

Sensors and Emerging Technologies for Sustainable Dairy Systems: A PRISMA Systematic Review (2010-2025)

Sensores y tecnologías emergentes para sistemas lácteos sostenibles: revisión sistemática PRISMA (2010-2025)

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ABSTRACT

In this article, we present a PRISMA-guided systematic review of emerging technologies for sustainability in the dairy industry, based on a two-phase Scopus protocol with an operational publication window from January 1 2010 to November 10 2025. During Phase 1, a base corpus (2010-2023; n = 38 included studies) was consolidated, while Phase 2 consisted of a sensor-focused Scopus update (January 1 2024 to November 10 2025; additional n = 12), yielding a final corpus of 50 peer-reviewed studies. We placed sensor technologies —including on-animal wearables/accelerometers, rumen boluses, environmental monitors (e.g., THI/CO₂/NH₃), in-line milk/process sensors, and computer-vision/thermal systems— at the center of the analysis, in order to generate the real-time data streams that facilitate precision livestock farming, and to amplify the impact of artificial intelligence, renewable energy systems, water-efficiency strategies and animal-welfare tools. Across the relevant literature, sensors have been shown to contribute to carbon-footprint reduction, energy and water optimization, and livestock welfare, via early-warning health monitoring and data-driven decisions at the farm and along processing lines. However, critical gaps persist in the validation and standardization of sensor outputs, deployment in low-infrastructure contexts, and data governance/interoperability. Future research will be needed that prioritizes policy design for the adoption, socioeconomic impact assessment and scalable integration of sensor-enabled solutions in emerging rural settings, including benchmarking protocols and open datasets, in order to strengthen reproducibility.

Keywords: Dairy industry, sensors, internet of things (IoT), precision livestock farming, sustainability, animal welfare

RESUMEN

Este artículo presenta una revisión sistemática guiada por PRISMA sobre tecnologías emergentes en sistemas lácteos sostenibles, basada en un protocolo de dos fases en Scopus con una ventana operativa de publicación comprendida entre el 1 de enero de 2010 y el 10 de noviembre de 2025. La Fase 1 consolidó un corpus base (2010-2023; n = 38 estudios incluidos) y la Fase 2 correspondió a una actualización en Scopus centrada en sensores (1 de enero de 2024 a 10 de noviembre de 2025; n = 12 estudios adicionales), para un corpus final de 50 estudios revisados por pares. Se ubican las tecnologías de sensores —incluyendo dispositivos IoT portables/acelerómetros, bolos ruminales, monitores ambientales (por ejemplo, THI/CO₂/NH₃), sensores en línea de leche/proceso y sistemas de visión por computador/termografía— en el centro del análisis, dado que generan flujos de datos en tiempo real que habilitan la ganadería de precisión y amplifican el impacto de la inteligencia artificial, las energías renovables y la agricultura regenerativa. En la literatura, los sensores contribuyen a la reducción de la huella de carbono, la optimización energética e hídrica, y el bienestar animal tanto en finca como en las líneas de procesamiento. No obstante, persisten vacíos críticos en la validación y estandarización de salidas, la adopción en pequeños productores y la interoperabilidad de sistemas. La investigación futura debe priorizar el diseño de políticas de adopción, la evaluación del impacto socioeconómico y la integración escalable de arquitecturas basadas en sensores, junto con protocolos de trabajo abiertos y conjuntos de datos de acceso abierto que fortalezcan la reproducibilidad.

Palabras clave: industria láctea, sensores, internet de las cosas (IoT), ganadería de precisión, sostenibilidad, bienestar animal



1. Introduction

Globally, the dairy industry is undergoing a structural transition in which sensor-enabled technologies are central to the modernization of production and the reduction of environmental impacts. In the face of rising social and regulatory pressures associated with the issue of sustainability, increasingly producers and researchers are deploying on-animal wearables/accelerometers, rumen boluses, environmental monitors (e.g., THI/CO₂/NH₃), in-line milk/process sensors, and computer-vision/infrared thermography systems, in order to generate high-frequency data streams that support previous health interventions, tighter process control, and evidence-based resource management.

This transformation is especially consequential in the context of developing and emerging economies, where the dairy sector underpins food security, rural employment and local livelihoods. However, adoption faces the challenges of structural constraints—limited digital connectivity, skills gaps, uncertain total cost of ownership, and inadequate public investment—that can decouple technological promise from realized sustainability gains. Such constraints heighten the need for validated, interoperable and affordable sensing solutions, and for practical pathways that translate data into decisions at both farm and plant levels.

Academic interest has increased accordingly, examining how sensors, analytics/AI, renewable energy and precision livestock farming (PLF) can be combined and adapted across diverse production systems and climatic conditions. However, the literature remains fragmented: thematic trends are unevenly mapped, sensor-to-impact pathways (e.g., sensing → decision → energy/water outcomes) are not consistently quantified, and cross-study comparability is limited by heterogeneous devices, metrics and validation protocols.

In order to address these gaps, in this article we present a PRISMA-guided systematic review of 50 studies, assembled through a two-phase Scopus protocol: a base corpus covering January 1 2010 to December 31 2023; and a sensor-focused update covering January 1 2024 to November 10 2025. Our aims were to: (i) identify dominant research lines and position sensors as the data-generating substrate feeding analytics and automation; (ii) map technological approaches across animal-, process- and environment-centric applications; and (iii) assess reported contributions to sustainability—energy and water efficiency, emissions/quality, and animal welfare— together with adoption barriers and evidence gaps. The results are organized into five thematic clusters—digitalization, sensors and automation; renewable energy and energy efficiency; water resource management; animal welfare and monitoring; and organizational eco-efficiency—thereby providing an integrated view of the

current situation and the challenges ahead for the delivery of sensor-driven, sustainable dairy systems.

2. Methodology

In our research we followed the PRISMA framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to support a transparent and reproducible workflow for identifying, selecting and analyzing relevant scientific literature. For the revised manuscript, the protocol was rewritten as a single operational workflow with two clearly delimited Scopus phases: (1) a base search covering January 1 2010 to December 31 2023; and (2) a sensor-focused Scopus update covering January 1 2024 to November 10 2025. The final audited corpus comprised 50 included studies (38 + 12).

Given its broad coverage of peer-reviewed journals in sustainability, engineering and agricultural sciences, Scopus was used as the sole bibliographic source. Unlike the earlier wording of the manuscript, the revised protocol does not state «no date restriction». Instead, the operational publication window was explicitly delimited to January 1 2010 to November 10 2025, with the phase-specific windows indicated above and the detailed reproducibility fields documented in Appendix A.

We included studies that: (a) address technological applications in the dairy sector (farm or plant); (b) provide empirical, review-based or theoretically grounded evidence related to innovation and/or sustainability (e.g., energy, water, welfare, emissions/quality); and (c) are written in English or Spanish and published as peer-reviewed journal articles or reviews. We excluded items not directly related to dairy applications, duplicate records and grey literature (e.g., theses, conference abstracts without full peer review).

Titles and abstracts were screened against the eligibility criteria, followed by full-text assessment of potentially relevant papers. To improve auditability, the revised manuscript incorporates auditable phase definitions and a reproducibility appendix (Appendix A), rather than reasserting inconsistent intermediate counts from the archived draft. The final synthesis, therefore, is based on the verified phase totals (38 base studies + 12 update studies = 50 included studies).

