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Invited review: Milking the data for value-driven dairy farming

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ABSTRACT

Precision dairy farming is rapidly transforming the global dairy sector through the application of data-driven technologies. This review explores current knowledge and emerging ideas across 5 key areas: (1) the economic value of data, highlighting its role in optimizing productivity and profitability; (2) advances in integrating artificial intelligence (AI), sustainability, and innovation, showcasing how these elements drive efficiency; (3) the drivers and barriers to technology adoption, data integration, and connectivity, identifying factors that enable or hinder progress; (4) sustainable data stewardship, addressing governance, standardization, and ethical concerns to ensure responsible data use; and (5) cross-sector insights from healthcare that can inform and strengthen dairy practices. It also provides recommendations for the dairy industry stakeholders on how best to promote, apply, and benefit from data-driven technologies in dairy farming. Emerging technologies such as AI, sensor-based monitoring, and automation are discussed for their potential to disrupt traditional practices and open new possibilities in dairy management. To advance the dairy industry and maximize the value of these technologies, it is essential to prioritize sustainable data stewardship, ensure clear data ownership, and uphold robust cybersecurity measures. Equally important is the need for increased investment in data infrastructure and the integration of computer science into agricultural and veterinary education. Effective interdisciplinary collaboration and structured support for technology adoption are critical to achieving these goals. Emphasizing practical opportunities and challenges, the review offers a forward-looking perspective on shaping a resilient, efficient, and technology-driven dairy industry.

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INTRODUCTION

The transformative impact of big data and technology was a key topic at the 2016 Discover Conference on Big Data Dairy Management. Since then, significant progress has been made in artificial intelligence (**AI**), sensor technologies, and predictive data analytics across a range of sectors, including agriculture, healthcare, and manufacturing. In today's fast-evolving and resource-conscious world, where efficient use of natural and economic resources is increasingly prioritized, the dairy sector faces growing societal demands regarding sustainability, which encompasses environmental responsibility, economic viability, and well-being in production practices. The concept of precision dairy farming (**PDF**) has emerged as a key driver in this transformation, using vast amounts of data collected through various technologies, including automated milking systems (**AMS**) and wearable devices, to optimize operations. Precision dairy farming is playing a critical role through real-time monitoring of various cow metrics, including those quantifying production, reproduction, health, and welfare, as well as environmental factors. These tools are essential for creating more resilient and sustainable dairy farming globally (Stone, 2020; Aquilani et al., 2022; Pakrashi et al., 2023) and allow for more precise and data-driven decision making (Pakrashi et al., 2023). For example, precision dairy and health monitoring technologies, as highlighted by Hogan et al. (2022), automate routine tasks and thereby save time, enabling more flexible working hours for veterinarians and farm workers. In addition to enhancing operational efficiency, PDF technologies are being used to address important public health concerns, such as antimicrobial resistance, by supporting more informed

The list of standard abbreviations for JDS is available at adsa.org/jds-abbreviations-26. Nonstandard abbreviations are available in the Notes.

antimicrobial stewardship. Furthermore, they contribute to environmental sustainability and climate change mitigation by optimizing resource use, reducing emissions, and promoting eco-friendly farming practices (Kebreab et al., 2019; Qureshi et al., 2019; Lakhiar et al., 2024).

Moreover, the potential of predictive data analytics and machine learning (**ML**) in the dairy sector has been recognized in recent times. For instance, Marques et al. (2024) demonstrated how integrating automated activity monitoring with ML algorithms can predict pregnancy in dairy cows, thereby optimizing reproductive management and improving herd health. Similarly, Punyapornwithaya et al. (2020) showcased the application of statistical process control to monitor milk quality, underscoring the role of data-driven approaches in maintaining high production standards. Similarly, Cabrera (2018) emphasized the role of data-driven decision support tools in improving economic performance of dairy farmers, suggesting that these tools are essential for navigating the complexities of modern dairy farming. The integration of diverse data sources, including structured data, which are organized and stored in a predefined format such as tables, and unstructured data, which does not follow a specific format or structure, plays a pivotal role in enhancing precision dairy farming by enabling informed decision making across, as illustrated in Figure 1. Unstructured information such as farm records, veterinary reports, sensor outputs, surveillance data, market indicators, and research can now be combined with structured data such as milk yield, health records, genomic profiles, nutrition metrics, and environmental conditions. When these data types are linked through probabilistic models, these datasets support applications such as health-risk prediction, production optimization, reproductive monitoring, market decision support, and disease forecasting, demonstrating how combined data sources enable more informed decision making across the dairy value chain.

