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Economic and environmental benefits of digital agricultural technological solutions in livestock farming: A review

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ABSTRACT

This review paper delved into the economic and environmental benefits of Digital Agricultural Technological Solutions (DATSs) in livestock farming systems. Synthesising data from 52 peer-reviewed papers it presents the outcomes of a systematic literature review on livestock farming DATSs, conducted with the use of the PRISMA methodology. The analysis highlighted the contribution of DATSs across three main livestock farming DATSs categories: Automated Milking Systems (AMS), Feed and Live Weight Measurement technologies, and Health Monitoring Systems. The results showed that AMS has the potential to boost cow productivity by up to 15 % while also reducing energy consumption by 35 %. Feed and Live Weight Measurement technologies contribute notably to sustainability and cost savings, with feed waste reductions of 75 % and feeding savings of 33 %. Health Monitoring Systems are especially effective in improving herd health and productivity through early detection of clinical issues, which directly enhances animal welfare and farm efficiency. Environmentally, AMS and health monitoring tools play a vital role in reducing greenhouse gas emissions, with AMS lowering global warming potential by up to 5.83 %. Overall, the findings of this review highlight the potentials of livestock DATSs towards economic viability and environmental sustainability, suggesting that the wider adoption could offer substantial benefits for the livestock farming sector. Up to now, DATSs have shown great potential in dairy cattle by improving milk yield, quality, and animal health, with advancements such as AMS increasing productivity and health monitoring systems enhancing early disease detection. In contrast, their application in sheep, goats, and pigs is still in its early stages, mainly limited to basic health monitoring and feeding technologies, despite the economic importance of these species, especially in the Mediterranean area, where most of the studies are conducted.

1. Introduction

As livestock production systems evolve, the adoption of digital agricultural technological solutions becomes increasingly vital. These technologies enhance efficiency, optimise resource management, and improve animal welfare, ensuring sustainable livestock production that can effectively address the challenges of a growing global population [32]. The need for the optimisation of livestock technologies arises from the increased demand for meat and dairy products [2,13,46,65,84]. As an essential component of the global food supply chain, livestock farming plays an important role in meeting this demand while also contributing to economic stability.

Nevertheless, traditional livestock farming and production methods are becoming increasingly unsustainable, as inefficiencies in production and rising operational costs intersect with growing concerns about environmental sustainability. These practices, which are often labour-intensive [45], pose significant challenges to scalability and efficiency, particularly as farmers struggle to adapt to modern demands.

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Furthermore, the high costs of inputs and fodder place substantial pressure on profitability, leading to a gradual decline in traditional livestock husbandry [59]. This issue is further compounded by market fluctuations and the exploitation by middlemen, which create additional barriers and undermine the viability of traditional farming systems [82].

Environmental challenges are becoming increasingly severe, with climate change and prolonged droughts driving many pastoralists to abandon traditional herding practices [63]. These shifts are further compounded by ineffective range management, which undermines ecological sustainability and complicates efforts to maintain livestock populations while preserving natural resources [59]. The dairy sector also plays a significant role in environmental degradation, contributing to global greenhouse gas (GHG) emissions through methane from enteric fermentation and nitrous oxide from manure management [48]. Climate change is another factor that could exacerbate welfare issues, potentially affecting the performance and reproductive capacity of ruminants raised on pasture and to a lesser extent those raised intensively, where mitigation strategies are more feasible [25]. Addressing these interconnected risks demands the adoption of improved management practices and modern technologies to mitigate climate change effects and ensure sustainability [20,73].

Therefore, there is an increasing adoption of technologies in livestock production, commonly referred to as Precision Livestock Farming (PLF), Smart Livestock Farming, Digital Livestock Farming, or more broadly as Digital Agricultural Technological Solutions (DATSs), representing a diverse set of approaches aimed at enhancing efficiency, productivity, and sustainability in livestock operations. Livestock DATSs, including big data analytics, sensors, geographic information systems, unmanned aerial vehicles, and blockchain technologies, offer innovative solutions to these challenges [7,27,85]. By enabling real-time monitoring, automated decision-making, and precision management, livestock DATSs can help reduce the environmental footprint of farming while improving productivity and profitability [57]. In addition, they enable comprehensive individual monitoring throughout the supply chain, facilitating precise feeding, health management, and early detection of inefficiencies, which enhance production efficiency, resource management, and profitability while reducing the environmental footprint of livestock farming. Through the use of mathematical, statistical, and machine learning models, DATSs support the decision-making in livestock farming allowing breeders to identify behavioural patterns, minimise errors, and reduce losses [83]. The mechanisation and scaling of livestock operations further enhance production efficiency while lowering costs, making food products more accessible, especially for economically vulnerable populations [15]. Moreover, DATSs promote sustainable livestock management practices by enabling precise feeding, health monitoring, and timely detection of inefficiencies, ultimately contributing to reducing the environmental footprint of livestock farming while improving overall productivity and profitability.

Many studies, such as this by Bretas et al. [22], have highlighted the importance of DATSs, emphasising their impact on production efficiency, particularly in milk production [30]. For example, studies on Automatic Milking Systems (AMS) indicate that they reduce labour costs, enhance animal welfare, and provide more flexible working and leisure time for producers, thereby improving overall operational efficiency and competitiveness [47,70,77]. Moreover, another study by Banhazi et al. [8], highlighted that DATSs integration contributes to sustainable farming practices by minimising waste and optimising feed and water usage thus reducing the environmental footprint and supporting the global sustainability goals. Additionally, their adoption can lead to increased profitability through enhanced productivity and reduced operational costs [8]. Therefore, as DATSs become more accessible, they can drive economic development in rural areas by improving farm viability [44].

The integration of digital technologies in livestock production is closely aligned with global sustainability and food security goals, particularly under initiatives such as the European Green Deal and its 'Farm to Fork Strategy' [33]. Such initiatives aim to revolutionise the agricultural system by setting ambitious targets for reducing greenhouse gas emissions, improving animal welfare, and promoting sustainable farming practices by 2030. DATSs in livestock farming, such as precision monitoring, automated feeding systems, and advanced data analytics, have the potential to play a pivotal role towards this transformation. They offer a balanced approach to enhance productivity, reduce environmental impacts and support animal welfare, while improving the economic viability of farms. In addition, and apart from the economic and environmental benefits, DATSs are in alignment with the ethical framework of the Five Freedoms, ensuring humane treatment and well-being of livestock which promotes both higher productivity and ethical standards in livestock management [32].

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Despite significant technological advancements, the livestock sector, particularly in developing regions, continues to face significant barriers to fully integrate these solutions. This highlights a critical gap in the literature, emphasising the need for a thorough examination of how these technologies can enhance both the economic viability and environmental sustainability of livestock systems. Addressing this challenge, the EU-funded project QuantiFarm (QuantiFarm Project Website. URL: https://quantifarm.eu/) focuses on evaluating the impact of DATSs and actively promoting their integration to improve sustainability and competitiveness. As part of QuantiFarm, this review paper presents the outcomes of a systematic literature review on livestock DATSs, conducted using the PRISMA methodology, to delve deep and explore their key economic and environmental benefits.

2. Methodology

2.1. Categorisation of livestock DATSs

The application of DATSs is vital for addressing key challenges in livestock management, including animal health, welfare, productivity, and environmental sustainability. These technologies enable precise monitoring and analysis of various parameters such as milking performance, feed intake, climate conditions, and physiological indicators, which are crucial for optimising farm operations. For example, technologies that monitor feed intake, body temperature, breathing frequency, and animal mobility are essential for preventing thermal stress, directly impacting both animal welfare and productivity. Similarly, early diagnosis of metabolic disorders like ketosis is facilitated by tracking rumination and resting times, as well as analysing blood markers such as free fatty acids. In cases of subclinical mastitis, which can severely affect milk production, DATSs allow for continuous monitoring of body and udder temperatures, animal mobility, and relevant blood indicators, ensuring timely intervention.