Once the eligible articles had been selected, a thematic content analysis was conducted to identify common technological categories, sustainability approaches and future research needs. The extracted information supported the clustering logic, the traceability notes for predictive-model evidence, and the keyword co-occurrence analysis reported in Section 3 and Appendix C.

2.1. Sources of information and search strategy

The bibliographic search was carried out in Scopus, which was selected for its broad coverage of literature in

engineering, environmental sciences, food systems and agribusiness. For reproducibility, the revised manuscript defines the search as a two-phase Scopus protocol: Phase 1 (base corpus) covered January 1 2010 - 31 December 31 2023, and Phase 2 (sensor-focused update) covered January 1 2024 - November 10 2025. The last search date was November 10 2025. No subject-area restriction was applied; document-type and language filters were used instead to retain peer-reviewed articles and reviews in English or Spanish.

The executable one-line query and the reporting fields used to reconstruct the final corpus are provided in Appendix A. In brief, the search equation combined three thematic blocks –sustainability, emerging technologies and the dairy chain– with an explicit sensor block (sensor*, wearable*, accelerometer*, ear-tag*, collar*, rumen bolus, computer vision, thermal imaging/IRT, in-line/process sensors, THI, NH₃, CO₂) linked through Boolean operators. For replicability, exported metadata fields and the deduplication rule are also documented in Appendix A.

2.2. Criteria for inclusion and exclusion

We included full-text journal articles and reviews in English or Spanish that examined technological applications in the dairy sector and reported environmental, productive, organizational, welfare or process implications relevant to sustainability. Publications focused on medicine, pharmacology, astronomy, pure mathematics or other areas without a direct link to dairy production or agro-industrial sustainability were excluded.

2.3. Selection and codification process

Screening followed a two-phase workflow consistent with the revised protocol: a base corpus (2010-2023) followed by a sensor-focused Scopus update (January 1 2024-November 10 2025), yielding 50 included studies. Because the archived draft contained non-reconcilable intermediate counts, the revised manuscript reports the auditable phase totals explicitly and supports them through Appendix A.

After screening and full-text eligibility checks, 12 additional studies from the sensor-focused update were retained and integrated into the final synthesis.

In total, the final corpus comprises 50 studies (38 base + 12 sensor-focused update). All included papers were double-coded using a structured extraction sheet covering: (i) dominant technology/modality; (ii) study design/context; and (iii) sustainability outcomes (energy, water, welfare, emissions/quality). The coding unit was the individual article. When a paper reported hybrid or multi-technology designs, the dominant modality was defined as the technology explicitly evaluated as the main analytical or operational input, while secondary

modalities were recorded in the extraction notes. Coding discrepancies were resolved through reviewer consensus; where discussion remained necessary, the full text was revisited against the operational definitions in Appendix B.

Detailed query, filters, exported fields, and deduplication rule are reported in Appendix A.

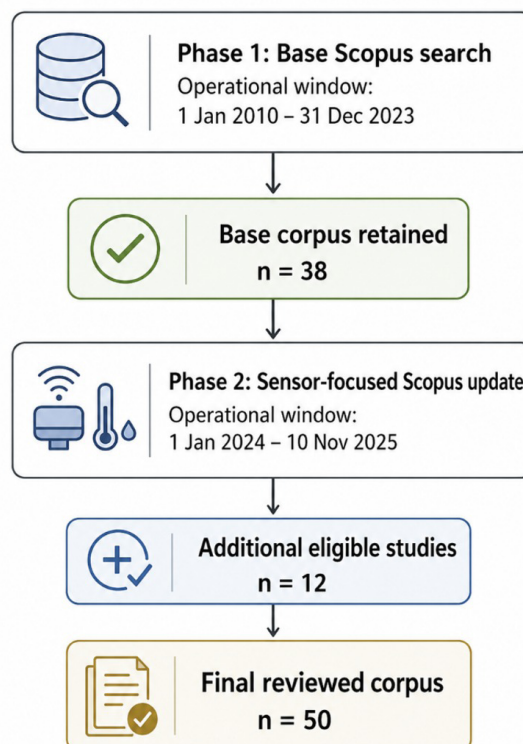


Figure 1. Auditable two-phase assembly of the revised PRISMA corpus

The complete search and coding workflow is summarized through an auditable two-phase corpus diagram (Figure 1) and a reproducibility appendix. Data extraction was carried out using standardized fields, including author, year, type of technology, contribution to sustainability, geographical region, study design/context, validation note and main results. Because the original independent coder logs were not preserved in a form that allowed for retrospective calculation of Cohen's kappa, no inter-coder coefficient is claimed. This is acknowledged explicitly in the limitations section and addressed by publishing the operational coding rules in Appendix B.

2.4. Methodological considerations

It should be noted that the review was limited to a single database (Scopus), which may limit coverage of the documentary universe. Furthermore, quantitative analysis techniques (such as meta-analysis) were not applied, as the heterogeneity of methodological approaches across studies made direct comparison of results difficult. For proper contextualization, these limitations are addressed in the final section of the article.

3. Results and discussion

Based on the PRISMA selection, we analyzed 50 studies (2010–2025). Five thematic clusters predominate in the literature on emerging technologies for the dairy sector: (1) Digitalization, Sensors and Automation; (2) Renewable energy and energy efficiency, (3) Water resource management; (4) Animal welfare and monitoring; and (5) Organizational eco-efficiency. In this sensor-centered reframing, sensors –on-animal wearables/accelerometers, rumen boluses, computer vision/infrared thermography, in-line milk/process probes and environmental monitors– are treated as the data-generating substrate that feeds the analytics and AI across farm and plant contexts. This perspective clarifies how sensing streams translate into sustainability outcomes

(energy and water savings, improved welfare, lower emissions and higher product quality) and spotlights implementation challenges, including validation and benchmarking, interoperability and data governance, total cost of ownership and device durability, and adoption in low-infrastructure settings.

3.1. Characterization of studies included

The final corpus comprises 50 studies assembled through a two-phase Scopus protocol: 38 in the base corpus (2010–2023) and 12 in the sensor-focused update (January 1 2024 to November 10 2025). This explicit phase definition replaces the earlier overlapping narrative and is consistent across the abstract, methods section and Figure 1.