Despite the numerous benefits of PDF technologies, challenges remain in several areas, including inadequate infrastructure, gaps in technological literacy and data interpretation, issues around data governance, limited access to reliable internet, and affordability barriers in terms of both economic cost and access to technology. Other issues include data privacy, lack of standardization in data formats and protocols, and insufficient interdisciplinary integration (Pakrashi et al., 2023). Many proposed PDF technologies struggle to transition from research to practice, with concerns around return on investment limiting their widespread adoption and complicating effective data analysis across farms. Addressing these challenges requires robust interdisciplinary collaboration, with expertise from fields such as animal and veterinary science, engineering, and computer science, to create solutions that are practical and scalable (Liu et al., 2021).

This review explores current knowledge and emerging ideas across 5 key areas shaping the future of the dairy industry: the economic value of data in optimizing productivity and profitability; advances in AI; the drivers and barriers to technology adoption, data integration, and connectivity; the importance of sustainable data stewardship through governance, standardization, and ethical practices; and cross-sector insights from healthcare that can inform and strengthen dairy practices. Offering a forward-looking perspective, the review can serve as a valuable resource for policymakers, with a goal to make the regulatory environment support the expansion and sustainability of the dairy industry with the use of data. It also provides practical advice for industry stakeholders to apply these understandings in their settings. Finally, for readers outside of animal science or related disciplines, the paper highlights how data, similar to healthcare, is transforming dairy farming into a more efficient, sustainable, and transparent industry, benefiting farmers, consumers, and the environment alike.

THE ECONOMIC VALUE OF DATA IN DAIRY FARMING

The economic value of data in dairy farming is big in terms of increasing productivity, raising the quality of production, and improving animal health and welfare. A survey by Borchers and Bewley (2015) found that 68% of US dairy farms used some form of precision dairy technology. Whereas the researchers noted that this figure may have been influenced by the enthusiasm of respondents already interested in such technologies, rather than representing widespread adoption across the entire sector (Borchers and Bewley, 2015), it still highlights the growing relevance of data-driven tools in dairy production. Another study in Ireland found that around 70% of farmers use a combination of precision and automated technologies, including milk meters, automatic feeders, washers, and cluster removal (Palma-Molina et al., 2023). As adoption continues to expand globally, precision dairy farming is slowly becoming the new norm, providing prospects for reducing expenses while increasing production efficiency and sustainability.

For dairy producers, the true economic value of data lies in its transformation into actionable insights that can directly influence farm profitability. Whereas data themselves are intangible, they become a valuable asset when applied to optimize herd health and resource allocation (Mwalupaso et al., 2020; van der Voort, 2024). However, quantifying the financial effect of data remains a complex task. Data have unique properties, such as infinite