Moreover, the reliable detection of oestrus, a key factor in reproductive efficiency, is made possible through the detailed recording of body temperature, mobility patterns, and behavioural changes, including vocalisation and mounting activity. During the perinatal period, when animals are particularly vulnerable to inflammation, oxidative stress, and metabolic diseases, DATSs provide crucial insights by monitoring resting time and evaluating blood indicators like haptoglobin and calcium levels. Additionally, environmental performance, increasingly important in sustainable livestock farming, is assessed through the measurement of greenhouse gas emissions such as methane and ammonia, linking environmental health with animal management. Finally, technologies that optimise milking processes contribute significantly to both feed efficiency and overall farm productivity, underscoring the interconnected nature of these technological applications. By systematically recording and analysing these diverse parameters, DATSs offer a comprehensive framework for enhancing livestock management, ensuring that animal welfare, health, and productivity are maintained at optimal levels.

In the literature, various approaches have been used to categorise livestock DATSs, helping to clarify their functions and applications. One such approach was employed by Monteiro et al. [60], who organised DATSs into four distinct categories: Automatic Milking Systems, Feed and Live Weight Measurement, Animal Monitoring, and Animal Health and Welfare. This categorisation provides a structured way to understand the diverse range of technologies available and their respective roles in livestock management.

For the purposes of this study, a slight modification to the categorisation by Monteiro et al. [60] was implemented to better reflect the interconnectedness of certain technologies and their practical application on farms. Specifically, the categories of Animal Monitoring and Animal Health and Welfare have been merged into a single category. This decision is driven by the overlap between monitoring activities and health/welfare outcomes. Technologies designed for monitoring, such as systems for tracking animal behaviour, movement, and physiological parameters, are inherently linked to the health and welfare of livestock. The data generated by these systems are critical for the early detection of illness, stress, or other welfare-related issues, making them directly relevant to maintaining and improving animal health. Therefore, the categorisation of livestock DATSs guiding this study is structured as depicted in Table 1.

This revised categorisation reflects the practical realities of how these technologies are deployed on farms and aligns with the broader trend towards more integrated and efficient DATSs systems. By organising DATSs in this manner, the study aims to provide a thorough review of the economic and environmental benefits associated with these technologies in modern livestock farming.

2.2. Search query

A systematic search procedure was developed by employing Scopus (www.scopus.com) and Web of Science (www.webofscience.com) for the selection of the research articles that were used in the analysis. The search queries were constructed to include key terms related to various aspects of DATSs, such as ``automatic milking,'' ``precision feeding,'' and ``animal health monitoring,'' combined with terms related to economic and environmental outcomes, such as ``economic benefit,'' ``cost efficiency,'' and ``greenhouse gas emissions.'' The full list of search terms used in each database is provided in Table 2.

Table 1
Categorisation of Livestock DATSs.

Category	Description	Example technologies
Automatic Milking Systems	Automate the milking process, enhancing labour efficiency and ensuring consistent and stress-free milking environments.	Robotic Milking Systems, Automated Milking Parlours
Feed and Live Weight Measurement	Monitor and optimise feeding practices and track live weight for improved productivity and profitability.	Precision Feeding Systems, Weighing Scales, Automated Feeders
Animal Health, Welfare, and Monitoring	Continuously monitor animal behaviour, movement, physiological parameters, and oestrus cycles to maintain health, welfare, and support breeding management.	Wearable Sensors, GPS Tracking, Health Monitoring Devices, Behaviour Monitoring Systems

2.3. Study selection and screening process

Following the search, a total of 821 articles were initially identified. The articles were then subjected to a screening process to refine the selection. This involved removing duplicate records, excluding studies

Table 2
Search engines and queries that were used for the scope of this study.

Search engine	Query
Scopus (www.scopus.com)	***TITLE-ABS-KEY*** *("automati* milking" OR "robotic milking" OR "AMS" OR "milking robot" OR "AFS" OR "automati* feeding" OR "precis* feeding" OR "live weight measure*" OR "animal monitoring" OR "behavi* monitoring" OR "animal behavi*" OR "animal health" OR "animal welfare" OR "heat detection" OR "estrus" OR "oestrus" OR "collar" OR "face recognition" OR "automated sensor*" OR "mastitis detection" OR "mastitis prediction" OR "lameness detection" OR "IoT" OR "AI" OR "machine learning" OR "precision feeding system" OR "animal tracking" OR "environmental monitoring" OR "disease detection" OR "health tracking" OR "veterinary care")* ***AND TITLE-ABS-KEY*** *("milk production" OR "milk yield" OR "labo* saving" OR "labo* efficiency" OR "labo* reduc*" OR "milk yield" OR "milk quality" OR "energy saving*" OR "reduced production cost" OR "cost saving*" OR "economic* benefit*" OR "efficiency improvement" OR "productivity enhancement" OR "feed optimi?ation" OR "feed efficiency" OR "feed saving" OR "profitability" OR "cost reduction" OR "profitability" OR "cost efficiency" OR "return on investment" OR "ROI" OR "profit" OR "environmental benefit" OR "greenhouse gas emission*" OR "GHG" OR "methane emission*" OR "carbon footprint" OR "ammonia emission*" OR "nitrogen excretion" OR "reduction in emission*" OR "freshwater eutrophication" OR "water consumption")* ***AND TITLE-ABS-KEY*** *("PLF" OR "precision livestock" OR "smart livestock" OR "smart agriculture" OR "smart farming" OR "digital farming" OR "data-driven farming" OR "data-driven agriculture")*
Web of Science (www.webofscience.com)	***(TS=*** *("automati* milking" OR "robotic milking" OR "AMS" OR "milking robot" OR "AFS" OR "automati* feeding" OR "precis* feeding" OR "live weight measure*" OR "animal monitoring" OR "behavi* monitoring" OR "animal behavi*" OR "animal health" OR "animal welfare" OR "heat detection" OR "estrus" OR "oestrus" OR "collar" OR "face recognition" OR "automated sensor*" OR "mastitis detection" OR "mastitis prediction" OR "lameness detection" OR "IoT" OR "AI" OR "machine learning" OR "precision feeding system" OR "animal tracking" OR "environmental monitoring" OR "disease detection" OR "health tracking" OR "veterinary care"))* ***AND (TS=*** *("milk production" OR "milk yield" OR "labo* saving" OR "labo* efficiency" OR "labo* reduc*" OR "milk quality" OR "energy saving*" OR "reduced production cost" OR "cost saving*" OR "economic* benefit*" OR "efficiency improvement" OR "productivity enhancement" OR "feed optimi?ation" OR "feed efficiency" OR "feed saving" OR "profitability" OR "cost reduction" OR "profitability" OR "cost efficiency" OR "return on investment" OR "ROI" OR "profit" OR "environmental benefit" OR "greenhouse gas emission*" OR "GHG" OR "methane emission*" OR "carbon footprint" OR "ammonia emission*" OR "nitrogen excretion" OR "reduction in emission*" OR "freshwater eutrophication" OR "water consumption"))* ***AND (TS=*** *("PLF" OR "precision livestock" OR "smart livestock" OR "smart agriculture" OR "smart farming" OR "digital farming" OR "data-driven farming" OR "data-driven agriculture"))*

published before 2014, and limiting the selection to those published in English. The study followed the PRISMA 2020 methodology, an evidence-based approach that utilises a structured checklist encompassing four key phases: identification, screening, eligibility, and inclusion [67]. The study selection and screening process is illustrated in Fig. 1.

2.4. Data extraction and analysis

For the selected articles, data extraction focused on key elements relevant to the objectives of the review. This included the year of publication, the category of DATSs studied, the animal type and the reported economic and environmental benefits (Table 3). The DATSs were categorised according to the framework adapted from Monteiro et al. [60], with modifications as described earlier.

The extracted data were analysed to identify trends, assess the reported benefits of DATSs, animal types, and evaluate the consistency of findings across different studies. The results are presented in a manner that highlights the economic and environmental impacts of the livestock DATSs, with a focus on their practical applications in modern livestock farming.

3. Results & discussion

3.1. General overview of the selected articles (2014–2024)

A total of 52 articles were selected for this review, covering a range of DATSs applied in livestock production from 2014 to 2024. This selection reflects the broad range of technologies developed and studied for optimising livestock production systems. Research on livestock DATSs has significantly increased over the past decade, with the highest number of publications occurring between 2020 and 2022 (Fig. 2). This trend highlights the growing focus on applying digital solutions to address challenges in livestock farming, particularly in recent years.