Table 1. Articles included in the systematic review

Author	Year	Evaluated technology	Primary modality/role	Main contribution
Place and Mitloehner	2010	Carbon footprint review	Non-sensor (footprint/efficiency)	Mitigation via improved production efficiency
Belflower <i>et al.</i>	2012	Environmental impact (systems)	Non-sensor (systems analysis)	Comparison of dairy production systems in Georgia
Soberon <i>et al.</i>	2012	Prewaning nutrition	Non-sensor (nutrition/welfare)	Long-term productivity effects
Wayua <i>et al.</i>	2012	Solar pasteurizer (Kenya)	Energy (renewables)	Design and performance of solar pasteurizer
Bourlakis <i>et al.</i>	2014	Supply chain sustainability	Non-sensor (supply chain)	Environmental performance in Greek dairy supply chains
Buys <i>et al.</i>	2014	Sustainability scorecard	Non-sensor (organizational)	Predictive tool for social/economic/environmental impacts
Glover <i>et al.</i>	2014	Supply chain sustainability	Non-sensor (institutional theory)	Institutional drivers of sustainable practices
Jabbari Rad and Lewis	2014	Water/energy/wastewater	Non-sensor (water/energy)	Water and energy use and wastewater management review
Nacer <i>et al.</i>	2014	Grid-connected PV dairy	Energy (renewables)	PV feasibility for dairy
Krauß <i>et al.</i>	2015	Water productivity	Non-sensor (water)	Effects of management strategies on water productivity
Vázquez Diosdado <i>et al.</i>	2015	Accelerometer behavior classification	Wearables/accelerometers	Behavior classification in housed cows
Soteriades <i>et al.</i>	2016	Eco-efficiency and intensification	Non-sensor (eco-efficiency)	DEA/LCA of eco-efficiency vs intensification
Baldini <i>et al.</i>	2017	Life cycle assessment (LCA)	Non-sensor (LCA/footprinting)	Environmental impact assessment of milk production
Bewley <i>et al.</i>	2017	Dairy cattle management (historical)	Non-sensor (management review)	100-year review of housing/management for lactating cows
Challis <i>et al.</i>	2017	Energy efficiency in plants	Process (energy/CIP)	Human factors in process control for energy reduction
Murphy <i>et al.</i>	2017	Water footprinting (Ireland)	Non-sensor (water footprint)	Farm-level water footprinting
Norton and Berckmans	2017	Precision livestock tools	Digital (PLF concept)	Development of PLF for dairy
Rosenberger <i>et al.</i>	2017	Milk allowance (calves)	Non-sensor (welfare/management)	Effects on behavior and weight gains
Yu and Maeda	2017	Inline progesterone monitoring	In-line/process (endocrine)	Progesterone monitoring on-line
Gargiulo <i>et al.</i>	2018	Precision tech adoption	Digital (adoption/management)	Larger herds adopt more precision dairy technologies
Panchal <i>et al.</i>	2018	Solar for pasteurization	Energy (renewables)	Solar energy for milk pasteurization
Djekic <i>et al.</i>	2019	Environmental impacts (milk and yogurt)	Non-sensor (LCA/footprinting)	Monte Carlo LCA of production/consumption
Liu <i>et al.</i>	2019	Heat stress review	Environmental (heat stress)	Heat stress effects and monitoring concepts
Bánkuti <i>et al.</i>	2020	Sustainability typology	Non-sensor (organizational)	Typology of dairy farms by sustainability indicators
Capper and Cady	2020	Dairy productivity and footprint	Non-sensor (efficiency/footprint)	Efficiency improvements reduce environmental impacts
Feil <i>et al.</i>	2020	Sustainability in dairy (review)	Non-sensor (systematic review)	Systematic review of sustainability in dairy
Zhang <i>et al.</i>	2020	Manure/sewage management	Non-sensor (waste/valorization)	Pathways in manure/sewage management
Galliano and Siqueira	2021	Organizational design	Non-sensor (organizational)	Organizational design and environmental performance

Rotz <i>et al.</i>	2021	Environmental assessment (US farms)	Non-sensor (systems/LCA)	Environmental assessment of US dairy farms
Honan <i>et al.</i>	2022	Feed additives (methane)	Non-sensor (nutrition/mitigation)	Enteric methane reduction modes/effectiveness
Kato <i>et al.</i>	2022	Management and mental health	Non-sensor (social)	Management factors and mental health of farm managers
Silva <i>et al.</i>	2022	Compost barns (bibliometric)	Non-sensor (housing/bibliometric)	Research trends in compost barns
Verdon	2022	Welfare in pasture systems	Non-sensor (welfare review)	Welfare factors in pasture-based calves
Leliveld <i>et al.</i>	2023	Accelerometer under hot weather	Wearables/accelerometers	Behavior and heavy breathing signals under heat
Liu and Liu	2023	Digital tech and environmental efficiency (China)	Digital (efficiency/policy)	Green total factor productivity and digitalization
Liu <i>et al.</i>	2023	Digitalisation and env. efficiency (China)	Digital (efficiency/policy)	Carbon-aware digitalization in dairy farms
Neethirajan	2023	AI and sensors in livestock export	Digital + Sensors (overview)	Digital transformation via AI and sensors
Korelidou <i>et al.</i>	2024	Infrared thermography and mastitis (review)	Vision/IRT (udder health)	IRT as diagnostic for mastitis
Myint <i>et al.</i>	2024	Single-camera lameness detection	Vision/IRT (on-animal)	Real-time lameness detection (deep learning)
Pichlbauer <i>et al.</i>	2024	Accelerometer + ML for behavior	Wearables/accelerometers	On-pasture behavior classification; system evaluation
De Oliveira <i>et al.</i>	2024	Digital and precision technologies	Digital (bibliometric)	Bibliometric trends in precision/digital dairy
Antognoli <i>et al.</i>	2025	Computer vision in dairy farm management (review)	Vision/IRT (on-animal)	State-of-the-art applications and future perspectives
Brito <i>et al.</i>	2025	Sensors/PLF for genetic evaluations (invited review)	Cross-cutting (sensors + PLF)	Use of sensor data in breeding/genomic evaluations
Burner <i>et al.</i>	2025	Differential SCC for IMI	In-line/process (quality)	DSCC for detection/management of mastitis
Fromm <i>et al.</i>	2025	Rumen sensors (T°, rumination, activity, pH)	Rumen bolus	Early indicators of heat load in bulls
Girdauskaitė <i>et al.</i>	2025	In-line lactose monitoring	In-line/process (metabolic)	Metabolic health in early lactation via lactose
Martelli <i>et al.</i>	2025	Data practices in milk sensor platforms	In-line/process (data/analytics)	Good practices and pitfalls from field use
Pfrombeck <i>et al.</i>	2025	Economic evaluation of rumen-bolus monitoring	Rumen bolus (economics)	Cost-benefit of sensor-assisted health monitoring
Szyc <i>et al.</i>	2025	Video-based automated lameness pipeline	Vision/IRT (on-animal)	Detection-to-scoring pipeline in real farms
Weinert-Nelson <i>et al.</i>	2025	Ear-tag accuracy under heat stress	Wearables/accelerometers	Heat stress effects on rumination/eating accuracy

Note. Abbreviations: PLF = Precision Livestock Farming; IRT = Infrared Thermography; DSCC = Differential Somatic Cell Count.

Table 1 summarizes the included studies, listing the author, year, assessed technology and main contribution to sustainability. This classification allowed us to identify thematic patterns, predominant technologies and gaps in geographical and methodological coverage.

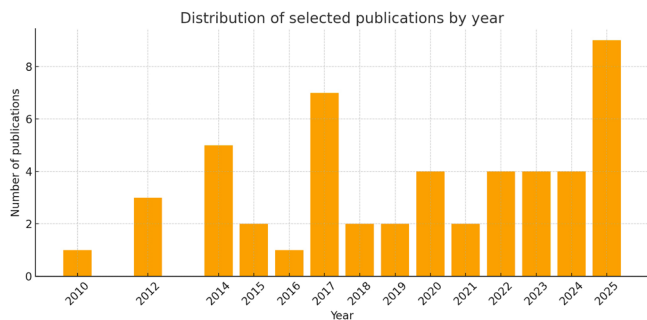


Figure 2. Distribution of selected publications by year

Figure 2 indicates a temporal shift from early footprinting/system-efficiency assessments toward diversified sustainability interventions, followed by a marked rise of sensor-enabled approaches in the most recent period. Recent studies emphasize on-animal sensing, vision/IRT and in-line/process analytics, increasingly tied to decision-support and operational

control. Overall, the trajectory supports a move from static assessment to real-time, sensor-driven management.