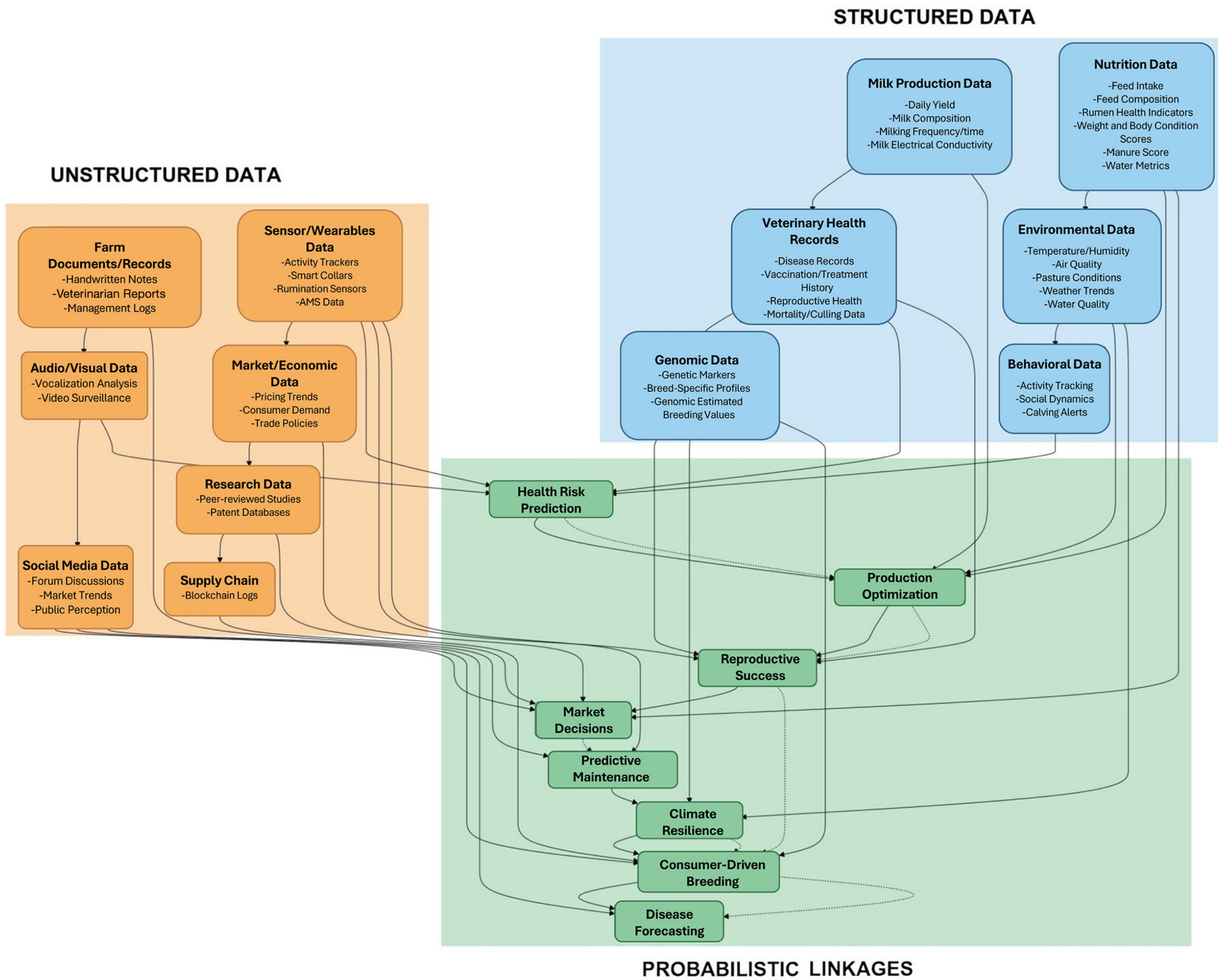

Figure 1. Overview of various data types in the dairy sector and examples of their integrations.

shareability, increased value with use, perishability, and diminishing returns when too much overwhelms human processing capabilities (Moody and Walsh, 1999). These properties contribute to the difficulty in capturing its full economic potential. Technologies that generate data, such as AMS and lameness detection systems, highlight these challenges by producing large volumes of data that require careful interpretation and timely action (Garcia et al., 2014; Lemmens et al., 2023). The economic returns from these technologies can vary depending on the farm's condition before implementation and the specific actions taken based on the data. On top of this, benefits related to animal welfare are difficult to describe monetarily (Cogato et al., 2021). Future research could therefore focus on identifying key data inputs, such as health and production metrics, that are most closely linked to measurable economic outcomes. The development of user-friendly simulation tools may further support producers in modeling alternative management scenarios and estimating potential effects, thereby facilitating more effective adoption of data-driven practices.

