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Decision Support Systems in dairy cows farming: A 20-year scoping review of characteristics, applications, and future challenges

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Abstract: Decision Support Systems (DSS) streamline dairy farm management by addressing challenges in productivity, animal welfare, sustainability, and economics. Yet, their precise impact on dairy cattle farm operations remains unclear. This scoping review systematically analyses DSS applications in dairy farming using studies from Scopus and Web of Science published between 2005 and June 2025, following PRISMA-ScR guidelines. From 1 112 identified records, 84 studies were included, after deduplication and screening, and classified into four mutually exclusive primary categories, namely data-, model- and knowledge-driven and other specialised DSS. The findings revealed that DSS complexity increased over time, with model-driven systems dominating (40.5%), followed by data- (38.1%) and knowledge-driven (15.5%) DSS, while other specialised systems accounted for the remaining 6.0%. Temporal multi-label analysis also highlighted trends towards integrated methodologies, with 20 DSS combining data- and model-driven approaches. DSS are mainly applied in Animal Health and Welfare (48% model- and 32% data-driven) and in Farm Business and Management (54.5% model- and 22.7% data-driven). Consequently, the top data inputs are Animal Health & Performance (28.0%), Farm & Business (22.4%), and Environmental & Spatial Data (21.3%). The most commonly applied models are Mathematical/Deterministic (22.7%) and Simulation (13.6%) models, increasingly alongside ML techniques. Key challenges include data integration, real-farm validation, model interpretability, bias reduction, and practical usability. Bridging these gaps will enhance DSS effectiveness and strengthen their potential to optimise dairy farming.

Keywords: animal health; dairy cows; decision support systems; farm management; machine learning; precision livestock farming; scoping review

INTRODUCTION

On a global scale, dairy cattle farming (hereafter referred to as dairy farming) significantly contributes to food security, rural livelihoods, and economic resilience (FAO et al. 2021). But modern dairy production systems must face increasingly complex issues, such as balancing rising demands for productivity with stricter animal welfare regulations while addressing climate change pressures and the need for sustainable resource management (Rotz et al. 2019). Accordingly, decision-making should integrate het-

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erogeneous data from biological, environmental and economic sources in real time. This complexity has spurred considerable research interest in Decision Support Systems (DSS).

DSS are interactive, computer-based systems that utilise data, mathematical models and expert knowledge to support decision-making by delivering actionable insights, diagnostics and recommendations (McCown 2002; Power 2002). In the dairy cattle sector, DSS facilitate data-driven and timely decision-making (Berckmans 2017). In fact, several DSS have been developed for a wide range of tasks, including disease prediction and early warning (Saro et al. 2024a), ration balancing and feed optimisation (Tedeschi et al. 2014), reproductive cycle monitoring (Reksen et al. 2014), and even environmental impact assessment (Gerber et al. 2013). Yet, despite the proliferation of DSS research in recent years, the lack of a comprehensive synthesis of DSS types, input data sources, algorithmic methods, and sectoral applications over the last 20 years continues to limit our ability to precisely assess the impact of these systems on dairy cattle farming. And while advanced techniques, such as machine learning (ML) and Internet of Things (IoT)-based monitoring, are increasingly integrated, several challenges remain concerning their adoption, integration, and usability in practical farm contexts (Eastwood et al. 2016). Solving these problems requires conducting a comprehensive analysis of field-specific literature.

This scoping review aims to map and analyse the landscape of DSS in dairy farming over two decades (2005–2025). The specific objectives of this study are to categorise these systems into data-, model- and knowledge-driven DSS and 'other specialised systems', based on (Power 2002), to identify the most commonly used input data and methods, and to flag the key challenges that limit DSS effectiveness and adoption in precision dairy farming. As such, this review is guided by the following research questions: (*i*) What are the prevailing types of Decision Support Systems (DSS) implemented in dairy farming research and how have their relative distributions evolved over time (2005–Jun 2025) and across dairy cattle sectors? (*ii*) Which input data and algorithmic methods are predominantly used in DSS to manage dairy farms, and how do they vary across herd management sectors? (*iii*) What challenges limit DSS development, implementation, and adoption in dairy farming research, particularly in the last five years (2021–Jun 2025). By answering these questions, this review will inform future research on the development and deployment of advanced DSS in precision dairy farming towards enhancing not only profitability but also animal welfare and sustainability.

MATERIAL AND METHODS

Databases and search strategy

This scoping review was conducted following the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines. To ensure comprehensive and representative literature coverage, two multidisciplinary databases, namely Scopus (Elsevier) and Web of Science Core Collection (Clarivate), were searched using advanced Boolean operators and field-specific queries. Both databases are recognised for indexing high-quality peer-reviewed publications. The literature search targeted studies on DSS applied to dairy farming published between 2005 and June 2025. By combining a comprehensive set of DSS-related terms with dairy-related keywords, this search strategy balanced specificity and sensitivity. The search was conducted using the title, abstract, and keyword fields in both databases. Where applicable, the query was adapted to comply with database-specific syntax conventions. Through iterative refinement, the search query below was developed to capture both classical and emerging DSS in dairy farming.

("decision support system*" OR "decision aid*" OR "decision-making tool*" OR
"data-driven decision support" OR "intelligent system*" OR
"knowledge-based system*" OR "decision model*" OR "farm management system*" OR
"precision dairy" OR "smart dairy" OR "dairy decision" OR "digital tool*" OR "ICT")
AND
("dairy cow*" OR "dairy cattle" OR "lactating cow*" OR "dairy herd*" OR
"dairy farm*" OR "milk production" OR "milk yield")

Truncation symbols (*) were used to retrieve both plural and derivative forms (e.g. "systems", "supporting"). If required, the query could be adapted for individual databases by incorporating appropriate field tags, such as TITLE-ABS-KEY for Scopus

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or TS (Topic Search: title, abstract, author keywords, and Keywords Plus) for Web of Science. This approach enabled us to comprehensively retrieve literature across both databases before applying inclusion and exclusion criteria.

Inclusion and exclusion criteria

For relevance and focus, we defined the inclusion and exclusion criteria outlined below. Articles were included in the final sample if they were:
- primary research studies (not reviews) on DSS;
- applied to dairy cows or dairy herds;
- written in English;
- aligned with the classification of DSS into data-, model- and knowledge-driven DSS and 'other specialised systems', based on the typology proposed by (Power 2002).

Articles were excluded if they:
- were review papers (e.g. systematic literature reviews and literature surveys);
- described standalone ML models not embedded in a DSS framework;
- focused on non-dairy livestock;
- written in a language other than English;
- were duplicates or lacked full-text availability.

Screening process and PRISMA Flow

In line with PRISMA-ScR recommendations, the screening process was conducted in multiple stages. Initially, 1 112 records were retrieved from the databases (656 from Scopus and 456 from Web of Science). After duplicate removal, 505 records remained for further screening.

Following language screening, 493 records were retained, while 12 non-English records were excluded; despite potentially overlooking regional innovation and local DSS developments in non-English-speaking dairy-producing countries, this approach was followed to ensure consistency and reproducibility in the screening and comparative analysis of the studies.

Thematic screening then excluded 409 records that did not meet the inclusion criteria, such as studies without a DSS framework, generic models without decision logic, and studies outside the scope of dairy farming. In total, 84 studies were included in the final synthesis (Figure 1).