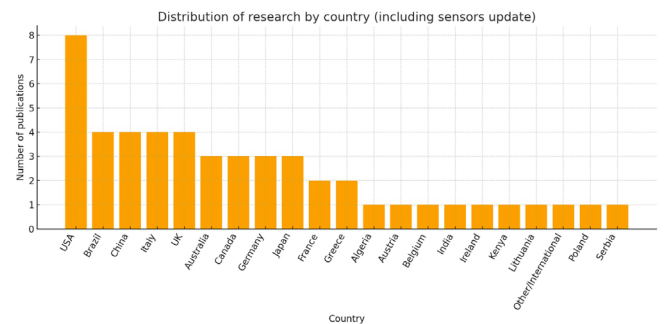


Figure 3. Distribution of research by country

The evidence base is geographically concentrated in high-infrastructure settings. The United States leads the corpus, followed by Brazil, China, Italy and the United Kingdom, with smaller contributions spread across Europe, Oceania and parts of Latin America and Africa. Although the sensor-focused update broadens coverage, the distribution remains uneven, highlighting the need for validation and cost-effectiveness evidence in low-infrastructure regions.



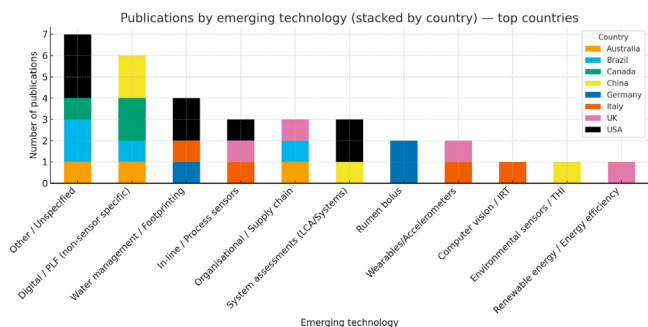


Figure 4. Distribution of research by emerging technology

Figure 4 shows that recent growth is driven by sensor-enabled modalities: wearables/accelerometers and rumen boluses dominate on-animal monitoring, while vision/IRT and in-line/process sensing expand rapidly; environmental sensing (e.g., THI) grows more modestly. Non-sensor streams (LCA/system assessments, renewables and water footprinting) remain relevant as complementary tracks supporting sustainability evaluation.

Non-sensor categories remain present but are no longer dominant. Digital/PLF (non-sensor specific) and system assessments (LCA/systems) characterize the early 2010s and provide the conceptual and evaluative backbone (Place and Mitloehner, 2010; Baldini et al., 2017; de Oliveira et al., 2024; Brito et al., 2025). Renewable energy/energy efficiency and water management/footprinting continue as complementary tracks (Panchal et al., 2018; Nacer et al., 2014; Murphy et al., 2017; Jabbari Rad and Lewis, 2014), but the charts indicate that recent gains are increasingly tied to real-time sensing that feeds analytics and automation across farm and plant.

Overall, Figure 4 supports a transition toward sensor-driven, closed-loop management in which animal and process signals feed analytics/automation and shape welfare, product quality and resource use —reinforcing the need for end-to-end evaluations of energy and water impacts.

3.2 Sensor platforms and measured outcomes (wearables, boluses, vision, in-line milk/process, environmental)

Sensor technologies constitute the enabling layer of precision dairy systems by providing high-frequency, animal- and process-level data that drive decision support and automation. Wearables —collars, ear-tags and pedometers integrating accelerometers, GPS and RFID— are widely used for estrus detection, activity and rumination profiling, and lameness screening. Recent field studies report robust performance across housing systems, while also noting accuracy degradation under heat stress conditions that must be accounted for in practice (Pichlbauer et al., 2024; Weinert-Nelson et al., 2025). Rumen boluses monitoring reticulorumen pH, temperature and activity enable early identification of subacute ruminal acidosis and heat load by capturing diurnal patterns otherwise missed by periodic checks, with emerging evidence on economic returns when integrated into herd-health programs (Fromm et al., 2025; Pfrombeck et al., 2025). Computer vision and infrared thermography (RGB/Depth/IR) extend sensing to morpho-functional traits and subclinical conditions —automated body-condition scoring, gait/posture analytics for lameness, individual identification and udder thermography for early mastitis screening— demonstrating rapid gains in real-world feasibility, including deployment alongside robotic milking (Myint et al., 2024; Korelidou et al., 2024; Antognoli et al., 2025; Szyk et al., 2025). Along the processing chain, in-line milk and process sensors (e.g., conductivity, flow, differential somatic cell count) provide immediate quality feedback and support CIP/throughput decisions tied directly to energy and water efficiency (Burner et al., 2025). Finally, environmental sensors tracking microclimate and air quality (e.g., THI, CO₂, NH₃) inform ventilation and cooling strategies and are increasingly integrated with animal-borne streams and genetic improvement pipelines (Brito et al., 2025).

Table 2 summarizes sensor modalities, measured variables, validated outcomes and sustainability links across farm and processing contexts.

Table 2. Sensor modalities in dairy systems: variables, validated outcomes and sustainability links

Modality	Core sensor/variable	Validated outcomes (examples)	Sustainability link	Exemplary studies (source journals; not a quality appraisal)
Wearables (collars, ear-tags, pedometers; accelerometers/GPS/RFID)	Activity, rumination, estrus, lying/ steps	Estrus detection; lameness screening; real-time health alerts; on-pasture behavior classification	Reproductive efficiency; reduced health losses; earlier interventions	Pichlbauer et al., 2024; Weinert-Nelson et al., 2025; Pfrombeck et al., 2025
Rumen boluses	Reticulorumen pH, temperature, activity, water intake	Early identification of SARA and heat load; diurnal pattern tracking	Fewer treatments, stabilized production; welfare under heat stress	Fromm et al., 2025
Computer vision and thermal imaging (RGB/Depth/IR)	BCS, gait/posture, ID, udder surface temperature	Lameness detection; early mastitis screening; automated BCS; robotic-milking streams	Milk quality; reduced culling; targeted interventions	Myint et al., 2024; Korelidou et al., 2024; Antognoli et al., 2025; Szyk et al., 2025
In-line milk / process sensors	Conductivity, flow, proxies for SCC; process analytics	In-process quality monitoring; intramammary infection surveillance; CIP/throughput optimization	Energy and water efficiency; waste reduction at plant level	Burner et al., 2025; Martelli et al., 2025
Environmental sensors	THI, CO ₂ , NH ₃ (barn microclimate/air quality)	Ventilation/cooling control; stocking decisions; heat-stress mitigation	Welfare protection; energy-efficient climate control	Brito et al., 2025

The modalities summarize high-frequency sensing streams, enabling precision decisions across farm and processing stages. Validated outcomes refer to peer-reviewed evidence under commercial or near-commercial conditions. Sustainability links map outcomes to energy/water efficiency, welfare and product quality improvements. The journal/source labels used for exemplary studies are descriptive publication context references only and should not be interpreted as a formal quality appraisal or risk-of-bias assessment.