From scientific, practical, and economic perspectives, the integration of data into dairy management, especially through digital platforms and cloud-based systems, has strong potential to support real-time data collection, analysis, and accessibility. This integration has already been shown to improve data sharing across various systems, enhancing decision making efficiency and overall operational outcomes. Seamless data sharing depends on digital tools that can exchange information effectively, which occurs when platforms use compatible data formats and communication protocols. Although many systems still operate in isolation, the development of more integrative data platforms, the industry-wide movement toward open data standards, and the use of interoperability protocols, such as application programming interfaces (**API**) for system communication, along with clear data ownership frameworks that maintain control with producers, are gradually reducing these limitations. Cross-vendor connectivity tools are also making it easier to combine information from different sources. Emerging solutions such as blockchain technology, particularly permissioned blockchain architectures, can support data integrity, access control, and auditability by offering a decentralized structure for secure data sharing (Makarov et al., 2019; Kasten, 2019; Shingh et al., 2020). For example, a dairy producer can selectively share milk quality data with processors or veterinary records with consultants while maintaining an immutable record of who accessed the data and when, thereby protecting proprietary information from unauthorized access. Such approaches address both data integrity and interoperability challenges in the dairy sector (Yaqoob et al., 2019; Carter et al., 2020), enabling secure, standardized, and shareable data and creating pathways for the seamless integration needed in precision dairy farming.

Precision dairy farming uses advanced, real-time technologies such as milking robots (Liseune et al., 2021), sensors (Hut et al., 2022b), and camera-based computer vision systems (H. Yang, E. Liu, J. Sun, S. Sharma, M. van Leerdam, S. Franceschini, P. Niu, and M. Hostens, Cornell University, Ithaca, NY; unpublished data). These technologies are applied to monitor various aspects of cow health, welfare, performance, and productivity. The data collected can be used to derive actionable insights on animal well-being, reproductive management, farm economics, and sustainability (Hostens et al., 2012; Chen et al., 2022; Hut et al., 2022a). For instance, the adoption of activity monitoring systems has improved reproductive management due to more effective heat detection, leading to reduced management time and enhanced milk production (Niles, 2024). Similarly, the use of cameras to consistently measure locomotion scores, thereby facilitating early detection of disease (Swartz et al., 2024). Furthermore, the ability to collect detailed individual animal data has opened up new opportunities for genetic improvement, such as the development of breeding values for methane emissions (Worku, 2024). The AI-driven insights, derived from data collected by sensors and milking robots, help optimize feeding strategies, which in turn increases milk production. For instance, individualized feeding of concentrate supplements, based on continuously updated milk yield records obtained at each milking, with potential benefits for milk production, feed efficiency, reproduction, and animal health (Hills et al., 2015). Additionally, AI-driven systems can diagnose heat stress by detecting changes in behavior measured by sensors, enabling targeted intervention strategies and providing a means to evaluate their effectiveness (Davison et al., 2020). Another key innovation in the shift to PDF is the application of real-time analytics through predictive and dynamic dashboards. These tools have been shown to enhance decision making and resource management on farms, with the goal of optimizing production and profits (Mouzakitis et al., 2020; Hackfort, 2023).