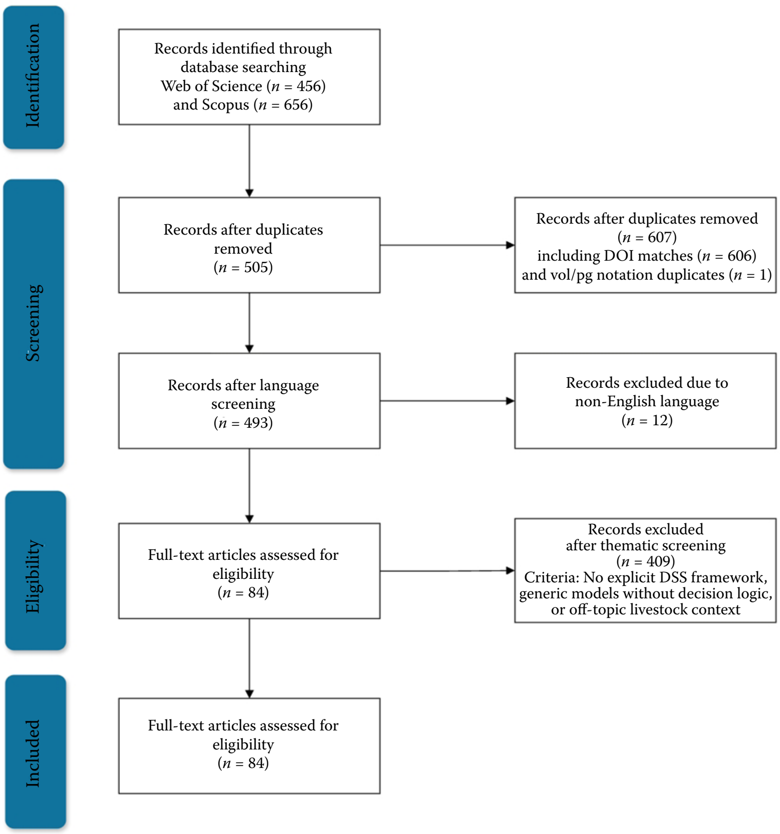

Figure 1. PRISMA-ScR flow diagram depicting the study selection process 1 112 records were identified through database searching, 505 records remained after duplicate removal, 493 records remained after language screening, 409 records were excluded after thematic screening, and 84 studies were included in the final synthesis

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DSS classification framework

Each study included in this scoping review was classified according to the dominant DSS logic described in the article, following the typology proposed by (Power 2002). This classification was based on the primary decision-support mechanism emphasised in the study, considering the system description, input data, analytical method, and intended decision-support function. A detailed extraction and classification matrix of all included studies, including DSS type, problem solved, dairy cow sector, model used, author, purpose, and input data, is provided in Electronic Supplementary Material (ESM) Table S1.

For the primary frequency distribution (Figure 2; Table 1), each study was assigned to one mutually exclusive dominant category: data-, model- and knowledge-driven DSS and 'other specialised systems'. For the temporal evolution analysis (Figure 3), all DSS types explicitly reported within combined or hybrid systems were counted to better reflect integrative methodological development across the literature. No formal inter-reviewer agreement statistic was calculated; this should be deemed a methodological limitation of the classification process.

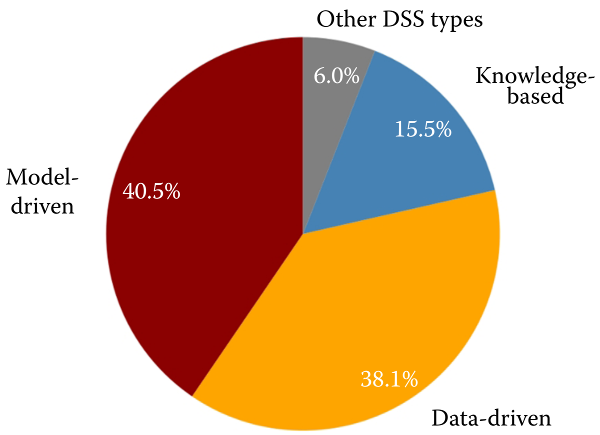

Figure 2. Primary distribution of Decision Support Systems (DSS) types in dairy cattle research from 2005 to June 2025

Model-driven DSS account for the largest share (40.5%), highlighting the predominance of systems based on mathematical, simulation, or optimisation models; data-driven DSS, for 38.1%, reflecting the growing use of real-world data for prediction and decision support; knowledge-driven DSS, for 15.5%; and other specialised systems, for the remaining 6.0% of the studies. For this primary classification, each study was assigned to one dominant DSS type to provide a simplified overview of the main decision-support logic addressed in the literature

Table 1. Percentage distribution of primary DSS in key operational and management areas of dairy cattle farming (2005–June 2025)

Operational and management areas of dairy cattle farming	Data-driven DSS (%)	Knowledge-driven DSS (%)	Model-driven DSS (%)	Other specialised systems (%)
Animal health, welfare	32.0	16.0	48.0	4.0
Farm business, management	22.7	6.8	54.5	15.9
Environmental impact, resource management	11.1	11.1	61.1	16.7
Nutrition, pasture management	23.8	0.0	66.7	9.5
Reproduction, genetics	10.0	10.0	70.0	10.0
Milk production, quality	16.7	0.0	66.7	16.6
Supply chain, logistics	25.0	25.0	25.0	25.0
Housing, infrastructure	0.0	0.0	50.0	50.0
Other livestock management (small ruminants)	50.0	50.0	0.0	0.0
Management (feedlot)	50.0	0.0	50.0	0.0
Disaster management	50.0	0.0	50.0	0.0
Other livestock management (beef cattle)	50.0	0.0	50.0	0.0
Risk	50.0	50.0	0.0	0.0

'Other specialised systems' include communication-driven, protocol-based, dynamic simulation, integrated assessment, multi-criteria, spatial, and web-based DSS categories. Percentages may not add to exactly 100% due to rounding

DSS = Decision Support Systems

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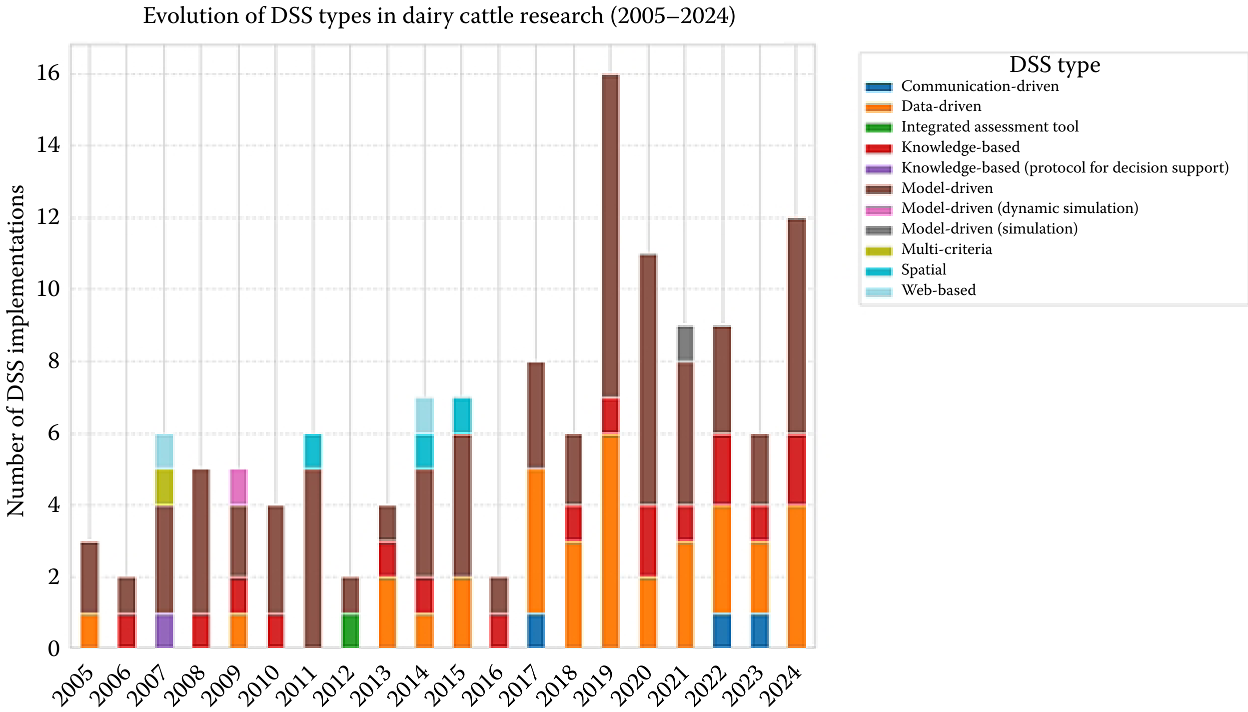