In line with the abovementioned clarification, Table 2 no longer presents Q1-Q2 as an implicit quality label. Instead, the table identifies exemplary peer-reviewed studies that illustrate each modality without ranking their evidentiary weight beyond the scope of this narrative systematic review.

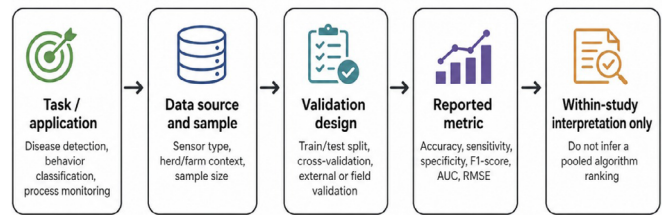
3.3. Digitalization, sensors and automation

We conceptualize sensor technologies as the enabling substrate of digitalization in dairy systems: high-frequency animal- and process-level data from wearables, rumen boluses, computer vision/infrared thermography, in-line milk/process probes and environmental monitors feed the analytics and AI layers, rather than the other way around. This data substrate underpins precision decisions that affect health, welfare, product quality and resource use, and it is increasingly embedded in breeding and management pipelines as evidence accumulates on fitness-for-purpose and validation under real-world conditions (Brito *et al.*, 2025; Pichlbauer *et al.*, 2024; Antognoli *et al.*, 2025).

Digitalization has been one of the most dynamic fields in the transformation of the dairy industry. Technologies such as artificial intelligence (AI), the Internet of Things (IoT) and big data analytics have been applied to optimize livestock management, improve traceability and increase production efficiency (Gargiulo *et al.*, 2018; Liu *et al.*, 2023). Smart sensors allow real-time monitoring of physiological and environmental variables, while machine learning algorithms predict diseases or nutritional deficiencies with a high degree of accuracy (Neethirajan, 2023).

Automated milking systems, blockchain for food traceability and computer vision for welfare monitoring are among the most prominent innovations (Murphy *et al.*, 2017; Hoyos *et al.*, 2019; de Oliveira *et al.*, 2024; Myint *et al.*, 2024; Antognoli *et al.*, 2025). At the same time, studies have shown that their adoption is concentrated in regions with more technological infrastructure, revealing a gap with regard to their applicability in emerging rural environments.

Compare predictive models only when task, data source, validation design, and reported metric are aligned.



Avoid pooled rankings across heterogeneous studies.
Accuracy, sensitivity, specificity, F1-score, AUC, RMSE, and task-specific metrics are not directly comparable by default.

Figure 5. Interpreting predictive-model evidence in the reviewed subset

The reviewed subset reports model performance across heterogeneous tasks, datasets, validation schemes and metrics. Therefore, the evidence should not be interpreted as a pooled algorithm ranking. In the revised manuscript, Figure 5 is presented as a comparability guide rather than a leaderboard, and Appendix C provides study-level traceability notes indicating the task, validation context, metric type and reasons for the limited direct cross-study comparison. The main conclusion is therefore modified: machine-learning approaches can support early disease detection, behavior classification and process monitoring within the original task definition of each study, but not all the reported values are directly comparable.

3.4. Renewable energies and energy efficiency

The energy transition in the dairy sector has been driven by the need to reduce the carbon footprint and improve operational profitability. The literature reviewed documents successful experiences of implementing solar panels, wind turbines and manure-based biodigesters, with emission reductions of up to 30% (Nacer *et al.*, 2014; Panchal *et al.*, 2018).

Energy efficiency improvements through heat recovery technologies, LED lighting and optimized cooling systems are also highlighted (Challis *et al.*, 2017). However, few studies address adoption costs or return on investment on small farms, suggesting the need for economic feasibility analyses tailored to varying production scales (Wayua *et al.*, 2012).

3.5. Water management and water footprint

Water is one of the most critical resources for agricultural sustainability. In our review, we identified technological practices focused on reducing consumption and promoting water reuse, such as smart irrigation systems, wastewater recycling and water footprint analysis (Murphy *et al.*, 2017; Jabbari Rad and Lewis, 2014).

Studies such as Krauß *et al.* (2015) have proposed strategies to increase water productivity without compromising herd health and milk yield. However, few

articles have addressed the incorporation of integrated water management indicators, such as economic water efficiency or drought resilience, and this line of research remains underdeveloped.

Energy and water efficiency in dairies are increasingly sensor-mediated. Environmental monitors (e.g., temperature-humidity index, CO₂, NH₃) inform ventilation and cooling strategies, linking microclimate control to animal comfort and energy demand in housing and milking parlors (Liu et al., 2019; Brito et al., 2025). Downstream, in-line milk and process sensors (e.g., conductivity, flow, differential somatic cell count) provide immediate quality feedback that guides throughput and cleaning-in-place (CIP) decisions, thereby addressing product quality together with resource use and waste minimization (Burner et al., 2025; Martelli et al., 2025; Jabbari Rad and Lewis, 2014), and closing the sustainability loop from barn microclimate to plant operations.

3.6. Animal welfare and innovation monitoring

In both ethical and production terms, animal welfare has become an increasingly relevant ethical component. Technologies such as accelerometers, activity sensors and facial recognition enable the early detection of abnormal behavior, heat stress and a range of health conditions (Leliveld et al., 2023; Vázquez Diosdado et al., 2015).

Automated ventilation systems, environmental enrichment and intelligent feeding management have also been shown to improve herd health and milk quality (Soberon et al., 2012; Verdon, 2022). Despite advances, in the literature there is a relative absence of longitudinal studies that measure the long-term impacts on physiological and reproductive parameters across different breeds or climates.

Animal-centered sensing streams are central to welfare monitoring. Accelerometer-based wearables (ear-tags, collars, pedometers) support estrus detection, activity/rumination profiling, and lameness screening. Recent field studies report robust performance, while also noting accuracy degradation under heat-stress conditions requiring recalibration *in situ* (Pichlbauer et al., 2024; Weinert-Nelson et al., 2025; Leliveld et al., 2023). Rumen boluses that track reticulorumen pH, temperature and activity provide early indicators of subacute ruminal acidosis and heat load by capturing diurnal patterns that are otherwise missed by periodic checks, and emerging analyses have addressed the cost-benefit of integrating them into herd-health programs (Fromm et al., 2025; Pfrombeck et al., 2025). Computer vision and infrared thermography (RGB/Depth/IR) extend sensing to morpho-functional and subclinical traits—automated gait/posture and body-condition scoring, individual identification, and udder surface-temperature mapping for early mastitis detection—including deployment alongside robotic milking, with the latest reports showing

rapid gains in accuracy and real-world feasibility (Myint et al., 2024; Korelidou et al., 2024; Antognoli et al., 2025; Szyk et al., 2025).

3.7. Organizational eco-efficiency and sustainable models

Beyond the technological component, several studies have analyzed sustainability from an organizational perspective. Process redesign, life cycle analysis (LCA) and the adoption of eco-efficiency indicators have been shown to reduce costs and improve environmental performance (Baldini et al., 2017; Soteriades et al., 2016; Pinedo-López et al., 2024).

While it has been demonstrated that the internal structuring of farms, organizational culture and access to knowledge networks influence technological adoption (Glover et al., 2014; Galliano and Siqueira, 2021; Carriazo-Regino et al., 2024), research on the social dimensions of technological change, such as gender equity in adoption processes or the impact on labor welfare, remains incipient.