Also, effective data management and connectivity can drive substantial improvements in efficiency, profitability, and consumer transparency outside of the farm. Wiedmann (2024) emphasized using data not only for operational efficiency or monetary gain but also to improve consumer-facing data, meaning information shown directly to consumers such as accurate product labels and "best by" dates. These details help consumers make informed decisions, reduce food waste, and improve inventory management by tracking and controlling stock levels and product turnover within processing and retail environments to minimize unsold or expired products, ultimately benefiting both producers and consumers. Integrating data analytics into processing operations can enable the prediction of future outcomes, such as shelf life and spoilage issues, by leveraging dynamic ML models that learn and adapt from data, alongside predictive algorithms that focus on forecasting outcomes based on predefined patterns (Qian et al., 2023; Tarlak, 2023; Chhetri, 2024). These tools analyze historical and real-time data to identify spoilage patterns and optimize inventory turnover, leading to fewer losses in storage, such as products lost due to spoilage, expiration, or damage before reaching consumers. Furthermore, techniques such as Monte Carlo simulations can facilitate better forecasting and demand planning, helping dairy processors optimize operations (Lau et al., 2022). Qian et al. (2023) developed a Monte Carlo simulation-based tool to predict spoilage of HTST fluid milk due to psychrotolerant sporeformers across the full supply chain, accounting for temperature variability from processing to consumer storage. The model estimated that ~44% of half-gallon containers would spoil after 21 d under baseline conditions and showed that interventions such as microfiltration and improved temperature control could significantly reduce spoilage. Similarly, Su et al. (2025) developed a fluid milk spoilage simulation framework that models bacterial growth from postpasteurization contamination and demonstrates how intervention strategies tailored to specific contamination frequencies can significantly extend shelf life. In addition, Fizza et al. (2025) developed an inexpensive Internet of Things (**IoT**)-powered sensor for continuous monitoring of raw milk fat and protein content from farm to factory, allowing for real-time quality control. Another promising innovation explored combining odor sensing with ML to estimate the shelf life of packaged fresh milk (using a multilayer perceptron neural network, the study achieved 85% to 100% accuracy for maximum shelf-life prediction, though minimum shelf-life prediction was less accurate at 43% to 67%), offering a feasible, noninvasive method to improve spoilage prediction and demonstrating how sensory data can enhance accuracy (Mamat et al., 2024). Together, these tools exemplify the shift from basic monitoring systems to integrated, data-driven platforms that improve inventory turnover, reduce food waste, and boost consumer confidence. Similar to the enterprise resource planning revolution in manufacturing, such innovations are enabling the dairy industry to transition toward real-time, end-to-end data integration (Haberli Junior et al., 2019; Hatanaka et al., 2021). It also highlights the initial stages of using herd management software and evolving into more sophisticated systems where data flow from farm to dairy product consumer is streamlined and transparent, similar to Nestlé's data-driven initiative to enhance consumer insight into the products they consume (Taylor, 2024). Some relevant datasets for these consumers can include sourcing origin, production methods, nutritional content, and sustainability metrics related specifically to dairy products.

As PDF innovations develop, the integration of digital technologies drives economic growth while simultaneously addressing sustainability challenges across environmental and social dimensions. The theoretical benefits of data-driven technologies are increasingly being validated through concrete, measurable outcomes in dairy production. For instance, the adoption of AMS has been associated with increased milk yields, ranging from 2% to 25% (Meijering et al., 2004; Bernier-Dodier et al., 2010). At the same time, these systems drastically reduce labor requirements, cutting the time spent on milking-related activities by 62% (Tse et al., 2018). Whereas AMS systems do require occasional maintenance and may face some operational challenges, such as errors and time spent managing large herds for milking, they continue to offer substantial improvements in labor efficiency and productivity. Precision nutrition models have demonstrated the potential to improve dairy performance by meeting cows' nutritional needs more precisely, leading to gains in milk yield (Wang et al., 2000; White and Capper, 2014). Barrientos-Blanco et al. (2020) demonstrated that implementing nutritional grouping could yield an additional \$31 per cow annually in income over feed costs (**IOFC**) compared with conventional grouping systems, highlighting the economic benefits of precision feeding strategies. Another example of integrated precision technologies is the "Dairy Brain" system, designed to integrate and analyze real-time data streams from dairy farms. It has demonstrated a potential annual reduction in diet costs of \$99 per cow through improved nutritional grouping. The system also identified 90% of clinical mastitis cases 5 milkings before disease onset, potentially reducing production loss and treatment costs through early intervention (Cabrera et al., 2020).