Figure 3. Decision Support Systems (DSS) types by year, highlighting their frequency over the study period (2005–2024); no articles were found in 2025

For a structured synthesis, each of the 84 studies was categorised into four mutually exclusive primary DSS types, based on the typology adapted from (Power 2002):

- Data-driven DSS: systems primarily based on real-time or historical data collection and analytics;
- Model-driven DSS: systems developed using mathematical, statistical, or simulation models;
- Knowledge-driven DSS: systems incorporating expert rules or heuristics to provide decision support.
- Other specialised systems: systems primarily relying on communication-driven, spatial, web-, protocol-based, multi-criteria, or other specialised decision-support approaches.

This classification enabled us to conduct a nuanced analysis of trends in DSS development and applications across different domains of dairy farm management, such as health, reproduction, nutrition, and productivity.

RESULTS

Based on the dataset from 2005 to June 2025, we identified the most frequently developed and applied DSS in dairy cattle farming (Research Question 1), as well as input data and algorithmic methods used across herd management areas (Research Question 2). We also summarised DSS challenges and limitations reported in the last 5 years of the study period (2021 to June 2025) (Research Question 3).

Research Question 1 – Characteristics of Decision Support Systems (DSS) in dairy farming (2005–June 2025)

DSS type frequency from 2005 to June 2025. Figure 2 shows the most prevalent experimental paradigms of DSS development in dairy cattle research. Model-driven DSS accounts for the largest share (40.5%), indicating a strong emphasis on systems that rely on explicit (mathematical, simulation, optimisation) models to generate recommendations. Following closely in second place, data-driven DSS (38.1%) reflect the increasing availability and use of real-world data for pattern recognition, prediction, and decision support. Leveraging expert knowledge and rules, knowledge-driven DSS (15.5%) also make up a signifi-

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cant portion of the pie chart. This chart assigns hybrid DSS (e.g. "Model- and Data-driven DSS") to the first type mentioned, which is considered the primary or dominant component, in line with the literature. This approach provides a clear, simplified view of the primary focus of each system for initial categorisation.

DSS types and evolution. To examine the prevalence and temporal evolution of DSS types, we assessed the frequency of DSS types in dairy cattle research from 2005 to June 2025. For a more detailed analysis, we plotted the cumulative frequency of all DSS types identified in dairy cattle research during the study period into a histogram. In other words, we considered not only model-, data- and knowledge-driven DSS but also communication-driven, multi-criteria, spatial and web-based approaches (Figure 3).

Many DSS combine multiple approaches, as reflected in the counts above. Unlike the pie chart shown in Figure 2, this histogram accounts for all DSS types mentioned in a combined approach. For example, a 'model- and data-driven' DSS contributed one count to 'model-driven' and one to 'data-driven' DSS. This approach provided a more comprehensive view of the prevalence of each DSS.

Model-driven DSS (37 instances) remained the most frequently reported DSS. However, a significant number of DSS were hybrid, most often combining data- and model-driven approaches (20 instances). In addition, knowledge-driven systems were frequently combined with model-driven approaches (11 instances). Purely data-driven DSS (5 instances) were less common than hybrid data-driven/model-driven systems, suggesting that real-world applications benefit from incorporating predictive models. Lastly, communication-driven systems were the least common, usually appearing in hybrid systems. Overall, these findings highlight a trend towards integrated methodologies.

DSS types by operational and management area of dairy farming. As shown by the analysis of DSS implemented in the dairy cattle sector from 2005 to June 2025 (Figure 4), the predominant DSS vary across operational and management areas. During the study period, model-driven DSS were the most frequently used DSS in sectors such as Reproduction, Genetics (70%), Nutrition, Pasture Management (66.7%), Milk Production, Quality (66.7%), and Environmental Impact, Resource Management (61.1%). This high prevalence of model-driven DSS reflects a strong research and application focus on quantitative analysis, optimisation, and predictive modelling for complex biological and environmental processes in dairy cattle farming.

Complementing these systems, data-driven DSS consistently hold a significant share in Animal Health, Welfare (32%), Supply Chain, Logistics (25%), Nutrition, Pasture Management (23.8%) and Farm Business, Management (22.7%). These areas benefit considerably from real-time monitor-

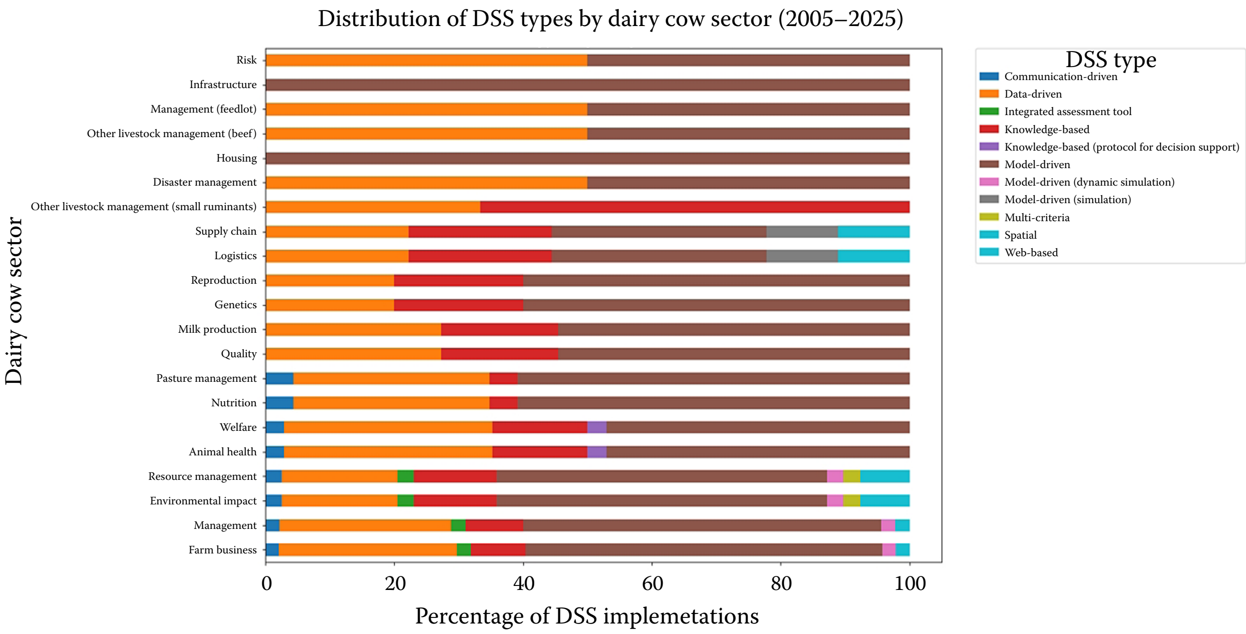

Figure 4. Percentage distribution of Decision Support Systems (DSS) by dairy sector (January 2005–June 2025)

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ing and large-scale data collection through sensors for evidence-based decision-making. Accordingly, the results underscore the increasing use of empirical data for decision-making, leveraging advances in technology and data collection.