This figure illustrates the distribution of 52 selected articles across three DATs categories, Automatic Milking Systems (13/52, ~25 %), Feed and Live Weight Measurement (17/52, ~33 %), and Animal Monitoring, Health, and Welfare (25/52, ~48 %), based on emerging animal types identified in the reviewed literature. The database search did not pre-define animal categories, allowing for the organic identification of trends (Fig. 3).

Table 3
Types of data extracted throughout the review process.

Type of data	Data recorded
Year of publication	2014–2024
DATS Category	Automatic Milking Systems / Feed and Live Weight Measurement / Animal Health, Welfare, and Monitoring
Animal Type	Animal Categories (e.g. dairy cattle, small ruminants, beef cattle, pigs, poultry)
Benefits	Economic benefits (e.g., labour reduction, feed efficiency and waste reduction, increased milk yield, cost savings, reduction in veterinary costs, profitability improvements, improved reproductive efficiency). Environmental benefits (e.g., GHG and carbon footprint reduction, energy efficiency and savings, lower environmental impact, health-related environmental benefits). Other benefits (e.g., animal stress reduction, heat stress mitigation, enhanced predictive capabilities, improved health monitoring).

The results emphasise the significant focus on dairy cattle, which highlights the sector's advanced integration of DATs, particularly in areas such as health monitoring and milking automation. This prominence reflects the economic importance of dairy farming and the relatively higher adoption of precision technologies within this industry. However, the limited representation of other livestock species, such as pigs, beef cattle, and small ruminants, signals a disparity in the development and application of DATs. For instance, while pigs and beef cattle play critical roles in global livestock production, their specific challenges, such as health monitoring, feed efficiency, and environmental impact management, remain underexplored. Similarly, small ruminants, despite their economic and cultural significance in many regions, are underrepresented, especially in the context of emerging technologies like AMS. Moreover, the absence of poultry in the reviewed articles is notable, given its significant contribution to protein supply and its unique requirements for disease control, environmental monitoring, and productivity optimisation. These gaps underline the need for more inclusive research efforts that address the distinct needs of these underrepresented species. Developing precision technologies tailored to diverse livestock systems will ensure broader adoption and enhance the overall impact of DATs in promoting sustainable and efficient livestock production globally.

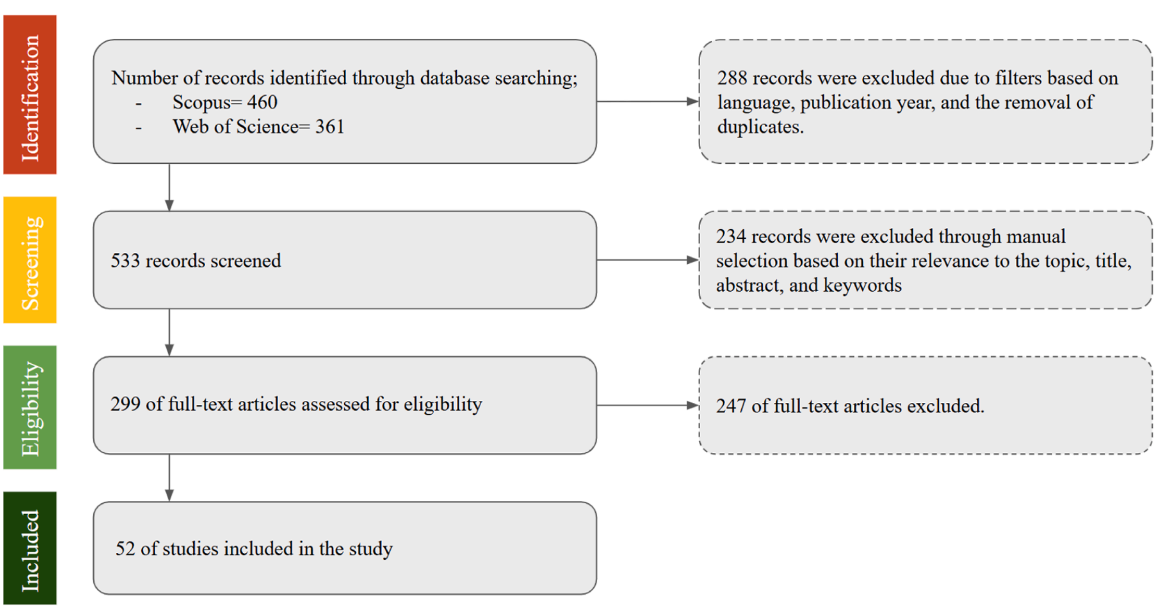

Fig. 1. PRISMA flow diagram to illustrate the steps involved in the review.

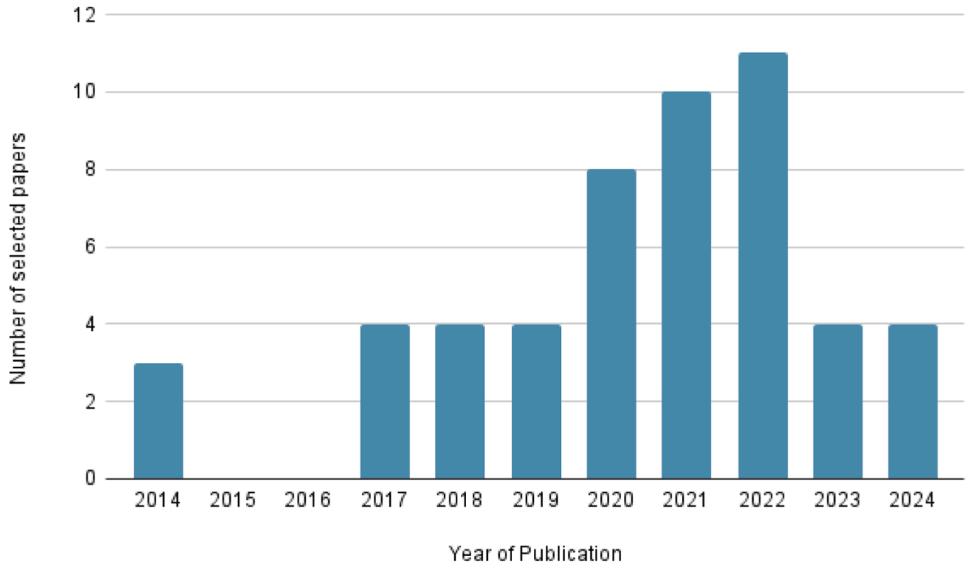

Fig. 2. Number of papers published by year up until analysis was completed on Oct 10, 2024.

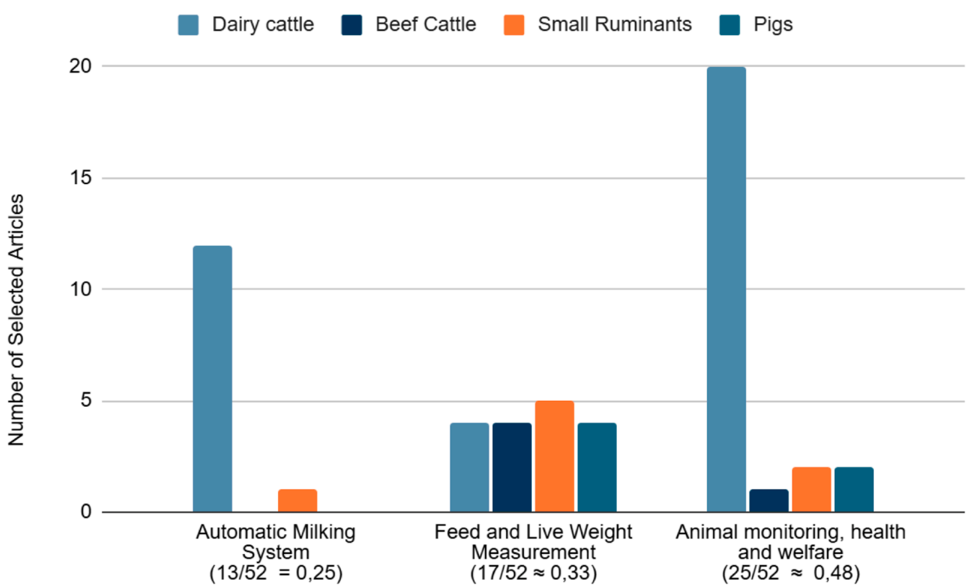

Fig. 3. Number of Papers by each DATSs Category and Animal type up until analysis was completed on Oct 10, 2024.