The environmental dimension of sustainability is increasingly supported by precision technologies that help reduce the ecological footprint of dairy farming while maintaining or improving productivity. Research has shown that precision livestock farming (**PLF**) technologies can offer significant reductions in GHG emissions. The AI-powered tools can aid in emission reduction strategies, allowing farms to meet climate goals while maintaining productivity (Neethirajan and Kemp, 2021). Additionally, the use of big data analytics can optimize resource allocation and feed efficiency, which is critical for long-term dairy production (Liu et al., 2023). For instance, McNicol et al. (2024) conducted a study using Scottish cattle data to model the effects of adopting PLF technologies on whole farm and product emissions. Their research found that implementing automatic weight platforms, accelerometer-based sensors for estrus detection, and health monitoring sensors could lead to substantial reductions in GHG emissions. Specifically, use of health sensors reduced total emissions by 6.1% (housed) and 4.4% (grazing), automatic weight platforms decreased total emissions by 6.8% (grazing) by reducing age at slaughter, and health sensors reduced product emissions by 12.0% (housed) and 10.5% (grazing; McNicol et al., 2024). These findings illustrate that the value of data extends beyond immediate farm profitability to encompass broader sustainability metrics that enhance the industry's resilience and social acceptance. The emphasis on sustainable practices is supported by research that shows that technology adoption can result in significant improvements in economic performance and environmental efficiency (Sarie et al., 2023).

The social dimension of sustainability is addressed through PDF technologies that improve both worker and animal welfare. One of the most commonly reported advantages of AMS is time savings, with studies reporting a 29% to 30% reduction in labor time on farms using such systems (Heikkila et al., 2010; Rodenburg, 2012). Digital tools within PDF not only reduce physical strain but also enhance work flexibility and lower mental stress, supporting better work-life balance for farmers. For instance, sensor-based systems for estrus detection and health monitoring help reduce the physical and cognitive workload associated with manual observation while also enabling more informed animal care decisions (Allain et al., 2016; Goller et al., 2021). Interviews with farmers further reveal that these technologies are generally perceived positively, particularly for their role in simplifying herd management and improving day-to-day decision making (Goller et al., 2021; King et al., 2021). Moreover, farms with higher levels of automation, integrated into broader PDF systems, have reported better human-animal interactions, fewer lameness cases, and improved cow hygiene, contributing to higher animal welfare standards (Lavrijsen-Kromwijk et al., 2024). This ongoing evolution toward integrated digital solutions is part of a broader trend often referred to as "Dairy 4.0," which employs robotics, AI, and the IoT to enhance sustainability and efficiency in large-scale dairy farming operations (Sangode, 2024).

In conclusion, data and their analysis bring economic value in numerous ways to all stakeholders involved in the dairy industry, spanning direct economic returns, environmental sustainability, and social benefits across the entire value chain from farm to consumer. Additional applications of data-driven solutions and their future directions are discussed later in this review.

ADVANCES AND FUTURE TRENDS IN DAIRY FARMING: INTEGRATING AI, SUSTAINABILITY, AND INNOVATION

Artificial intelligence is a broad umbrella term encompassing computational systems capable of performing tasks that typically require human intelligence, such as learning from data, recognizing patterns, and supporting decision making. Within this broad domain, ML refers specifically to data-driven methods that learn predictive relationships from examples. In practice, most contemporary AI applications in dairy science have been implemented through ML methods, so it can be viewed as the primary methodological driver through which AI capabilities are realized in dairy systems. Machine learning approaches can enable the analysis of large and heterogeneous datasets, including data generated by milk analyzers, cameras, and veterinary diagnostics, which can improve the accuracy and precision of predictions. These methods have the potential to transform dairy farming by reshaping traditional approaches to milk composition analysis, health monitoring, and farm management. A clear example of this evolution is provided by the use of mid-infrared spectroscopy (**MIR**). Initially, MIR data were primarily used to estimate a limited number of milk components using traditional quantitative methods, such as linear regression. With the adoption of ML methods, MIR spectra can now be exploited more fully to extract additional information, including indicators of cheese-making properties, methane emissions, and negative energy balance, as illustrated in Figure 2 (the timeline of progression of milk composition analysis using MIR).