Despite being much less prevalent in dairy farming than model- and data-driven DSS, knowledge-driven DSS contributed to specific areas requiring expert-rule logic or diagnostic decision-making, such as Supply Chain and Logistics (25.0%) and Animal Health and Welfare (16.0%). In these areas, expert input complements or substitutes for large-scale data or formal modelling. By contrast, in Other Livestock Management (Small Ruminants), knowledge-driven DSS account for 50% systems as expert knowledge remains a primary decision-support resource in underrepresented or less data-intensive sectors where formal models are scarce.

Other specialised systems (e.g. Communication-driven, Spatial, Web-based, Multicriteria DSS) are present, albeit in smaller percentages, as they typically address niche or underserved application areas. Nevertheless, these 'Other specialised systems' collectively account for all (100%) systems applied in Risk management. These patterns suggest a mature research landscape that prioritises model-based predictions and data-driven insights into dairy production.

The stacked bar chart in Figure 4 breaks down DSS types in various dairy sectors, ranked by the total number of DSS implementations (the most frequent at the top) from 2005 to June 2025. Each bar represents a dairy cow sector, and its segments show the proportional contribution of each DSS type.

Together, these findings (Figures 2–4) directly answer Research Question 1. Model-driven DSS (40.5%) were the most prevalent primary category in dairy cattle research between January 2005 and June 2025, followed by data- (38.1%) and knowledge-driven (15.5%) systems, while other specialised systems accounted for 6.0%. Model-driven systems were particularly dominant in areas requiring complex modelling and optimisation, such as reproduction, nutrition, and environmental/resource management. Data-driven DSS were also highly represented, especially in animal health and welfare and in farm business and management, reflecting the increasing use of sensor-generated and operational data. Knowledge-driven DSS were less frequent and mainly concentrated in expert-oriented domains. In a separate temporal analysis, hybrid combinations, particularly data- and model-driven DSS, further highlighted the growing trend toward integrative methodological approaches. Overall, the choice of DSS type appears to align with the type of decision problem, data availability, and analytical complexity of each dairy management domain.

Research Question 2 – Input data and algorithmic methods across dairy cow sectors

In this section, we classified the types of input data and algorithmic methods used in DSS, correlating them with specific application areas in dairy herd management, such as animal health, reproduction, nutrition, and farm business management.

Algorithmic methods used in DSS for dairy farm management. Figure 5 presents a heatmap of algorithmic methods used in DSS across operational and management areas of dairy farming from 2005 to June 2025. Colour intensity indicates how frequently each method is applied, highlighting domain-specific methodological preferences. The breakdown also reveals data input requirements, which are essential for evidence-based decision-making.

Based on established equations and logical frameworks, Mathematical/Deterministic Models have been widely applied in areas such as Nutrition (8), Pasture (8) and Resource Management (7) and Farm Business (7) to simulate biological processes or farm economics (Figure 5). Optimisation algorithms have also been used in multiple areas, primarily Resource Management (4) and Environmental Impact. In turn, Statistical Models have been mainly leveraged in Animal Health (4) and Welfare (4) and, moreover, in Farm Business (6).

In this analysis, Farm Business emerges as the most diverse operational and management area in terms of algorithmic methods, involving nearly all techniques. By contrast, Animal Health and welfare areas mainly employ Case-Based Reasoning, Expert Systems and Statistical Models to meet their diagnostic and health-monitoring needs. Supply Chain and Logistics use Rule-Based Systems, Statistical Models and Optimisation, in line with their operational and routing challenges. Nutrition and Pasture Management mostly rely on Mathematical

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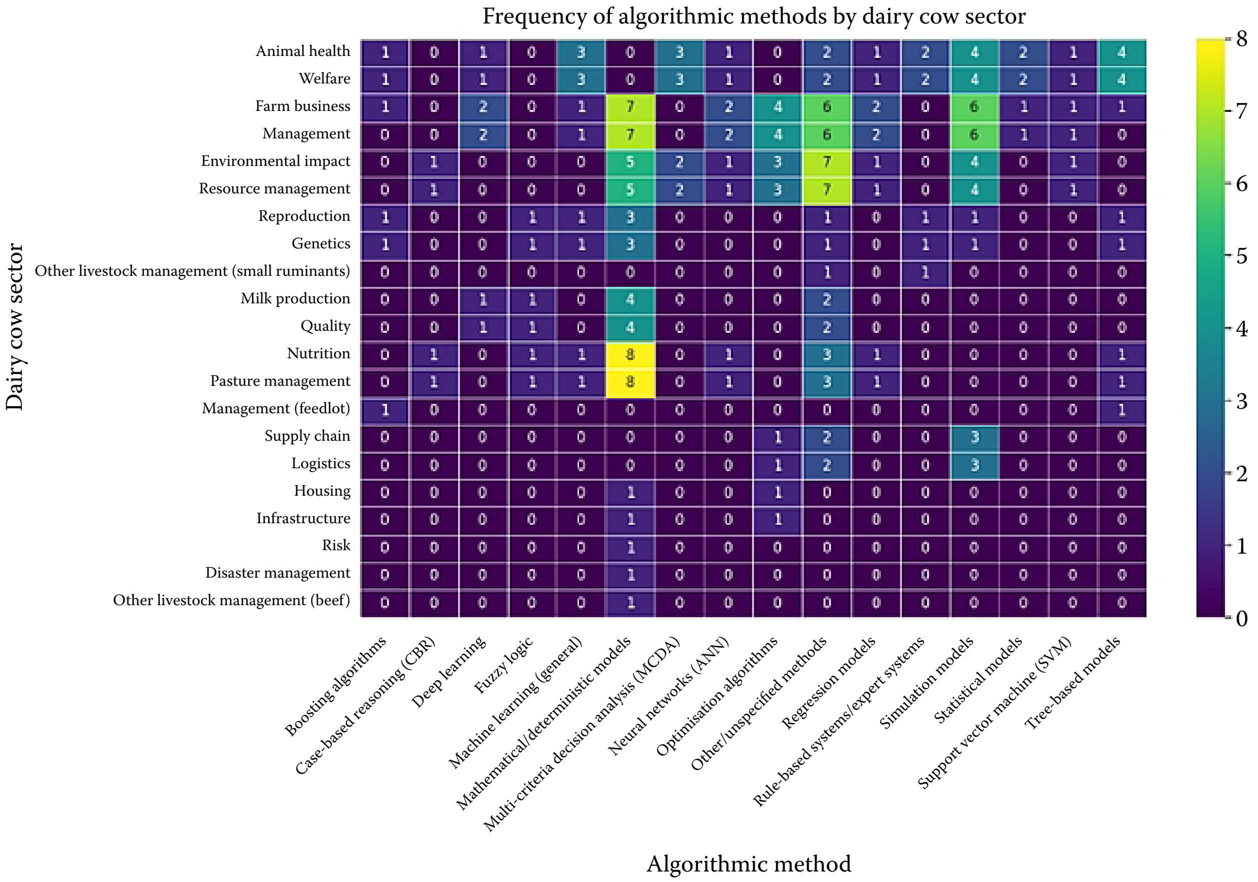

Figure 5. Frequency of algorithmic methods by operational and management area of dairy cows farming (2005–June 2025)

Models for quantitative optimisation and simulation (Figure 5).