3.2. *Automatic milking systems*

The adoption of AMS represents a transformative shift in modern dairy farming, offering substantial benefits for improving productivity, efficiency, and sustainability. These systems have demonstrated significant potential to enhance milk yield, quality, and overall herd management while reducing labour costs and energy consumption. The integration of AMS is widely considered a game-changer for farm management, offering benefits such as enhanced milk yield, labour reduction, and more efficient monitoring of animal health and productivity. Dairy farmers leverage these systems to optimise their operations, improve herd health management, and reduce operational costs. From the selected articles, two animal categories were identified; dairy cattle and small ruminants.

3.2.1. *Dairy cattle*

The integration of AMS in dairy cattle has demonstrated significant potential to improve milk production, quality, and overall farm management. The adoption of AMS is driven by the need to enhance productivity, reduce labour costs, and ensure better health monitoring of dairy herds. These systems contribute to optimising resource use, reducing operational demands, and improving profitability through advanced automation and data integration.

Economic analyses strongly highlight the benefits of AMS adoption. Gargiulo et al. [37] developed a web-based Decision Support System (DSS) known as the Integrated Management Model, utilising data from 37 dairy farms. The model evaluated physical and economic performance with a prediction accuracy margin of 2 % to 14 %. By forecasting changes in profitability, the model provided a flexible tool for optimising farm operations. Similarly, Heikkilä and Myyrä [43], using data from 1966 observations of Finnish dairy farms, demonstrated that transitioning to AMS resulted in total factor productivity growth of 3.1 % annually, outperforming the 1.7 % growth of conventional milking systems.

Operational efficiency is further supported by studies such as Pezzuolo et al. [68], which highlighted AMS's ability to reduce labour costs, increase milking frequency, and improve milk yields. Productivity gains of 10–15 % and enhanced operator efficiency by 1.5–2 times were reported, along with improved cow health monitoring. Furthermore, AMS has been shown to enhance operator productivity by 1.5–2 times and increase cow productivity by 10–15 %, while also improving milk quality monitoring and cow health assessment according to Sitdikov et al. [76]. In another study, Priekulis et al. [71] estimated milk yield increases of 5–10 % and significant labour reductions through immediate milk quality testing. Expanding on these findings, Pezzuolo et al. [69] conducted an experiment on a dairy farm in Treviso, Italy, equipped with AMS– two Lely Astronaut A4 robots for voluntary milking, along with Automated Feeding Systems (AFS), and Robotic Scrapers. Energy consumption was reduced by at least 35 %, reflecting the efficiency gains of automation compared to traditional systems.

In addition to economic benefits, AMS also supports environmental sustainability. Bianchi et al. [14] used a Life Cycle Assessment across five dairy farms in Lombardy, Italy, to evaluate the environmental impacts of AMS. The study reported reductions in global warming potential by 1.20 % to 5.83 %, alongside mitigations in acidification and eutrophication when energy use was optimised. These improvements were linked to increased milk production efficiency, highlighting the delicate trade-offs between productivity gains and energy consumption.

Beyond economic and environmental benefits, AMS offers powerful tools for health and welfare monitoring. Televičius et al. [79] used Lely Astronaut® A3 milking robots for monitoring key health indicators like rumination time, milk fat/protein ratio, milk yield, milk lactose concentration, electrical conductivity, somatic cell count, and feed intake. The study revealed that cows with higher milk lactose concentrations (≥4.70 %) exhibited increased activity and a reduced risk of mastitis and metabolic disorders. Similarly, Bonora et al. [18] emphasised the value of AMS-generated data in herd segmentation and management. Benni et al. [12] used numerical models to assess cows' responses to high Temperature-Humidity Index conditions, by integrating technologies like the AMS 'Astronaut A3 Next' system and Lely Qwes-H collars, highlighting AMS's role in targeted cooling strategies. These strategies not only reduced heat-related losses but also improved milk quality and quantity, showcasing the comprehensive utility of AMS in addressing heat stress. AMS also plays a crucial role in predictive decision-making. Bovo et al. [19] developed a Random Forest model that predicted milk yield based on environmental conditions and AMS data, achieving a low prediction error of 2 %. This highlights the potential of AMS in supporting farm-level decision-making and planning future revenue.

Despite these advantages, the adoption of AMS faces notable challenges. High upfront costs and ongoing maintenance requirements remain significant barriers, particularly for smallholder farms with limited financial and technical resources. The scalability of AMS is further hindered by the lack of targeted support and training programmes, which are essential for ensuring equitable access. Additionally, while studies such as Pezzuolo et al. [69] and Bianchi et al. [14] provide compelling evidence of AMS's benefits, gaps persist in understanding its long-term sustainability across diverse farm sizes, regions, and production systems.

Further research should focus on addressing these limitations by expanding the scope of AMS integration to include advanced machine learning algorithms and predictive analytics. These technologies could enhance AMS's functionality, enabling the simultaneous achievement of short-term productivity goals and long-term sustainability objectives. Moreover, future studies should prioritise standardising metrics to resolve conflicting results, such as variations in reported productivity gains or environmental impacts. For instance, while AMS reduces energy consumption in some contexts [69], the trade-offs between energy savings and increased automation demand further exploration.

The benefits of AMS, as demonstrated in the reviewed studies, are significant and multifaceted, encompassing productivity, sustainability, and animal welfare. However, realising its full potential requires a comprehensive approach that combines technological innovation, targeted policy support, and interdisciplinary research. Addressing the challenges of cost, scalability, and long-term sustainability will be crucial for ensuring that AMS benefits are accessible to a wider range of producers, thereby contributing to a more resilient and efficient agricultural sector.

3.2.2. *Small ruminants*

The adoption of AMS in small ruminants, such as sheep and goats, has lagged behind dairy cattle due to lower milk production levels, differing production systems, and unique anatomical and physiological characteristics. These factors necessitate specific adaptations, such as tailored teat cup sizes, optimised vacuum settings, and cluster removal strategies, to improve milking efficiency and animal welfare [31]. For instance, small ruminants exhibit a higher proportion of cisternal milk, which influences milking routines and reduces the necessity for pre-milking teat preparation except in herds with high mastitis risks [31]. Furthermore, advancements like automatic cluster removal have been shown to reduce overmilking, improve teat health, and enhance milking efficiency in small ruminants [31].

Despite these technological advances, significant gaps persist in understanding the long-term economic viability and broader adoption of AMS in small ruminant systems, particularly for small-scale or extensive operations. The cost of implementing AMS, combined with the unique anatomical challenges such as unbalanced udders and varying milk flow profiles, underscores the need for further optimisation and standardisation of these systems [31]. Additionally, conflicting findings on cost-effectiveness, milk quality, and udder health in AMS-equipped farms highlight the need for research to resolve these discrepancies and adapt AMS technologies to diverse production systems.

Future efforts should prioritise developing cost-effective AMS technologies tailored to the physiological traits of small ruminants and adaptable to extensive and smallholder farming contexts. Research should also focus on optimising milking parameters, such as vacuum levels and pulsation frequencies, to improve animal welfare and milk quality [31]. Addressing these gaps can pave the way for broader adoption of AMS, enhancing productivity, sustainability, and animal welfare in small ruminant farming.

3.3. *Feed & live weight measurement*

The adoption of Feed and Live Weight Measurement technologies has demonstrated significant potential in improving the efficiency and sustainability of livestock farming. These technologies optimize feeding practices, reduce waste, and enhance live weight monitoring, thereby contributing to both economic and environmental benefits. This section presents an analysis of these advancements, highlighting their impact on productivity, resource management, and cost savings across various livestock systems, including dairy cattle, beef cattle, small ruminants, and pigs.