As shown in Figure 2, MIR spectral analysis has progressed from conventional linear models to a range of ML approaches, including partial least squares (**PLS**) regression, support vector machines, decision trees, and deep neural networks. In the context of milk composition analysis, both neural networks and PLS regression have proven effective for handling complex and highly correlated infrared spectrometry data, enabling more accurate predictions of milk nutritional and technological properties, as well as disease detection and environmental fingerprinting. A relevant initiative in this area is the ExtraMIR project, a joint effort by International Dairy Federation (**IDF**) and International Committee for Animal Recording (**ICAR**; Soyeurt, 2023). This initiative aims to provide a more comprehensive understanding of how Fourier transform mid-infrared (**FT-MIR**) milk spectra can be used in the dairy sector. Based on the needs mentioned by Soyeurt (2023), the ExtraMIR initiative focuses on establishing standards for handling spectral data and reference data used in predictive models, while also enhancing communication about the potential of milk FT-MIR spectrometry for all stakeholders. Ultimately, these outputs could help to support better assessments of animal health and sustainability at a global level (Suharso et al., 2022). Although simpler models such as PLS regression demonstrate comparable efficacy with lower computational costs, a key challenge arises in the ongoing debate about the necessity of more complex algorithms, especially when factoring in issues such as data sharing and confidentiality. For instance, PLS models require running all records together, which can be difficult when reference datasets are not shared for privacy reasons. In contrast, the use of more complex algorithms, such as neural networks, is becoming increasingly attractive, as they can manage large datasets without the need for access to complete records, particularly when techniques such as transfer learning are employed (Soyeurt, 2024).

In addition to milk composition analysis, ML could revolutionize phenotyping and farm management by integrating genomics with advanced sensing technologies, such as computer vision systems (Oliveira et al., 2021). Moreover, the integration of enviromics and genomics could offer a deeper understanding of how genetic and environmental factors shape phenotypic outcomes, which are vital for improving animal breeding strategies (Rosa, 2024). In the context of beef cattle, projects such as "Precoce MS" (Amaral et al., 2024; SEMADESC, 2024), in Brazil, showcase a different application of these technologies, where they incentivize the early harvesting of animals based on carcass quality, thereby predicting farm performance and identifying key production variables (Rosa, 2024). Also, analytical methods such as the Finlay-Wilkinson models (Finlay and Wilkinson, 1963), originally developed for plant breeding and used for analyzing genotype-environment interactions by assessing how different genotypes perform under varying environmental conditions, can be