Consistent with the findings in Figures 2–4, these results underscore emerging interdisciplinary trends. The development of DSS for dairy farming may be shifting towards hybrid or ensemble methods as multiple algorithmic approaches are increasingly applied in areas ranging from Farm Business and Resource Management to Animal Health. In parallel, Expert Systems have been combined with Optimisation, pointing to integrative approaches where expert logic is coupled with mathematical efficiency to advance DSS. As researchers begin to explore AI-enhanced methods for developing DSS, these trends reflect efforts to balance quantitative rigor with domain-specific needs in a maturing field of research.

Corroborating these findings, Mathematical/Deterministic Models were the most frequently reported approach in the studied period, accounting for 22.7% of all documented methods (Figure 6), followed by Simulation Models (13.6%), enabling dynamic evaluation of complex systems, and by Other/Unspecified Methods (12.5%), encompassing proprietary algorithms or uncategorised methods applied in commercial DSS tailored to specific management needs. These results highlight the strong foundation of quantitative modelling in dairy farming research.

Bar height in Figure 6 represents the proportion of DSS that use a specific method, providing insights into the predominant computational approaches in the field.

Figure 6 also shows an increasing adoption of advanced analytical techniques, such as ML (General) (6.8%) and Tree-based (6.8%) Models, alongside other data-driven techniques, including Regression Models (3.4%), Statistical Models (3.4%), Artificial Neural Networks (ANN) (3.4%), Boosting Algorithms (3.4%), Support Vector Machine (SVM) (2.3%), and Deep Learning (DL) (2.3%). This trend reflects the increasing availability of data and the shift towards predictive and prescriptive analytics.

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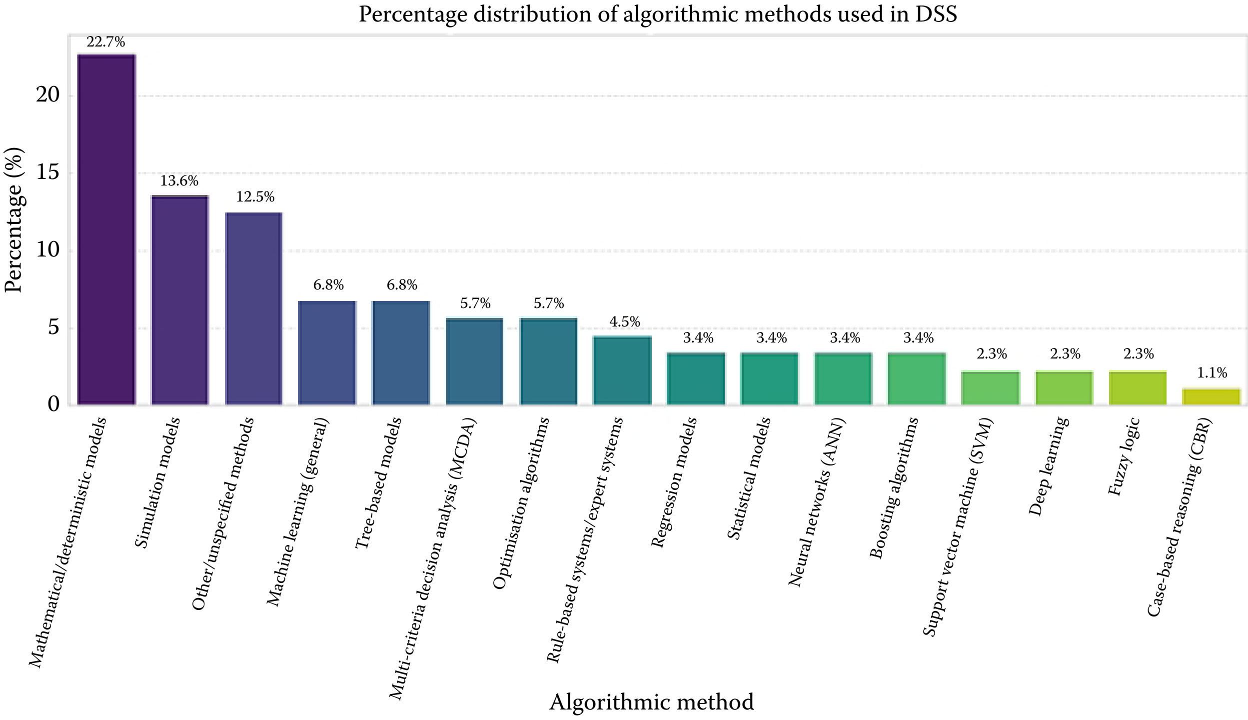

Figure 6. Percentage distribution of algorithmic methods used to develop Decision Support Systems (DSS) for dairy farming from January 2005 to June 2025

Notwithstanding these promising indicators, this analysis also reveals minimal algorithmic diversity and usage in Infrastructure, Disaster Management and Risk (Figure 5), exposing limited DSS development in these areas. Other limitations in data acquisition and interpretability may explain why DL, Boosting Algorithms and SVM are so infrequently used in this field of research (Figure 6). Nevertheless, Multi-Criteria Decision Analysis (MCDA) (5.7%) and Optimisation Algorithms (5.7%) prove effective in DSS designed to balance multiple objectives and to find optimal solutions. Furthermore, Rule-Based/Expert Systems (4.5%), Fuzzy Logic (2.3%), and Case-Based Reasoning (CBR) (1.1%) have also been adopted during the study period. On balance, this wide range of methods provides compelling evidence of the diverse computational strategies that researchers employ to address multifaceted challenges in dairy farming.

Types of consolidated input data. To flag priorities in DSS development for dairy farming, we analysed the results by type of consolidated input data (Figure 7). The most dominant category was Animal Health & Performance Data, comprising 28.0% of all data mentions. This result demonstrates that DSS research and development are focused on solutions with a direct impact on the well-being, productivity, and reproductive efficiency of both individual animals and the herd. Not far behind this category, Farm & Business Data (22.4%) and Environmental & Spatial Data (21.3%) also reached high percentages, highlighting a dual emphasis on optimising farm-level operations, financials, and resource consumption and on managing environmental interactions and leveraging geographical information for broader sustainability goals.