3.3.1. *Dairy cattle*

DATSs significantly enhance feeding efficiency, energy management, and health monitoring in dairy cattle systems. In a study by Abeni et al. [1], an automated precision feeding system optimised the dietary intake of Italian Friesian cows by using a near-infrared analyser to monitor and adjust dry matter levels in corn silage. This ensured cows received a balanced and consistent diet, demonstrating the potential of such systems to improve feeding efficiency and milk production. However, while promising, the broader application of such systems in varying production environments warrants further investigation to assess their scalability and long-term economic benefits.

Similarly, Conboy et al. [26] highlighted the role of automated milk feeders in identifying health issues in calves, particularly Neonatal Calf Diarrhoea. Reduced milk intake emerged as a reliable early indicator, allowing farmers to intervene promptly and reduce medical costs. Despite these findings, challenges remain in integrating such systems into small-scale or extensive farming operations due to high initial costs and data management complexities. Expanding research to include diverse herd sizes and environmental contexts could enhance the accessibility and utility of automated milk feeders.

Energy efficiency is another critical area addressed by DATSs. Tangorra and Calcante [78] demonstrated that an AFS reduced energy consumption, underscoring the substantial operational benefits of automation. Additionally, feed waste was reduced by 75 %, leading to a 33 % reduction in daily feeding costs. However, Wardal et al. [87] found that while robotic feeding systems required less direct energy than conventional systems, their cumulative energy consumption was 35.18 % higher due to the production and maintenance demands of automated technologies. This discrepancy highlights the need to balance immediate operational efficiencies with the long-term sustainability of robotic systems. Comparative studies across farming contexts could further clarify these trade-offs and guide the design of more energy-efficient technologies.

Although DATSs offer significant advancements in feeding management, gaps in understanding remain. For instance, while technologies like near-infrared analysers and automated milk feeders show potential in optimising feed efficiency and early disease detection, the long-term impacts on animal health, welfare, and overall productivity require further study. Additionally, the economic viability of these systems in smallholder and resource-constrained settings remains uncertain. Future research should focus on developing cost-effective, adaptable technologies that cater to diverse farming systems while addressing the environmental and economic challenges associated with their adoption.

3.3.2. Beef cattle

Beef cattle farming prioritises growth efficiency, animal welfare, and environmental sustainability. The integration of livestock DATSs has significantly advanced feed conversion, weight management, and herd monitoring. By leveraging technology, the industry can optimise resource use and improve productivity while addressing sustainability goals.

One notable development is the body weight prediction model proposed by Biase et al. [15]. This model integrates meteorological data such as temperature, precipitation, humidity, and wind speed with dry matter intake, demonstrating moderate-to-high accuracy in predicting body weight. Compared to traditional models like Autoregressive Integrated Moving Average and Seasonal Autoregressive Integrated Moving Average, the deterministic model provides superior support for decision-making processes in feed efficiency and supply chain optimisation. However, its adoption may require further refinement to account for region-specific climatic variability and operational differences in beef farming systems. This highlights a gap in assessing its applicability across diverse production systems.

In a complementary approach, Garcia et al. [36] explored machine learning techniques to detect weight anomalies during the fattening process. Their study, using Decision Trees, Random Forests, Gradient Boosting, and K-Nearest Neighbours, identified Decision Trees as the most accurate model with a mean absolute error of 5.4 kg. By constructing ideal weight intervals through a forest isolation algorithm, the framework enabled early detection of anomalous weight changes, improving paddock management and identifying underperforming animals. Despite its promise, further validation is required in large-scale commercial systems to ensure its robustness and scalability.

Bartels et al. [9] proposed an AI-based device using Recurrent Neural Networks and TinyCowNet to monitor cow behaviour with 95.7 % accuracy. The system, tested on six Japanese Black beef cows (Kuroge Washu), utilised cameras and neck-attached accelerometers to track feeding times and grass intake. While the results underscore the potential of such systems in refining feeding schedules and enhancing efficiency, the limited sample size and focus on a single breed highlight the need for broader trials across varied production environments.

While these studies showcase the potential of DATSs to enhance feeding efficiency, weight management, and behavioural monitoring in beef cattle, certain limitations and gaps remain. The economic feasibility of these technologies for smallholder farms and extensive systems requires further exploration, as does their adaptability to diverse environmental and operational conditions. Additionally, conflicting results regarding the scalability and accuracy of machine learning models suggest a need for standardised evaluation metrics and cross-context validation.

Future research should prioritise developing cost-effective, scalable systems tailored to the needs of diverse farming operations. This includes incorporating real-time data analysis, improving user-friendly interfaces, and integrating multi-species applications. Such advancements will enable broader adoption, bridging the gap between research innovations and practical implementation, ultimately supporting both academic understanding and commercial viability.

3.3.3. Small ruminants

The integration of DATSs in small ruminant production has demonstrated potential benefits in terms of labour efficiency, animal welfare, and sustainability, although challenges and gaps remain in optimising their use across diverse systems. Morgan-Davies et al. [61] conducted a three-year study on an extensive mountain farm with 900 ewes, comparing conventional management with a DATSs-enabled approach using electronic identification technology. While lambs in the DATSs group exhibited slightly lower final weights than the conventional group, the difference was not significant. Importantly, the DATSs approach resulted in a 36 % cumulative reduction in labour, with 19 % less time required per ewe-lamb pair and annual savings of £3 per ewe. This study underscores the potential of electronic identification systems to enhance labour efficiency without compromising flock health, although the slightly reduced lamb weights suggest that further optimisation of feeding or management protocols may be needed.

Toro-Mujica et al. [81] examined strategies to reduce emissions per kilogram of live or carcass weight by improving animal efficiency through performance recording and artificial insemination. While initial findings indicated a higher carbon footprint for DATSs compared to traditional methods, the integration of artificial insemination with performance recording significantly improved carbon efficiency. This study highlights the trade-offs inherent in adopting advanced technologies, emphasising the need for comprehensive evaluations of their environmental impacts under varying production conditions.

Behavioural monitoring is another critical application of DATSs, as changes in feeding and rumination patterns can indicate health issues. Thorup et al. [80] highlighted the value of monitoring instruments for analysing factors affecting animal health and welfare, providing actionable insights for decision-making. However, while such tools improve management efficiency, challenges remain in ensuring affordability and accessibility for smaller producers. Addressing these barriers is essential to maximise the adoption of behavioural monitoring systems across the industry.

Weight management remains a cornerstone of profitability in meat production, as highlighted by Brown et al. [21], who demonstrated that consistent weight management across all growth stages positively affects animal development and economic outcomes. This underscores the critical role of accurate and efficient weight monitoring tools in maximising returns in small ruminant systems. Samperio et al. [74] proposed a novel 3D imaging system for weighing lambs, offering significant welfare benefits by reducing stress during weighing. With an 86 % accuracy rate and a mean absolute error of 1.15–1.37 kg, the system demonstrated real-time capabilities and cost-effectiveness, priced at approximately €200 per camera. The study monitored 272 Rasa Aragonesa lambs, with weights ranging from 13.5 to 27.7 kg. This technology has the potential to streamline weight monitoring processes and improve management efficiency. However, the study primarily evaluated the system in controlled conditions, leaving questions about its performance in diverse farm environments. Future work should assess its scalability and compatibility with extensive systems.

The studies reviewed illustrate the promising applications of DATSs in small ruminant farming, particularly for labour efficiency, carbon efficiency, and animal welfare. While technologies like electronic identification technology and 3D imaging systems have shown potential, challenges such as scalability, cost-effectiveness, and adaptation to varied production contexts must be addressed to realise their full benefits. Additionally, results regarding carbon efficiency and lamb weight outcomes highlight the need for standardised methodologies to evaluate these technologies across diverse systems. Future research should prioritise developing affordable, adaptable DATSs that cater to the specific needs of small ruminant producers, particularly in resource-constrained settings.

