articles on dairy, general livestock, or digital agriculture were only used if they had clear transfer relevance to smallholder beef cattle farming.

Strategies for Overcoming Implementation Barriers

Based on the 43 articles analyzed, Table 8 lists strategies for overcoming barriers to AI implementation in smallholder beef cattle farming, which can be grouped into technological strategies, economic strategies, and institutional strategies. This pattern follows the example article that differentiates practical barriers from knowledge barriers and links them to research and knowledge transfer strategies (Huayama Sopla et al., 2026). The most basic strategy is to ensure that the technology is cheap, easy to use, and meets the needs of farmers. In a study (Never Assan, 2026), technologies such as smartphone-based weight estimation, simple temperature sensors, cheap smart collars, and digital recording applications are more realistic for smallholder farms than expensive automation systems designed for industrial farms. The second strategy is to build a mentoring and knowledge transfer system. Many barriers to adoption are not just because the technology is not available, but because farmers do not yet understand the benefits, do not trust the system results, or do not know how to use data to make decisions. Therefore, digital extension approaches need to be combined with direct mentoring,

farmer groups, demo farms, and real case-based training. The third strategy is to strengthen the community livestock data ecosystem. AI requires consistent data, but small farmers often do not have as neat production, health, weight, reproduction and feed records as in studies (Nilchuen et al., 2025). Therefore, simple digital record-keeping needs to be the foundation before more complex AI technologies are implemented. Without basic data, AI will find it difficult to produce reliable recommendations.

Table 8. Strategies to overcome barriers to AI adoption in smallholder beef cattle farming

Major Obstacles	Recommended Strategy	Actors Involved	Expected results
High technology costs	Development of low-cost sensors, smartphone-based tools, and simple applications	Academics, startups, government, cooperatives	Technology is more affordable for small farmers
Low digital literacy	Practice-based training, demo farm, video tutorials, group mentoring	Extension workers, universities, livestock groups	Farmers understand the benefits and how to use it
Weak infrastructure	Offline-first system, edge computing, local storage	Government, technology providers, villages	Technology continues to operate in low connectivity areas
Data is not integrated	Integrated digital record-keeping platform and interoperability between applications	Government, industry, digital platforms	Livestock, feed, health and market data are interconnected
Lack of trust	Algorithm transparency, explainable AI, field validation, technology certification	Researchers, government, livestock associations	Farmers trust the system's recommendations
The economic benefits are unclear.	ROI analysis, cooperative business model, subsidy scheme or equipment rental	Government, cooperatives, financial institutions	Farmers see real financial benefits
Lack of institutional support	AI integration with extension, animal health, markets, and traceability	Government, academics, industry, livestock groups	Adoption is more sustainable and less individualized

A synthesis of 43 articles shows that AI research in smallholder beef cattle farming needs to move from developing a single technology to a more integrated system. Many studies still focus on a single function, such as weight estimation, disease detection, feed monitoring, or remote sensing. In the future, these technologies need to be integrated into decision support systems that connect livestock, environmental, economic, and market data (Gandal et al., 2026). Table 9 explains that the most important research direction is an integrated AI decision support system for smallholder beef cattle farming. Such a system should not only provide technical information but also be able to help farmers make practical decisions, such as when to buy feeders, when to sell livestock, what feed is most efficient, which livestock are at risk of disease, and how to deal with market price fluctuations.

Table 9. Future research directions based on the synthesis of 43 articles

Future Research Areas	Development Focus	Important Reasons
Farmer-centered AI	Designing AI based on the needs, capabilities, and limitations of farmers	Avoid overly complex and unused technologies
Low-cost PLF	Cheap sensors, smartphone tools, simple cloud, edge computing	Suitable for small farmers with limited capital
Integrated decision support	Combining health, feed, weight, price and risk	Assisting in more comprehensive management decisions
Explainable AI	model interpretation, transparency of recommendations	Increasing the confidence of farmers and extension workers
Digital traceability	Blockchain, biometric ID, smart tags, national livestock data	Improving food safety, record keeping and market access
Climate-smart livestock AI	Methane emissions, feed carrying capacity, heat stress, climate adaptation	Linking productivity with sustainability
Participatory technology development	Co-design with farmers, farmer groups, extension workers, and industry	Ensuring technology is appropriate to the local context
Economic feasibility	willingness to pay, cooperative business model, technology subsidies	Determining whether the technology is truly worth implementing

Based on the 43 articles analyzed in Table 10, the AI-based transformation of smallholder beef cattle farming can be understood as a phased process. The first stage is digital recording,

which involves establishing baseline livestock data, such as livestock health, weight gain, and feed expenditure. The second stage is digital monitoring, which involves the use of sensors, IoT, and computer vision to capture data more accurately. The third stage is AI analytics, which involves the use of machine learning, deep learning, or decision support systems to transform data into predictions and recommendations. The fourth stage is farmer decision and action, which involves how these recommendations are used in real-world decisions. The final stage is system transformation, where technology not only changes the way farmers work but also improves their productivity, bargaining position, and welfare (Umsura and Chaidee, 2024; Bai et al., 2025).

Table 10 demonstrates that AI should not be viewed as a stand-alone technology. AI will only be beneficial if supported by sound data, simple infrastructure, designs tailored to smallholder farmers, mentoring, and relationships with markets and institutions. In other words, the AI transformation in smallholder beef cattle farming is a socio-technical transformation, not simply a technological one.

Table 10. AI transformation synthesis model in beef cattle farming

Transformation Stage	Forms of Technology	Output	Expected Impact
Digital recording	Recording application, smart tag, livestock database	Basic livestock and business data	Recording is neater and more accurate
Digital monitoring	Sensor, IoT, smart collar, remote sensing, computer vision	Real-time data on livestock and the environment	Early detection and faster decision making
AI analytics	Machine learning, deep learning, DRL, predictive model	Weight prediction, health, risks and recommendations	More precise management
Farmer decision and action	Dashboard, mobile apps, advisory system	Recommendation-based farmer actions	Feed efficiency, health and productivity increase
System transformation	Traceability, blockchain, platform pasar, integrasi kelembagaan	Digital livestock ecosystem	market access, and increased sustainability

4. CONCLUSION

This review shows that the transformation of smallholder beef cattle farming based on artificial intelligence and digital technology is still in its early stages but holds significant

potential to improve decision-making and system sustainability. Of the 43 articles analyzed, the most prominent technologies include machine learning, deep learning, the Internet of Things, sensors, smart collars, computer vision, remote sensing, blockchain, and decision support systems. Several studies indicate that these technologies can assist smallholder farmers in monitoring feed consumption and improving supply chain record-keeping and transparency. This demonstrates that AI can be a crucial instrument for shifting smallholder farming practices from experience-based management to data-driven management.

The review results indicate that the benefits of this technology are not yet immediately felt by smallholder farmers. The main obstacles stem not only from technical aspects but also from social and institutional ones. Some of these obstacles can be understood as knowledge barriers, as farmers do not yet fully understand the benefits and how the technology works. Therefore, AI development strategies for smallholder beef cattle farming must not only focus on improving algorithm accuracy but must also consider affordability, ease of use, and compatibility with local practices.

Future development directions need to place farmers at the center of innovation. The technologies most likely to be implemented are simple, inexpensive, and can be used via mobile devices. Future research needs to develop low-cost precision livestock farming, farmer-centered AI, and traceability systems connected to markets. Furthermore, technology research needs to be complemented by economic feasibility analyses, business models for cooperatives or farmer groups, including digital training and mentoring from extension workers, and policy support that allows for the inclusive implementation of AI technology.

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