Another category, Nutrition & Feed Data, also accounted for a significant share of mentions (15.1%), reflecting continuous efforts to refine feeding strategies and pasture management for optimal animal health and production. With lower percentages of mentions, Sensor & Automated Monitoring Data (8.5%) and Expert Knowledge & Observational Data (4.8%) are, nonetheless, key inputs of DSS with an evolving role in their development. The increasing use of sensor data points in DSS shows a clear trend towards real-time, automated data acquisition and precision farming. Concurrently, the inclusion of expert knowledge emphasises the value of qualitative insights and practical experience in informing decision-making. This distribution collectively illustrates a comprehensive, multi-factorial approach to data integration in dairy DSS, spanning biological, operational,

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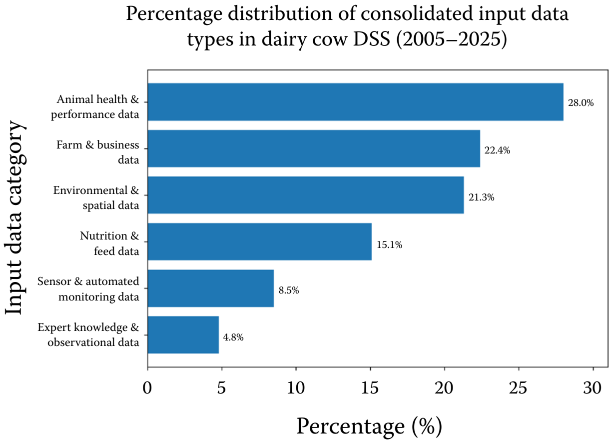

Figure 7. Percentage distribution of types of consolidated input data in dairy cow Decision Support Systems (DSS) from January 2005 to June 2025

environmental and technological domains supporting holistic farm management.

Six broad categories of input data used in DSS for dairy cattle research were considered in this analysis, and their percentage distribution is presented in Figure 7. The y-axis represents the input data categories, and the x-axis shows their percentage. Each bar is annotated with its precise percentage value. The chart is sorted from the most to the least frequent types of data.

In summary, input data most frequently derive from Animal Health & Performance (28%), followed by Farm & Business (22.4%) and Environmental & Spatial (21.3%) data. These datasets illustrate a comprehensive, data-rich approach to herd management. Emerging techniques, such as ML, ANN, and Tree-Based Models have been gaining traction in this field of research, but their use remains limited to areas with sparse data, mainly Risk and Infrastructure. These findings showcase ongoing disparities in technological integration across dairy management domains.

Research Question 3 – Challenges and limitations of DSS for dairy cattle farming in the last 4.5 years

This section synthesises the key challenges (Table 2) and limitations (Table 3) of DSS for dairy farming identified in the scientific literature published between January 2021 and June 2025. The purpose of this analysis is to shed light on the most recent trends and recurring themes across operational and management areas, including animal health, productivity, management, and environmental impact.

Challenges in DSS adoption and implementation. The main challenge in the development and practical adoption of DSS for dairy farming lies not only in integrating heterogeneous data sources but also, and above all, in identifying, validating and interpreting meaningful health-related features for decision-making in animal health and welfare. Recent DSS increasingly rely on diverse inputs such as activity, body temperature, milk parameters, feeding behaviour, locomotion traits, reproductive records, and historical herd health data. Although these variables provide valuable signals of cow condition, they differ substantially in format, frequency, and biological interpretation. As a result, transforming raw data into reliable and actionable health indicators remains a challenge. This challenge is evident both in studies integrating multidimensional sensor data for disease prediction (Zhou et al. 2022) and in broader systems combining production, environmental, and animal-level data, where interpretability is still a persistent concern (Alwadi et al. 2024).

In animal health applications, a central issue beyond data availability is the selection of robust and generalisable health features that can support reliable predictions across farms, breeds, and management systems. For example, real-time detection of abnormalities in cow behaviour (Nogoy et al. 2021), prediction of lameness using ML algorithms (Shahinfar et al. 2021), delineation of mastitis cases (Khan et al. 2024), and identification of sub-fertile cows using limited reproductive data (Zaborski and Grzesiak 2021) all depend on subtle and often complex relationships among behavioural, physiological, and historical variables. These relationships are frequently context-dependent, which limits generalisability and may reduce farmer trust in DSS outputs. Therefore, future DSS research should place greater emphasis on clinically meaningful, interpretable, and farm-relevant health features rather than focusing solely on predictive complexity.

Another major challenge concerns the balance between analytical sophistication and practical usability. In herd health management, DSS must not only achieve satisfactory predictive performance but also provide understandable and useful outputs for both farmers and veterinarians. This issue is particularly evident in diagnostic contexts, where selecting the optimal test involves balancing mul-

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Table 2. Challenges of Decision Support Systems (DSS) (2021–June 2025)

Challenge description	Dairy cow sector	APA citation	Title
Selecting the optimal test involves balancing multiple, conflicting criteria.	animal health, welfare	Akkose and Polat (2023)	Multicriteria decision analysis for supporting the selection of subclinical mastitis screening test.
Integrating heterogeneous data sources and model interpretability.	milk production, quality, farm business, management	Alwadi et al. (2024)	Smart dairy farming for predicting milk production yield based on deep ML.
Forecasting accuracy drops in late-lactation periods.	milk production, quality, reproduction, genetics	Innes et al. (2024)	Fitting mathematical functions to extended lactation curves and forecasting late-lactation milk yield.
Lacking affordable technologies for small farms; complex relationships between cow behaviour and health.	animal health, welfare	Khan et al. (2024)	Delineating mastitis cases in dairy cows: Development of an IoT-enabled intelligent decision support system for dairy farms.
Aligning scoring system with practical farm application requirements.	animal health, welfare	Saro et al. (2024a)	A decision support system based on disease scoring enables dairy farmers to proactively improve herd health.
Balancing system simplicity with practical usability in farming practice.	animal health, welfare, farm business, management	Saro et al. (2024b)	A decision support system for herd health management for dairy farms.
Complexity of decision-making between various diagnostic strategies and cost-effectiveness.	animal health, welfare	Um et al. (2024)	Development of a decision support tool to compare diagnostic strategies for establishing the herd status for infectious diseases.
Integrating multidimensional sensor data for disease prediction.	animal health, welfare	Zhou et al. (2022)	The early prediction of common disorders in dairy cows monitored by automatic systems with ML algorithms.
Designing predictive DSS for cross-border livestock health threats.	animal health, welfare	Bradhurst et al. (2022)	Development of a transboundary model of livestock disease in Europe.
Detecting sub-fertile cows with limited available reproductive data.	reproduction, genetics	Zaborski and Grzesiak (2021)	Utilisation of boosted classification trees for the detection of cows with conception difficulties.
Integrating heterogeneous data formats from different sources.	nutrition, pasture management, farm business, management	Bolodurina and Akimov (2021)	Intelligent methods for assessing the productivity of dairy cattle based on a comprehensive study.
Detecting cow behaviour abnormalities in real time using AI systems.	animal health, welfare	Nogoy et al. (2021)	Precision detection of real-time conditions of dairy cows using an advanced artificial intelligence.
Accurately predicting lameness using ML algorithms.	animal health, welfare	Shahinfar et al. (2021)	ML approaches for the prediction of lameness in dairy cows.
Developing a robust DSS for improving supply chain resilience.	supply chain, logistics	Tsiamas and Rahimifard (2021)	A simulation-based decision support system to improve the resilience of the food supply chain.