3.3.4. Pigs

The reviewed studies highlight the transformative potential of DATSs in pig farming, particularly for improving feed efficiency, monitoring growth, and enhancing productivity. The importance of feeding behaviour monitoring is underscored by Garrido-Izard et al. [38], who employed electronic feeding stations to analyse feed intake patterns during the fattening period of 30 Landrace pigs. While individual feed intake behaviours varied, the study found that weight gain, total feed intake, and efficiency were consistent across the group. Significant correlations between variations in feed intake rates and efficiency indicate the potential for tailored feeding strategies to enhance livestock management. However, the study highlights a gap in understanding the long-term impacts of such interventions on productivity and welfare, suggesting future research should explore the scalability and applicability of these technologies in larger and more diverse settings.

Fernández et al. [35] conducted three experiments involving 240 growing-finishing pigs to evaluate responses to changes in feeding strategies. Utilising a dynamic linear regression model, the study predicted individual pig weights with mean relative prediction errors of 1.0 % for one-day and 3.3 % for seven-day forecasts. The findings demonstrate the potential of precision feeding systems to optimise growth performance and feed utilisation while enabling real-time monitoring of feed efficiency. Precision feeding strategies, such as those evaluated by Remus et al. [72], offer a promising approach to optimising nutrient utilisation. Using the Individual Precision Feeding model developed by Hauschild et al. [42], the study tailored diets for 95 growing pigs based on their daily lysine and threonine requirements [72]. By aligning nutrient intake with the minimal requirements for sustaining growth performance, the approach improved nutrient efficiency while reducing feed costs.

In addition to these studies on precision feeding, Gauthier et al. [39] evaluated algorithms for predicting litter weight from lactating sows, demonstrating that an ensemble algorithm achieved a mean absolute percentage error of 9.01 %, closely followed by linear regression at 9.30 %. These findings highlight the utility of predictive algorithms in improving productivity by accurately estimating litter weight at weaning, a key phenotype closely related to milk production. Despite promising results, the study emphasises the need for further refinement of prediction models to account for farm-specific variables and improve accuracy across diverse systems.

While technologies like predictive algorithms, electronic feeding stations, and precision feeding strategies have shown promise, several challenges persist. These include ensuring scalability, adapting systems to diverse farm environments, and addressing the socio-economic barriers to adoption, particularly for small-scale producers.

Conflicting findings, such as the consistent weight gain in Garrido-Izard et al. [38] versus the individual variability in Remus et al. [72], underline the need for standardised methodologies to evaluate livestock DATSs across different contexts. Moreover, the potential trade-offs between efficiency gains and animal welfare must be carefully examined to ensure ethical and sustainable production practices. Future research should prioritise the development of adaptable, cost-effective solutions that cater to the diverse needs of pig producers.

3.4. Animal monitoring, health & welfare

The role of DATSs is increasingly critical for improving animal health, welfare, and productivity. These technologies enable real-time monitoring of animal behaviours and physiological conditions, facilitating the early detection of diseases and enhancing overall herd management. Monitoring serves not only as a tool for observation but also as a vital process for initiating data collection, which can be utilised in Artificial Intelligence (AI) and Machine Learning (ML) models to enable proactive interventions and informed decision-making. This section explores the benefits and applications of these technologies across various livestock systems, including dairy cattle, small ruminants, and pigs. The animal types discussed emerged organically from the selected studies, reflecting their relevance to the reviewed research, rather than being predefined categories.

3.4.1. Dairy cattle

Effective animal monitoring is indispensable in dairy cattle farming, as it directly influences milk production, reproductive performance, and overall farm profitability. Moreover, it helps address critical challenges such as disease prevention, heat stress, and environmental sustainability. The integration of DATSs provides real-time insights into cattle health and behaviour, enabling informed herd management decisions and proactive interventions.

For instance, the AFICollar® sensor system evaluated by Leso et al. [49] demonstrated the capability to track feeding and rumination behaviours accurately, aligning with visual observations. Such systems empower farmers to make timely adjustments to herd management practices, thereby enhancing overall productivity and health. Similarly, Mihai et al. [58] investigated the relationships among Body Condition Score, lying behaviour, and milk production, showing that variations in lying patterns could significantly influence milk yield efficiency. Despite these advancements, the accessibility of such technologies for small-scale farms remains a concern, necessitating scalable solutions.

The implementation of early disease detection systems leveraging DATSs enables timely interventions that prevent the escalation of health issues, thereby mitigating productivity losses [88]. For instance, the LiveCare system, an IoT-based framework utilising a cow disease prediction algorithm, has demonstrated impressive accuracy in diagnosing a range of conditions in dairy cows. This system, as presented by Chatterjee et al. [24], predicts diseases such as fever (detection probability above 95 %), cysts (90 %), mastitis (95 %), pneumonia (85 %), black quarter (83 %), and foot-and-mouth disease (72 %) by monitoring cow behavioural changes. Its cloud-based infrastructure allows farmers to track individual cow health in real time, supporting effective herd management and timely treatment. Despite its effectiveness, integrating LiveCare with other decision-support tools and expanding its application to diverse farming contexts could enhance its utility. In disease prediction, ML models have shown significant promise. Fadul-Pacheco et al. [34] employed multiple classification methods, including a random forest algorithm, achieving 85 % sensitivity and 62 % specificity for predicting clinical mastitis. Building on this, Casella et al. [23] developed a cost-sensitive ML framework that integrated a Cost Optimisation Worth feature selection method. This framework achieved a remarkable 97 % accuracy in detecting Bovine Respiratory Disease up to five days before clinical diagnosis. By analysing data on activity, feeding behaviours, barn temperature, and manual health examinations, the study demonstrated the dual benefits of reducing data collection costs and maintaining high detection accuracy. While these tools are highly effective, standardising data collection processes across farms is crucial for broader adoption and improved predictive capabilities. Portable motion sensors, as used by Haladjian et al. [41], enable the early detection of lameness with a 91.1 % accuracy by comparing deviations from baseline gait models. This highlights their role in reducing productivity losses associated with mobility issues. Rumination monitoring, emphasised by Gusterer et al. [40], offers another dimension to early disease detection. Their study showed that rumination activity changes could predict diseases up to five days before clinical diagnosis, providing farmers with a valuable early warning system. However, standardised metrics for rumination monitoring across diverse farm setups are needed to ensure broader applicability.

Beyond disease detection, DATSs play a pivotal role in enhancing milk production through advanced monitoring and predictive analytics. Nguyen et al. [64] utilised machine learning algorithms, including Support Vector Machine Regression, Artificial Neural Networks (ANN), and Random Forest, alongside a multiple linear regression model, to analyse data from 36 Holstein–Friesian cows. By employing autoregressive models that used past data, the study improved the accuracy of milk production predictions. The findings revealed that higher milk yields (up to 20 kg/day) were associated with decreases in fat and protein content, offering actionable insights into nutritional management strategies. However, further exploration of these trade-offs is essential to balance productivity and milk quality. Similarly, Mota et al. [62] employed Near-Infrared Spectroscopy and ANN to monitor milk coagulation traits in real time, studying 499 Holstein cows. This approach optimised milk quality and cheese-making potential, providing an innovative tool for value-added dairy production. Further extending the utility of DATSs, Antanaitis et al. [3] examined milk lactose concentrations as indicators of health and productivity in Holstein cows. Their findings revealed that higher lactose levels were associated with a 16.14 % increase in milk yield but a 5.05 % reduction in milk protein concentration. These results suggest that milk composition monitoring could play a pivotal role in precision livestock farming, though additional studies across varying herd conditions are essential to confirm these findings. These advancements underscore the critical role of data-driven approaches in supporting farmers to plan for future revenue while ensuring product quality.

Heat stress significantly impacts dairy cattle productivity, underscoring the importance of advanced monitoring and management technologies. AI-based solutions have emerged as effective tools for detecting and mitigating heat stress. Ma et al. [54] developed an AI model capable of estimating deep-body temperature in cattle, enabling real-time health anomaly detection. Similarly, Levit et al. [50] tested a dynamic cooling system incorporating in vivo temperature sensors, resulting in a 61.1 % reduction in heat stress duration. This intervention notably increased milk fat, protein, and energy-corrected milk yields. In another approach, Shu et al. [75] used machine learning models, particularly ANN, to predict physiological responses such as respiration rate and vaginal temperature under heat stress. ANN demonstrated superior predictive accuracy, allowing farms to optimise cooling strategies like sprinklers, reducing operational costs by minimising water and energy use. Barn renovation, including fans and sprinklers, was also identified as an effective heat stress mitigation strategy, leading to a 20 % increase in milk yield during summer months [52]. Collectively, these findings highlight the importance of precision cooling strategies for improving animal welfare and profitability, though further research into cost-effective implementation is warranted.