3.8. Environmental impact and sustainability

A cross-cutting dimension across all clusters is the contribution of emerging technologies to reducing the environmental impact of dairy production; specifically, strategies to mitigate carbon footprint through the use of clean energy, automation and input optimization are highlighted.

Table 3. Carbon footprint reduction by methods in the dairy sector

Method	Typical carbon footprint reduction (%)	Examples / notes
Renewable energy / energy efficiency	20-40	Biogas/solar and plant efficiency [included: Panchal et al., 2018; Rotz et al., 2021; background: Nacer et al., 2016]
Sensor-enabled monitoring and control	5-20	THI-driven ventilation/cooling; in-line sensors informing CIP/quality [included: Challis et al., 2017; Yu and Maeda, 2017; Martelli et al., 2025]
Input optimization	10-30	Feed/management efficiency [included: Capper and Cady, 2020; Soteriades et al., 2016]
AI / analytics (incremental beyond sensors)	3-15	Decision support fed by sensor streams [included: de Oliveira et al., 2024; Brito et al., 2025]

Table 3 synthesizes indicative reduction ranges derived through narrative aggregation of the cited literature. To improve traceability, each supporting citation is tagged as either PRISMA-included or background literature. Renewable energy and energy-efficiency measures

typically deliver the largest carbon-footprint reductions (approximately 20-40%), consistent with biogas/solar integration and plant-level efficiency gains [included: Panchal *et al.*, 2018; Rotz *et al.*, 2021; background: Nacer *et al.*, 2016]. Sensor-enabled monitoring and control contribute a further approximately 5-20% by tightening operations—for example THI-informed cooling or in-line quality analytics that inform CIP and process set-points [included: Challis *et al.*, 2017; Yu and Maeda, 2017; Martelli *et al.*, 2025]. Input optimization (approximately 10-30%) captures management and feeding efficiencies that lower emissions intensity [included: Capper and Cady, 2020; Soteriades *et al.*, 2016].

AI/analytics yield an additional approximately 3-15% when layered on top of sensing, primarily through better decision-making rules and scheduling rather than through standalone effects [included: de Oliveira *et al.*, 2024; Brito *et al.*, 2025].

These ranges are context-dependent (herd size, climate, baseline technology, grid mix), should be read as min-max narrative ranges rather than as pooled effect estimates, and are not additive across rows. AI gains are interpreted as incremental to sensor deployments, in order to avoid double counting. Because several range-supporting references come from broader background literature, the revised table explicitly distinguishes between included and background sources, and the methodological note clarifies how the ranges were derived.

3.9. Keyword co-occurrence analysis

To complement the thematic clusters, we produced an updated keyword co-occurrence map that foregrounds sensor modalities (wearables/accelerometers, rumen boluses, vision/IRT, in-line/process and environmental sensing) alongside AI/automation and sustainability terms (energy efficiency, water footprint and animal welfare). In the revised manuscript, the network-construction settings are documented: the keyword source was the harmonized extraction matrix built from study descriptors and author/index terms, the minimum occurrence threshold was 1, full counting was used, and association-strength normalization guided the map layout. The thesaurus merges and the reproducible input structure are summarized in Appendix C and Supplementary File S1.

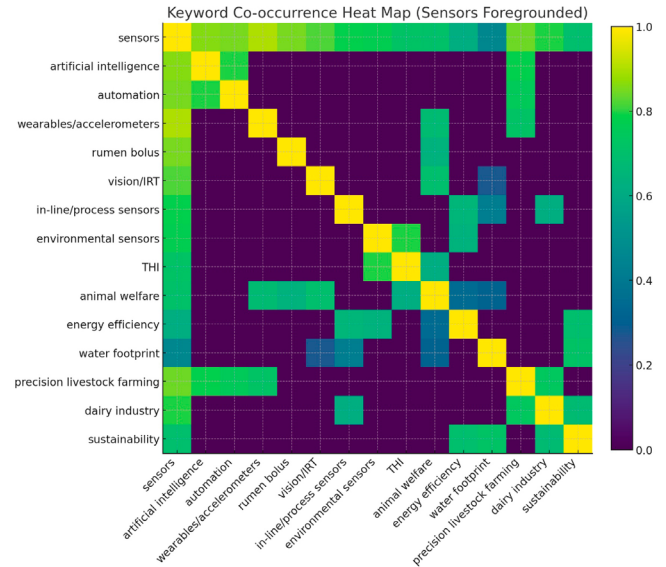
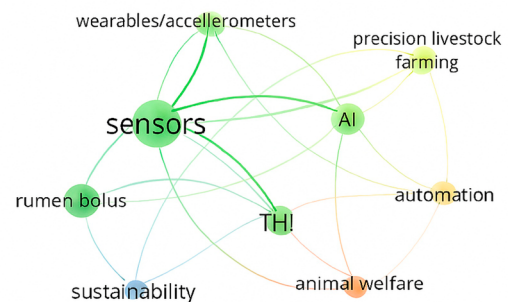


Figure 6. Heat map of keyword co-occurrence in the literature on emerging technologies in the dairy industry

Across both the intensity (Figure 6) and topology (Figure 7) views, sensors emerge as the central bridging hub linking animal-centric sensing, process analytics and environmental monitoring, with the closest proximity to AI/automation and precision-livestock terms. By contrast, end-to-end sustainability metrics—especially water-footprint links—remain comparatively under-represented, suggesting that many studies still stop short of quantifying the full chain from sensing to decision to resource outcomes. This interpretation should be read as a descriptive network result, rather than as a causal inference.



 VOSviewer

Figure 7. Keyword co-occurrence network with modular clusters (sensors as a bridging node).

Note. Generated from a harmonized keyword matrix using VOSviewer-compatible settings documented in Appendix C and Supplementary File S1

The keyword co-occurrence analysis and network view (Figures 6-7) foreground sensors as the dominant hub that bridges (i) animal-centric sensing (wearables/accelerometers, rumen boluses, vision/IRT); (ii) process-centric sensing (in-line milk and plant analytics); and (iii) environmental sensing (THI/CO₂/NH₃). In this sensor-led topology, the strongest structural proximities arise between sensors and AI/automation and between sensors and precision-livestock terms, consistent with real-time streams feeding analytical and decision-support layers. Thick ties with wearables and rumen boluses confirm the primacy of on-animal modalities, while links to THI highlight the consolidation of microclimate monitoring for heat-load management. By contrast, sensor-to-water-footprint links remain comparatively under-represented, and sustainability sits more peripherally, indicating that many studies still stop short of end-to-end quantification of sensor-enabled gains in energy and water.

Overall, the comparative patterns in Figure 6 (intensity) and Figure 7 (topology) converge on the same conclusion: sensors serve as the bridging substrate that links animal health and welfare to process quality and resource efficiency. The strongest links run through wearable accelerometry and rumen boluses toward AI/automation, with environmental monitors and in-line probes connecting to energy and water outcomes.

The weakest links—particularly those involving water footprint and some vision/IRT applications—flag a tractable agenda for end-to-end, sensor-to-sustainability study designs.