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Table 3. Limitations of Decision Support Systems (DSS) (2021–June 2025)

Limitation description	Dairy cow sector	APA citation	Title
Depends on expert-based weights, which may bias the final decision.	animal health, welfare	Akkose and Polat (2023)	Multicriteria decision analysis for supporting the selection of subclinical mastitis screening test.
Deep learning models are complex and difficult to interpret and validate on farms.	milk production, quality, farm business, management	Alwadi et al. (2024)	Smart dairy farming for predicting milk production yield based on deep machine learning.
Simpler models may fail to generalise across breeds or management systems.	milk production, quality, reproduction, genetics	Innes et al. (2024)	Fitting mathematical functions to extended lactation curves and forecasting late-lactation milk yield.
Susceptibility to class bias (most healthy cows) reduces prediction accuracy of the model for the minority class (mastitis).	animal health, welfare	Khan et al. (2024)	Delineating mastitis cases in dairy cows: Development of an IoT-enabled intelligent decision support system for dairy farms.
The DSS depends on the quality and completeness of disease diary records; errors, omissions, or inconsistent recording may affect scoring reliability.	animal health, welfare, farm business, management	Saro et al. (2024a)	A decision support system based on disease scoring enables dairy farmers to proactively improve herd health.
Need for extensive farmer training for proper system utilisation.	animal health, welfare, farm business, management	Saro et al. (2024b)	A decision support system for herd health management for dairy farms.
The tool is sensitive to input assumptions and probabilistic estimates that may not be readily available.	animal health, welfare	Um et al. (2024)	Development of a decision support tool to compare diagnostic strategies for establishing the herd status for infectious diseases.
Neither real-time nor prescriptive; limited to retrospective evaluation.	farm business, management, environmental impact, resource management	Wilfart et al. (2023)	DEXi-Dairy: An ex-post multicriteria tool to assess the sustainability of dairy production systems in France.
Need for real-farm testing to confirm predictive accuracy.	animal health, welfare	Zhou et al. (2022)	The early prediction of common disorders in dairy cows monitored by automatic systems with ML algorithms.
Limited availability of harmonised input data across countries.	animal health, welfare	Bradhurst et al. (2022)	Development of a transboundary model of livestock disease in Europe.
Model interpretability and generalisation to broader herds.	reproduction, genetics	Zaborski and Grzesiak (2021)	Utilisation of boosted classification trees for the detection of cows with conception difficulties.
Lack of connection between AI predictions and actionable decision support.	animal health, welfare	Nogoy et al. (2021)	Precision detection of real-time conditions of dairy cows using an advanced artificial intelligence.
Challenges in validation and generalisation across different farms.	animal health, welfare	Shahinfar et al. (2021)	Machine learning approaches for the prediction of lameness in dairy cows.
Not directly integrated with decision support systems.	housing, infrastructure, environmental impact, resource management	Tomasello et al. (2021)	Improving natural ventilation in renovated free-stall barns for dairy cows: Optimised building solutions.
Need for real-world application testing and cost-benefit validation.	supply chain, logistics	Tsiamas and Rahimifard (2021)	A simulation-based decision support system to improve the resilience of the food supply chain.

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tiple conflicting criteria (Akkose and Polat 2023), and where comparing alternative diagnostic strategies entails substantial complexity and cost-effectiveness considerations (Um et al. 2024). Similarly, disease scoring systems and herd health platforms must be aligned with practical requirements of farm management if they are to support proactive interventions effectively (Saro et al. 2024a,b). In this respect, adoption depends on the technical quality of the DSS and on whether the system can translate health features into clear, actionable, and economically meaningful recommendations.

The issue of supply chain resilience should be understood here as a broader systems-level consequence of effective health-oriented DSS. In the dairy sector, supply chain resilience refers to the ability of the production and distribution system to maintain essential functions, such as milk production, collection, processing, and delivery, despite disruptions such as disease outbreaks, transport interruptions, labor shortages, and input supply instability. This concept is broader than herd-level health management but directly relates to the present topic. Poor animal health, delayed disease detection, reduced milk quality and failures in preventive decision-making may disrupt farm output, thereby affecting downstream logistics and food supply continuity. From this perspective, DSS focused on early detection, disease monitoring, and risk-based herd health management may also strengthen supply chain resilience indirectly by reducing the likelihood that farm-level health problems escalate into wider operational disruptions (Tsiamas and Rahimifard 2021). This broader relationship also applies to transboundary livestock disease modelling, where predictive DSS promote preparedness against large-scale animal health threats that may affect both production systems and supply networks (Bradhurst et al. 2022).

Overall, these findings suggest that the next generation of DSS in dairy farming should move beyond generic data integration and focus more explicitly on interpretable, validated, and actionable health features. Such an approach may improve herd health monitoring and disease prevention, as well as the continuity, resilience, and sustainability of dairy production systems.

Limitations impacting DSS effectiveness. Recurring limitations prevent DSS from fulfilling their potential in dairy farming. Many systems lack validation under real-farm conditions, which weakens their practical applicability across diverse dairy production settings. For disease prediction, DSS must be tested and validated in real-farm settings to confirm their accuracy (Zhou et al. 2022) and to generalise models across diverse farm environments (Shahinfar et al. 2021). Case in point, simpler lactation curve models cannot be generalised across breeds and management systems, limiting their broad applicability (Innes et al. 2024). These findings suggest that promising performance under experimental conditions does not always translate into robust use in commercial farm practice.

Another important limitation relates to model interpretability, transparency, and potential bias. As shown in milk production prediction (Alwadi et al. 2024), DL models are often too complex to interpret and validate on farms. Similarly, other researchers have raised concerns about the interpretability and generalisation of classification trees boosted for detecting breeding difficulties (Zaborski and Grzesiak 2021) and about class bias in mastitis detection models, with reduced accuracy for the minority (mastitis) class (Khan et al. 2024). Also introducing a potential for bias, decision tools that rely on expert-based weights or input assumptions for mastitis test selection (Akkose and Polat 2023) or diagnostic strategy comparisons (Um et al. 2024) may not be easily adaptable without readily available probabilistic estimates. Taken together, these issues indicate that model opacity, limited transferability, and bias remain major barriers to the wider adoption of advanced DSS approaches in dairy farming.

A further limitation lies in the gap between analytical outputs and actionable decision support in everyday herd management. Many DSS are not directly integrated with actionable decision support either, creating a gap between AI predictions and practical farm management (Nogoy et al. 2021). Some DSS only enable retrospective evaluation rather than offering real-time or prescriptive guidance, as with sustainability assessment tools like DEXi-Dairy (Wilfart et al. 2023). The limited availability of harmonised input data across countries also hinders the development of comprehensive transboundary disease models (Bradhurst et al. 2022). Without extensive farmer training, complex DSS cannot be used for herd health management (Saro et al. 2024a). Altogether, these limitations reduce the usability, integration, and real-world effectiveness of DSS in dairy farming.

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DISCUSSION

This scoping review of DSS developed for dairy cattle farming over the past two decades (2005–June 2025) highlights a dynamic and evolving field. Increasing data availability and advances in analytical methods continuously drive this field of research. Building on this momentum, DSS optimisation may help to meet the growing demand for more efficient, sustainable, and welfare-conscious dairy production. Compared with earlier conceptual literature on DSS, our findings suggest that decision support in dairy farming has evolved from relatively isolated computational tools to increasingly hybrid, data-rich, and operationally embedded systems. However, this development is not uniform across all dairy sectors. While animal health and farm business management show a clearer shift toward integrated data- and model-driven approaches, other areas remain more strongly rooted in conventional model-based or expert-oriented systems. This uneven digital transformation of dairy DSS is shaped not only by technological progress but also by differences in biological complexity, data availability, and the immediacy of management decisions in specific domains.