In addition to addressing heat stress, monitoring technologies have revolutionised reproductive management, a critical factor in maintaining herd productivity and profitability. Oestrus detection technologies are central to improving breeding efficiency and reducing reproductive losses. Arago et al. [5] developed an IoT system for non-invasive oestrus detection, combining pan-tilt-zoom cameras and a web application to monitor standing-heat behaviours. Despite a moderate detection efficiency of 50 %, this system offers potential for minimising management workloads. Lin et al. [51] used neck-mounted activity monitoring tags and Transformer neural networks to detect pregnancy losses in 185 dairy cows with an 87 % accuracy. This model provides accurate, interpretable predictions, enabling farmers to prevent economic losses through timely interventions. Lovarelli et al. [53] further evaluated pedometer-based oestrus detection, demonstrating improved farm management by reducing reliance on manual observation and enhancing resource allocation. Advanced technologies like augmented reality combined with deep learning offer innovative solutions for oestrus detection and cow identification. Arıkan et al. [6] introduced a system leveraging YOLOv5 models to detect mounting behaviour with 99 % accuracy, integrating augmented reality for enhanced reproductive management. This approach reduces costs, prevents delayed calf births, and supports timely insemination, though scaling these technologies for smallholder systems remains a challenge. Silent oestrus, a significant issue in buffalo farming, has also been addressed through innovative solutions. Devi et al. [29] developed a DSS based on buffalo vocalisations, achieving a 95 % accuracy in distinguishing oestrus from non-oestrus phases. This system offers a cost-effective, automated alternative to labour-intensive methods, demonstrating the potential of integrating vocalisation-based algorithms into broader livestock management frameworks.

Environmental benefits of monitoring technologies are equally noteworthy. Improved udder health monitoring can lower greenhouse gas emissions by 0.04–0.06 % per 5 % increase in infected cow detection [14]. Lovarelli et al. [53] highlighted that integrating DATSs into dairy management practices, such as increasing pasture access during dry periods, reduced carbon footprints by 6–9 %. These findings underscore the dual benefits of monitoring technologies in enhancing sustainability and operational efficiency. McNicol et al. [57] explored the environmental benefits of livestock DATSs, focusing on technologies such as automatic weight platforms, fertility sensors, and health sensors. Their results showed a reduction in GHG emissions of up to 12 % in housed systems, with notable improvements in production efficiency. While these findings demonstrate the environmental potential of DATSs, the high initial costs and technical complexity of these systems often limit adoption, particularly among smallholder farmers.

Advanced monitoring technologies have revolutionised animal health, productivity, and sustainability in livestock farming, offering precise tools such as IoT-based systems, wearable sensors, and machine learning models for early disease detection and efficient herd management. These technologies have demonstrated clear benefits, including enhanced productivity, reduced greenhouse gas emissions, and improved resource utilisation. However, their adoption remains limited, particularly among smallholder farms, due to high costs and technical complexity. Addressing these barriers through the development of cost-effective, scalable solutions is essential to ensure broader accessibility. Furthermore, integrating monitoring systems with predictive analytics and decision-support tools can provide holistic insights, enabling farms to optimise health management and environmental practices. By fostering innovation and accessibility, monitoring technologies can transform livestock farming into a more sustainable and resilient sector.

3.4.2. *Small ruminants*

Monitoring technologies have increasingly demonstrated their capacity to transform the management of small ruminants, particularly in dairy goat farming. Belanche et al. [11] evaluated the Eskardillo tool on 12 Murciano-Granadina dairy goat farms, comparing them to 12 control farms over several years. The use of Eskardillo resulted in significant gains, including a 14–17 % increase in milk yield per lactation. These improvements were attributed to enhanced culling strategies and genetic progress achieved through precise selection of high-merit goats. Additionally, the tool effectively reduced seasonality in milk production, leading to a 17 % increase in off-season milk output. These findings emphasise the tool's potential to optimise productivity while supporting sustainable intensification in dairy goat farming.

Reproductive management also benefited significantly from the Eskardillo tool. Goats on Eskardillo-managed farms demonstrated shorter unproductive periods, with reductions in the age at first partum (−30 days) and dry periods (−20 days). Furthermore, dry periods were standardised to approximately two months, supporting consistent and optimised lactation cycles. These enhancements were achieved by leveraging precise monitoring of physiological status and reproductive cycles, enabling informed and timely breeding decisions. Expanding on the success of Eskardillo, Belanche et al. [10] introduced the RUMIA platform, which incorporated real-time feedback on milk yield, composition, health status, and reproductive performance. This platform advanced farm management by enabling customised lactation lengths, accelerating genetic progress, and further refining culling strategies. By reducing unproductive periods and mitigating production seasonality, RUMIA facilitated the adoption of more sustainable and economically viable practices in dairy goat farms.

While these tools underline the transformative potential of data-driven platforms in small ruminant management, gaps and challenges remain. The current research primarily focuses on Murciano–Granadina goats and intensively managed farms, leaving questions about applicability to other breeds, production systems, and regions unanswered. The effectiveness of these platforms in extensive or mixed farming systems remains unclear and warrants further exploration. Additionally, integrating advanced machine learning algorithms could enhance predictive health monitoring, improve welfare outcomes, and strengthen environmental sustainability through precision farming practices. The Eskardillo and RUMIA platforms highlight the importance of tailored monitoring technologies in driving productivity, sustainability, and welfare in small ruminant farming. However, future research should prioritise their scalability and adaptability across diverse farming contexts. This would enable broader adoption, ultimately benefiting both the academic and commercial communities while supporting the global push for sustainable livestock management practices.

3.4.3. Pigs

Monitoring technologies are increasingly pivotal in improving pig welfare and production efficiency, as evidenced by studies integrating novel tools and predictive models into pig farming. Garrido-Izard et al. [38] demonstrated the effectiveness of surface temperature recorders and electronic feeding stations in monitoring physiological responses during the fattening period. Their study showed that pigs with higher average surface temperatures exhibited lower variations in recorded temperatures, suggesting a potential link between thermal stability and overall health status. By combining temperature data with feeding behaviour, the research underscored the value of monitoring technologies in enhancing welfare through a deeper understanding of pigs' physiological conditions.

Aparna et al. [4] extended this approach to improve reproductive management, focusing on the use of precision livestock farming tools to predict the onset of farrowing in loose-housed sows. The researchers developed a Hidden Phase-type Markov Model (HPMM) that utilised sensor data, including water consumption and activity levels, to provide early warnings of farrowing with an average lead time of 11.5 h. This predictive system enabled better supervision and optimised resource allocation, significantly reducing piglet mortality by facilitating timely intervention. Furthermore, the system minimised energy waste by activating heating systems only when needed, showcasing a practical, cost-effective solution for improving management efficiency.

While these tools highlight the potential for advancing welfare and productivity, they also reveal gaps that merit further research. For instance, the link between thermal stability and health status identified by Garrido-Izard et al. [38] necessitates deeper exploration to understand its implications for broader health management strategies. Similarly, the generalisability of predictive farrowing systems like HPMM to other housing systems or pig breeds remains uncertain, emphasising the need for further validation across diverse contexts.

Moreover, the integration of multi-sensor technologies, as seen in Aparna et al. [4], could be expanded to include additional behavioural and physiological metrics, potentially enhancing predictive accuracy and enabling more holistic management approaches. Future research should also address the scalability of such systems, ensuring their accessibility for smallholder farms and commercial-scale operations alike.

The findings from these studies demonstrate the transformative potential of monitoring technologies in pig farming. By bridging the gap between research and practice, these tools not only improve welfare and productivity but also align with broader goals of sustainability and resource efficiency. However, a more comprehensive exploration of their long-term impacts and adaptability is essential to maximise their contribution to the academic and commercial communities.