4. Conclusions

This PRISMA-guided review demonstrates that the dairy sector's digital transition is fundamentally sensor-driven. Across the five thematic domains—digitalization, renewable energy, water management, animal welfare, and organizational eco-efficiency—sensor technologies provide the high-frequency animal- and process-level data that feed analytics and AI, enabling earlier health interventions, more precise herd management and tighter process control from milking to plant operations (Figure 4; Table 2). Evidence from wearables/accelerometers, rumen boluses, computer vision/infrared thermography, in-line milk/process probes and environmental monitors indicates tangible gains in productivity, quality, emissions mitigation and welfare, with consolidated use cases in estrus and rumination monitoring, lameness and mastitis screening, heat-load management (THI), and real-time quality surveillance on the processing line (Table 2; Table 3; Pichlbauer *et al.*, 2024; Fromm *et al.*, 2025; Antognoli *et al.*, 2025; Burner *et al.*, 2025; Brito *et al.*, 2025).

The updated keyword co-occurrence analysis reinforces this architecture: sensors act as the bridging node between animal-centric sensing, process-centric sensing, and environmental sensing, and show the

strongest structural proximities to AI/automation and precision-livestock terms (Figures 6-7; Appendix C). By contrast, links to water footprint and, more broadly, to end-to-end sustainability metrics remain comparatively under-represented, which is consistent with the more limited treatment of integrated water-footprint evidence in Section 3.5 and with the context-dependent resource/emission ranges synthesized in Table 3. This gap suggests that many studies still stop short of quantifying the full chain from sensing to decision to resource outcomes, particularly in low-infrastructure settings (Table 3; Figures 6-7).

In order to translate pilot-scale success into sector-wide impact, the next phase should prioritize standardized validation protocols: across breeds, housing systems and climates; interoperability and data governance (including FAIR data, cybersecurity and privacy); device longevity and total cost of ownership (battery life, robustness, maintenance); and economic and social evaluation in smallholder and emerging-market contexts. These priorities follow directly from the geographic concentration of the reviewed evidence (Figure 3), the comparability cautions documented for predictive-model studies (Figure 5; Appendix C), and the context sensitivity of environmental/resource ranges in the dairy sector (Table 3). Methodologically, future research should couple animal-borne, environmental and in-plant sensing with causal or quasi-experimental designs that report sensor-enabled savings in energy and water alongside welfare and product-quality outcomes, using open benchmarks and reproducible pipelines.

Finally, the present synthesis is bounded by the database choice, the explicit 2010-2025 operational window, and the language and document-type criteria specified in the revised protocol (Appendix A; Table 4). In its revised form, the manuscript states these boundaries consistently across the abstract, methods section, figures and appendices, thereby improving PRISMA traceability, despite the fact that some stage-by-stage counts from the earliest archived draft were not reasserted, because they could not be audited retrospectively (Figure 1; Appendix A).

5. Directions for future research

Building on the gaps identified in this review, future work should treat sensors as the enabling substrate that connects animal health, plant operations and sustainability outcomes. Firstly, there is a need for standardized validation protocols—across breeds, housing/feeding systems, climates and management intensities—for the main modalities (wearable accelerometers, rumen boluses, computer vision/infrared thermography, in-line milk/process probes and environmental monitors). Protocols should report calibration/drift, false-alert costs, battery life/device durability and interoperability, using open benchmarks and reproducible pipelines, to enable comparable results across farms and vendors.

Secondly, future research should prioritize end-to-end evaluations that quantify the causal chain sensing → decision → impact. This includes quasi-experimental or experimental designs that link early alerts (e.g., lameness, mastitis, heat load) to energy and water savings, quality gains and welfare outcomes —thereby closing the current evidence gap associated with water-footprint and resource-efficiency metrics. Coupling animal-borne, environmental and in-plant sensors with process control (e.g., ventilation and cooling set-points, CIP optimization, robotic milking) will be central to this agenda.

Thirdly, in order to scale adoption, future studies will have to address appropriateness and affordability in smallholder and low-infrastructure contexts: co-design with farmers and technicians; low-power/edge AI to reduce connectivity dependence; modular systems with clear total-cost-of-ownership models; and training packages that raise data and device literacy. Comparative cost-effectiveness and business-model analyses (purchase vs. service, shared platforms, cooperatives) will be essential in order to facilitate real-world uptake.

Fourthly, future work should develop integrated sustainability indicators that sensors can populate in real time —spanning economic, social, environmental and organizational dimensions— and embed them in Life Cycle Assessment (LCA) frameworks adapted to tropical and semi-arid regions. Sensor-informed LCA can replace static assumptions with observed process data (e.g., electricity for cooling/ventilation, water for cleaning, losses and rejects), thereby improving attribution and policy relevance.

Finally, future research must tackle data governance and the ethics of sensor ecosystems: FAIR data practices, cybersecurity, privacy/traceability, equitable data sharing and algorithmic transparency. Methodological good practices —pre-registered protocols, harmonized outcomes, effect-size reporting and uncertainty analysis— will improve the reproducibility and comparability of the evidence base.

6. Research limitations

This review inherits several limitations. Firstly, we interrogated Scopus only, which while ensuring broad coverage may also exclude relevant sensor studies indexed in Web of Science, PubMed or regional repositories. Given the rapid pace of sensor innovation, relevant conference proceedings, technical reports or preprints may also be under-represented; our choice to prioritize peer-reviewed sources has the potential to bias the corpus toward mature deployments and high-income settings.

Secondly, a quantitative meta-analysis was not feasible due to heterogeneous outcomes, devices, sampling frequencies, validation metrics and deployment contexts across different studies. Consequently, we relied

on qualitative/thematic synthesis, comparative mapping, and traceability tables; while appropriate in terms of scope, this limits causal inference and pooled effect estimates, particularly for sensor-enabled energy/water impacts and predictive-model performance.

Thirdly, the keyword harmonization used for the co-occurrence analysis (e.g., merging «wearables/accelerometers,» «vision/IRT,» and «in-line/process sensors») can lead to the introduction of thesaurus bias. Co-occurrence visualizations are descriptive —node proximity and link thickness should be interpreted as associational rather than causal. Reported gaps (e.g., weaker ties between sensors and water-footprint terms) should therefore be read as under-representation in the indexed literature, not as absence of effect.

Fourthly, the evidence base skews toward high-infrastructure geographies with advanced public policy and strong supply chains. Extrapolation to Latin America, Africa or South Asia requires caution, given that power reliability, connectivity, climate stressors and capital constraints differ markedly. These contextual factors also affect sensor accuracy and maintenance cycles.

Finally, the historical workflow files did not preserve all screening-stage counts or independent coder logs in a form that enabled full retrospective PRISMA auditing or formal computation of inter-coder agreement statistics (e.g., Cohen's kappa). Therefore, the revised manuscript improves transparency by reporting auditable phase totals, operational coding rules and study-level traceability notes, while explicitly acknowledging that some historical audit elements cannot be reconstructed without overstatement.

Declarations

Ethics approval: Not applicable (systematic review; no human or animal subject experimentation).

Data availability: The revised manuscript includes a reproducibility appendix and coding framework; a supplementary keyword matrix is provided as Supplementary File S1, and a structured extraction-sheet template is provided as Supplementary File S2.

Generative AI disclosure: Generative AI tools were used exclusively for language editing and formatting support; all scientific content, interpretations and references were reviewed and validated by the authors.

Authors' contributions

Tobías Alfonso Parodi Camaño: Conceptualization, methodology, writing (original draft), and writing, revision and editing.