Evolution and dominance of DSS types. Model-driven DSS remain the cornerstone of decision support in dairy farming, accounting for 40.5% of all systems identified in this scoping review. This prevalence underscores the inherent complexity of biological and economic processes in dairy production, which often require explicit mathematical, simulation or optimisation models to generate actionable insights. Operational and management areas, such as Reproduction & Genetics (70.0% model-driven) and Nutrition & Pasture Management (66.7% model-driven), rely on these approaches because they require precise quantitative predictions and optimal resource allocation. The strong representation of data-driven DSS (38.1%), particularly in Animal Health & Welfare (32.0%) and Farm Business & Management (22.7%), reflects the transformative impact of sensor technologies, automated data collection, and advanced analytics. Knowledge-driven DSS (15.5%) still play a key role, especially in diagnostic and rule-based applications that depend on expert heuristics, while other specialised systems account for the remaining 6.0% of the studies. In addition, the high number of hybrid data-driven/model-driven systems (20 instances) indicates a clear trend toward integrative methodological development, combining the strengths of empirical data and formal models to address the multifaceted demands of modern dairy farming.

Key application areas and methodological trends. The distribution of DSS across dairy sectors reveals a strong focus on core operational and strategic aspects. Animal Health & Welfare and Farm Business & Management consistently emerge as leading application areas, with a direct impact on productivity, profitability, and animal well-being. This focus on animal and herd health aligns with the increasing emphasis on precision livestock farming through individual animal monitoring and holistic farm management.

This pattern is unlikely incidental. The dominance of model-driven DSS in reproduction, nutrition, and environmental management reflects structured and constraint-based decisions in these areas, where biological processes, optimisation goals, and resource allocation can be formalised relatively well. By contrast, data-driven approaches are more frequently applied in animal health and welfare, reflecting the growing availability of behavioural and physiological data from sensors and monitoring systems. Furthermore, these approaches meet the need to detect subtle, early, and often non-linear signs of disease or distress. Technological novelty, rather than the underlying decision problem, seems to continue driving methodological choices in dairy DSS.

The continued dominance of Mathematical/Deterministic (22.7%) and Simulation (13.6%) Models suggests a mature field of research. However, surging ML techniques (e.g. 6.8% for general ML, 3.4% for neural networks and boosting, 2.3% for deep learning and SVM) point to a shift towards data-intensive and predictive analytics. This rise in ML applications may be directly linked to the increasing volume and rate of heterogeneous data (Animal Health & Performance Data ~28.0%, Farm & Business Data ~22.4%, Environmental & Spatial Data ~21.3%) generated on modern dairy farms. As sensor technology becomes more ubiquitous and affordable, this trend may accelerate further. Nevertheless, the effective application of machine learning and other AI-based approaches will depend on broader sensor adoption and on the credibility, consistency, and practical reliability of the data generated within livestock husbandry systems. Ultimately, the trajectory of DSS development

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in dairy farming will hinge on how effectively these emerging data-driven approaches can be integrated with established models to deliver robust, interpretable and actionable insights for farm management.

Challenges and future directions. Despite significant progress, persistent challenges constrain the widespread adoption of DSS in dairy farming. The main challenge lies in integrating heterogeneous data formats. Data silos, lack of interoperability between different farm technologies and varying data quality persist as major barriers. To solve these problems, we must develop standardised data protocols, robust API and centralised cloud-based platforms for harmonising diverse data streams.

The literature also reveals major tensions. On the one hand, many studies present AI-based and sensor-driven DSS as promising tools for earlier and more precise decision-making; on the other hand, these systems often remain limited by weak real-farm validation, poor interpretability, and uncertain transferability across herds. A further tension concerns practical usability as methodological sophistication has advanced faster than integration into routine herd management. In addition, the ambition to develop broadly generalisable DSS contrasts with the reality that many successful systems still depend heavily on farm-specific data structures, recording quality, and local management routines. These contradictions suggest that future progress in dairy DSS will depend on more advanced analytical methods and on stronger alignment between data credibility, interpretability, and practical applicability.

Another critical limitation is the need for real-farm testing and validation. Despite showing promising results in controlled environments, many DSS models with complex ML algorithms (e.g. deep learning models for milk yield prediction) struggle with generalisability and interpretability on commercial farms. Calls for "real-farm testing to confirm predictive accuracy" (Zhou et al. 2022) and addressing "challenges in validation and generalisation across different farms" (Shahinfar et al. 2021) only underscore this gap. Research must prioritise collaborative efforts between scientists and farmers to conduct long-term, multi-farm trials accounting for variations in breeds, management practices, environmental conditions, and farmer-specific needs.

Issues related to model interpretability and bias must also be solved in the near future. Potentially leading to farmer distrust and rejection, DL models are still too complex to interpret and validate on farms, requiring measures to promote adoption (Alwadi et al. 2024). Class imbalance, e.g. in mastitis detection, must also be addressed to ensure equitable and accurate disease prediction for minority classes in which healthy cows vastly outnumber those with the condition (Khan et al. 2024). Considering the above, DSS should be developed leveraging "explainable AI" (XAI) techniques to provide transparent insights into model decisions, thereby enhancing farmer confidence and facilitating more informed actions.

Concomitant with the challenges described above, practical integration and usability remain key hurdles in the design and development of DSS for dairy cattle farming. The gap between "AI predictions and actionable decision support" (Nogoy et al. 2021) suggests that many DSS are not sufficiently embedded within existing farm workflows or lack clear prescriptive guidance. "Balancing system simplicity with practical usability" (Saro et al. 2024a) in DSS development will require moving beyond mere data visualisation or retrospective evaluation and offering real-time, prescriptive recommendations tailored to specific farm contexts seamlessly integrated into daily farm operations, potentially through user-friendly mobile applications or automated systems. Rather than focusing on single objectives, these interfaces for "multi-criteria decision-making" will be crucial for fostering holistic farm management and farmer adoption.

The past two decades have witnessed substantial advances in DSS for dairy cattle farming. This field of research is maturing as DSS transition from basic computational aids to sophisticated, data- and model-driven intelligent systems. However, to fulfil their potential, DSS must overcome data integration challenges based on rigorous real-world validation. Moreover, only through model transparency and practical usability can DSS empower dairy farmers with truly actionable and reliable insights for decision-making.

CONCLUSION

Model-driven DSS maintain their dominance in dairy cattle farming (40.5%), followed by data-driven (38.1%) and knowledge-driven systems (15.5%), while other DSS types account for the remaining 6.0% of the studies. DSS are predominantly applied in animal health and welfare and in farm business and management, using diverse input data, particularly Animal Health & Performance (28.0%), Farm & Business (22.4%), and Environmental & Spatial Data (21.3%). Mathematical/Deterministic (22.7%) and Simulation (13.6%) models remain the most frequently applied algorithmic approaches, increasingly complemented by machine learning techniques. Despite these advances, key challenges persist in integrating heterogeneous data, ensuring rigorous real-farm validation, improving model interpretability, mitigating bias, and enhancing practical usability and interoperability. These issues must be addressed to provide dairy farmers with effective, actionable, and reliable decision-support tools capable of meeting the complex demands of modern production while contributing to a more sustainable and resilient dairy sector.

Conflict of interest

The authors declare no conflict of interest.

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