4. Limitations & future research

The present review provides a comprehensive analysis of the economic and environmental benefits of DATSs in livestock farming, synthesising findings from 52 peer-reviewed studies. While the systematic approach and structured categorisation of DATSs offer valuable insights, several limitations in our methodology and scope should be acknowledged, which could serve as focal points for future research. One of the primary limitations of our study lies in the specificity of the search queries used during the literature review process. By focusing predominantly on general terms related to DATSs and their economic and environmental impacts, our search queries may not have captured studies focusing specifically on certain livestock species, such as poultry or other less commonly studied categories, including small ruminants like sheep and goats, or dual-purpose breeds. Consequently, the systematic search may have unintentionally excluded relevant studies that could provide a more nuanced understanding of the benefits and limitations of DATSs for these species. While our categorisation framework enabled the analysis of broad trends, the lack of animal-specific search terms may have limited the exploration of technology applications tailored to specific species or production systems. Another limitation stems from the time frame and language restrictions applied during the screening process. The decision to include only studies published between 2014 and 2024 and to restrict the review to English-language publications, though methodologically sound, could have resulted in the omission of earlier or non-English studies that might offer valuable insights into the historical development or region-specific applications of DATSs. This limitation is particularly relevant for understanding the adoption and adaptation of these technologies in diverse cultural and economic contexts.

The selected studies also disproportionately focus on certain livestock species and production systems, with dairy cattle dominating. This reflects the relatively advanced state of DATSs adoption in the dairy sector but inadvertently limits the generalisability of the findings to other livestock systems. Small ruminants, pigs, and other species are underrepresented, which may obscure unique challenges and opportunities associated with implementing DATSs in these systems. Similarly, intensive and semi-intensive systems receive more attention than extensive or mixed systems, leaving gaps in understanding the scalability and applicability of these technologies in less controlled environments. Furthermore, the review did not extensively explore the socio-economic barriers to DATSs adoption, particularly in smallholder or resource-constrained settings. Although the results underscore the potential of DATSs to improve productivity and sustainability, high initial costs, maintenance demands, and technical complexity remain significant challenges for widespread adoption. Addressing these barriers would require a deeper investigation into policy frameworks, financial incentives, and capacity-building initiatives, aspects that fall beyond the scope of this review.

Another gap lies in the limited consideration of the integration of DATSs with other technological advancements, such as blockchain for traceability, advanced genetic tools, or renewable energy systems. While the reviewed studies emphasise the standalone benefits of DATSs, their potential synergy with complementary technologies represents an area ripe for exploration. Similarly, the long-term sustainability and lifecycle impacts of these technologies, including their end-of-life disposal and energy dependencies, were not comprehensively examined in the existing literature or our synthesis.

Finally, the dynamic and rapidly evolving nature of DATSs poses an inherent limitation to any review. As technological advancements and innovations continue to emerge, the findings of this study may require regular updates to remain relevant. Future research should adopt adaptive methodologies to track and incorporate the latest developments in DATSs, ensuring that the evolving landscape of digital agriculture is adequately represented. Despite these limitations, the findings of this review highlight the transformative potential of DATSs in livestock farming and provide a robust foundation for future investigations. Addressing the identified gaps through targeted research and methodological refinements will enhance the understanding of DATSs' benefits and challenges, supporting their broader adoption and integration into sustainable livestock systems.

5. Conclusions

The purpose of this review was to delve into the impact of livestock DATSs in terms of economic and environmental benefits, through a thorough analysis of 52 articles. The adoption of technologies such as AMS, Feed and Live Weight Measurement tools such as AFS, and Health Monitoring Systems has shown to drive significant efficiencies. The findings revealed that Europe mostly focuses its research in this field, since 72 % of the articles analysed in this review originated from the continent with half of them demonstrating the benefits of Health Monitoring Systems. The analysis highlighted a strong trend towards the increased research focus in this area, particularly between 2020 and 2022, reflecting a growing interest and need in the application of digital tools in livestock management.

This systematic review identified a range of economic benefits across key categories of livestock DATSs providing a detailed analysis. The most notable ones were found in Feed and Live Weight Measurement tools which showed the capacity to reduce energy consumption up to 97 %, alongside high accuracy in feeding time predictions by 95.7 %. In addition, the same tools further extended these benefits by reducing feed waste by up to 75 % and feed usage by 33 %, thereby enhancing farm profitability. On the other side, the analysis proved environmental benefits, as for instance, AMS showed potential for reducing greenhouse gas emissions, with a decrease in global warming potential up to 5.83 %, while Feed and Live Weight Measurement tools together with Health Monitoring Systems achieved a reduction of up to 39 % on energy consumption. Health Monitoring Systems, also provided important benefits especially regarding health predictions, including up to 95 % for conditions like fever, cysts, and 97 % for Bovine Respiratory Disease.

All these benefits highlight the potential of DATSs to support sustainable development goals within livestock farming, aligning with initiatives like the European Green Deal and the Common Agricultural Policy. Their adoption, however, still faces challenges, especially among small-scale farmers due to economic and cultural barriers, like high initial costs, limited technological infrastructure, and reluctance to embrace new technologies. Effective policy support, economic incentives, and enhanced technological infrastructure seems to be critical to encourage widespread adoption and maximise the benefits these technologies can offer, ensuring that sustainable, efficient livestock practices become accessible across diverse farming scales.

The integration of monitoring technologies in livestock systems has proven instrumental in improving animal health, welfare, and productivity through data-driven insights. While the advancements in dairy cattle demonstrate the sector's leading role in adopting precision technologies such as health monitoring and milking automation, a notable disparity exists in the application of these technologies across other livestock categories. The dominance of dairy cattle in the adoption of DATSs reflects its economic significance and relatively higher technological integration, but it also highlights the underrepresentation of other species. Dairy cattle studies predominantly focused on dairy cows, with minimal attention given to other species under the dairy category, such as buffaloes, despite the economic and cultural significance of buffalo farming in many regions and the growing body of research emphasising the applicability of DATSs in buffalo farming [16,17,55,56,86].

In addition, pigs, beef cattle, and small ruminants, despite their substantial contributions to global livestock production, face unique challenges, such as feed efficiency, health monitoring, and environmental impact management, that remain underexplored. There is an absence of poultry-focused studies in the reviewed articles, despite the crucial role of poultry in global protein supply and its specific requirements for disease control, environmental monitoring, and productivity optimisation. This gap contrasts with ongoing advancements in DATS adoption for poultry, as reported in studies such as Olejnik et al. [66] and Cruz et al. [28]. Addressing these gaps through the development of tailored precision technologies will be essential for achieving equitable and effective adoption across all livestock systems, fostering a more inclusive and sustainable approach to agricultural innovation.

In summary, DATSs present a compelling approach to advancing sustainable, efficient, and productive livestock systems, reducing labour requirements, conserving resources, and enhancing animal welfare. As these innovative technologies will evolve, they seem to play a crucial role in achieving EU targets under the European Green Deal and Common Agricultural Policy, which aim to create a competitive, sustainable and resource-efficient economy. This review calls for continued adoption, assessment and further development of these DATSs, recognising their essential role in transforming livestock farming systems. As the agricultural sector adapts to 21st-century challenges, deploying DATSs in Livestock production will be essential for enhancing food security, economic resilience, and environmental sustainability.

Ethics statement

Not applicable: This manuscript does not include human or animal research.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT, an AI language model by OpenAI, to improve the language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

George Papadopoulos: Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Maria-Zoi Papantonatou:** Writing – original draft, Resources, Investigation, Formal analysis. **Havva Uyar:** Writing – original draft, Methodology, Investigation, Formal analysis. **Olga Kriezi:** Writing – original draft, Resources, Investigation, Formal analysis, Methodology. **Alexandros Mavrommatis:** Writing – review & editing. **Vasilis Psiroukis:** Writing – review & editing, Validation, Resources, Methodology. **Aikaterini Kasimati:** Writing – review & editing, Methodology. **Eleni Tsiplakou:** Writing – review & editing, Methodology, Supervision. **Spyros Fountas:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available upon request.

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