Eduardo David Chalapud Narváez: Data curation, formal analysis, visualization, and writing, revision and editing.



Luis Enrique Mercado Hoyos: Methodology, investigation, and writing, revision and editing.

Mariano Esteban Romero Torres: Investigation, resources, and writing, revision and editing.

Luis Fernando Parodi Camaño: Supervision, project administration, and writing, revision and editing.

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Conflicts of interest

The authors declare no conflicts of interest.

AI declaration

The authors declare that no artificial intelligence tools were used in any part of the manuscript preparation process.

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Appendix A. Search reproducibility and phase reconciliation

This appendix consolidates the operational search protocol used in the revised manuscript and the auditable phase totals used to define the final corpus.

Protocol item	Specification
Database	Scopus only
Phase 1 (base corpus)	January 1 2010 to December 31 2023
Phase 2 (sensor-focused update)	January 1 2024 to November 10 2025
Last search date	November 10 2025
Document types	Peer-reviewed journal articles and reviews
Languages	English and Spanish
Subject-area filter	None applied explicitly; relevance was handled through query design and eligibility screening
Exported fields for reconstruction	Authors, title, source title, publication year, abstract, author keywords, indexed keywords, affiliation, DOI, document type, and citation metadata when available
Deduplication rule	Spreadsheet-assisted manual deduplication using DOI-first matching, followed by exact title/year matching and manual verification of near-duplicates

Executable one-line query used to define the revised protocol:

("sustainable innovation" OR "trends" OR "sustainable development" OR "sustainable advancements" OR "sustainable improvements" OR "sustainable progress") AND ("green technologies" OR "clean technologies" OR "eco-friendly technologies" OR "environmentally friendly technologies" OR "renewable technologies" OR "sustainable technologies" OR "best practices" OR "sustainable solutions" OR "sustainable systems" OR "sustainable practices" OR "low-impact technologies" OR "carbon-neutral technologies" OR "energy-efficient technologies") AND ("dairy production" OR "milk production" OR "dairy farming" OR "dairy industry" OR "milk industry" OR "dairy processing" OR "dairy supply chain" OR "milk processing" OR "dairy manufacturing") AND (sensor* OR wearable* OR accelerometer* OR "ear-tag*" OR collar* OR "rumen bolus" OR (rumen W/2 bolus) OR "computer vision" OR "thermal imaging" OR infrared OR IRT OR ("in-line" OR inline OR "process sensor" OR "milk-line") OR DSCC OR ("somatic cell count" W/3 differential) OR (lactose W/2 monitor) OR (progesterone W/2 monitor) OR THI OR "temperature humidity index" OR "environmental sensor*" OR NH₃ OR CO₂)

Terminology note: for consistency, the narrative text of the manuscript uses «in-line»; the variant «inline» is retained only where needed to reproduce the exact executable query and in original article titles reproduced verbatim in the references.

Phase reconciliation table:

Phase	Operational window	Included studies	Reconciliation note
Base corpus	Jan 1 2010 - Dec 31 2023	38	Broad Scopus search focused on dairy sustainability and emerging technologies
Sensor-focused update	Jan 1 2024 - Nov 10 2025	12	Supplementary Scopus update emphasizing sensor modalities and related precision-dairy applications
Final corpus	Jan 1 2010 - Nov 10 2025	50	Combined audited corpus after deduplication and eligibility checks

Methodological note: the earlier archived draft contained intermediate selection counts that did not remain fully auditable at the revision stage. To avoid overstatement, the revised manuscript privileges the auditable phase totals above and aligns all time-window references to them.

Appendix B. Extraction sheet and coding framework

The coding unit was the individual article. All included studies were coded against the same structured fields shown below, and the same field structure is provided as a reusable extraction-sheet template in Supplementary File S2.

Field	Operational definition	Primary coding rule	Rule for hybrid studies / discrepancies
Dominant technology / modality	Main technological focus assessed by the study (e.g., wearables, rumen bolus, vision/IRT, in-line/process, environmental sensing, digital/PLF, energy, water, organizational)	Code the technology explicitly evaluated as the principal analytical or operational input	If multiple modalities appear, record the dominant one in the main field and note secondary modalities in extraction notes
Study design / context	Empirical study, review, bibliometric study, process assessment, or organizational analysis; farm- or plant-level context	Record the design stated by the original article and the main deployment context	If mixed contexts are present, prioritize the context directly linked to the reported sustainability outcome
Sustainability outcome	Energy efficiency, water management, animal welfare, emissions/quality, or organizational eco-efficiency	Code all outcomes explicitly reported in results/discussion	If more than one outcome is present, retain the principal outcome in the summary table and list secondary outcomes in notes
Validation note	Type of evidence provided for the technology (field validation, review-level synthesis, conceptual discussion, economic evaluation)	Summarize the strongest validation statement supported by the article	Where validation is unclear, annotate as limited or conceptual rather than infer stronger evidence
Geographic setting	Country or region explicitly analyzed by the study	Use the study setting reported in the article	If the paper is a review or multi-country synthesis, code as cross-country/review

Consensus procedure: discrepancies between the two coding passes were resolved through discussion against the full text and the operational rules above. A formal inter-coder reliability coefficient is not reported because the independent coder logs were not preserved in a format that allowed retrospective computation without reconstruction; for the same reason, neither Cohen's kappa nor percentage agreement is claimed in this revision.



Appendix C. Traceability notes for predictive-model evidence and keyword networks

The revised manuscript softens cross-study claims for predictive models and documents the network-construction settings for Figures 6-7.

Study	Task / application	Validation context	Metric reporting note	Comparability caution
Vázquez Diosdado <i>et al.</i> (2015)	Behavior classification in housed dairy cows	Accelerometer-based activity monitoring under study-specific conditions	Classification performance is task-specific	Not directly comparable with disease detection or video-based tasks
Pichlbauer <i>et al.</i> (2024)	Behavior classification using accelerometer sensors and machine learning	On-pasture behavior classification and system evaluation	Reported performance depends on labelled behaviors, sensor setup and validation split	Cannot be pooled with lameness, mastitis, or process-control metrics
Myint <i>et al.</i> (2024)	Real-time lameness detection from side-view camera	Single-camera deep-learning pipeline in real-time setting	Visual-detection metrics reflect a different task family from wearable-based classification	Direct ranking against other tasks would overstate comparability
Szyc <i>et al.</i> (2025)	Video-based lameness pipeline from detection to scoring	Pipeline-level validation in real-farm context	Composite performance depends on both detection and scoring stages	Not equivalent to single-stage or review-level metrics
Neethirajan (2023)	Review of AI and sensor technologies in dairy livestock export	Narrative/review synthesis	Does not provide a pooled metric for direct algorithm ranking	Useful for contextual interpretation, not for quantitative comparison
Network-setting item		Setting reported in revised manuscript		
Keyword source		Harmonized matrix derived from study descriptors and author/index terms recorded during extraction		
Minimum occurrence threshold		1		
Counting method		Full counting		
Normalization		Association strength		
Thesaurus / merges applied		wearables + accelerometer* -> wearables/accelerometers; infrared thermography + thermal imaging -> vision/IRT; in-line sensor + process sensor + milk-line sensor -> in-line/process sensors		
Supplementary input file		Supplementary File S1 (keyword matrix in CSV format)		