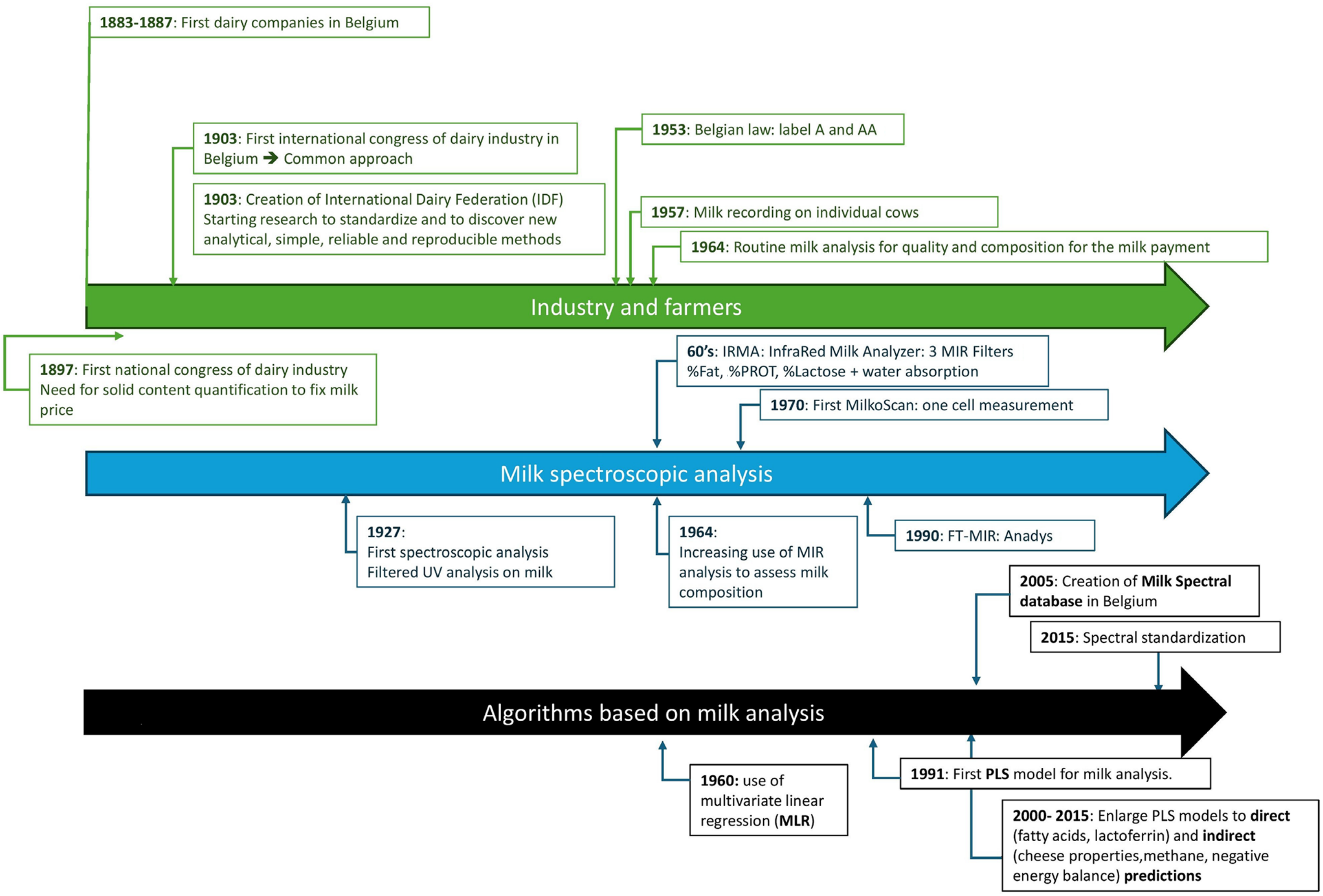

Figure 2. Timeline of advancements in milk analysis based on mid-infrared spectrometry in Belgium. A and AA refer to Belgian regulatory quality grades for raw milk; PROT denotes milk protein content (Soyeurt, 2024).

used to explore how different environmental factors affect dairy cattle and other livestock (Schmid and Bennewitz, 2017), thereby aiding selection for resilience and productivity (Rosa, 2024). Complementing these integrative genomic approaches, the growing use of automated sensors, milking robots, imaging systems, and other precision dairy farming tools means large volumes of high-frequency phenotypic data are now available. These data support the development of novel traits beyond traditional production or conformation measures, including those related to behavior, efficiency, health, resilience, welfare, and environmental impact, many of which show meaningful heritabilities and genetic correlations. For example, a study of over 5,000 US Holstein cows using 36 robotic milking stations derived behavioral traits such as average milking time, time between milkings, number of attempted visits, percentage of successful milkings, and a cow preference consistency score. Heritability estimates ranged from 0.10 to 0.46, suggesting potential for use in genetic evaluations (Bérat et al., 2025). Feed efficiency is another emerging focus; a meta-analysis in Holsteins reported heritabilities of ~0.20 for residual feed intake (**RFI**), 0.34 for DMI, and 0.22 to 0.24 for energy balance, and identified key genes and pathways related to ATP synthesis, oxidative phosphorylation, lipid metabolism, and tryptophan metabolism (Jiang et al., 2024). Sensor-derived health and welfare traits are also entering evaluations; an invited review summarized heritability estimates for traits such as activity, rumination, and lameness proxies and discussed standardization and integration into national evaluation systems (Brito et al., 2025). Additionally, the use of functional genomic variants has been shown to improve prediction accuracy for standard lactation traits compared with generic SNP panels, demonstrating that combining detailed phenotypic data with rich genomic information can enhance evaluation tools (Alemu et al., 2025). These advances are enabling more informed decisions in dairy cattle improvement programs, extending focus beyond milk yield to include health, behavior, efficiency, and sustainability traits that were previously difficult to measure.

The use of diverse data types, including video and sensor inputs, has also been shown to improve the accuracy of predictive models (for conditions such as subclinical ketosis and lameness) compared with models relying solely on traditional observation or single-source data (Ferreira et al., 2024; Menezes et al., 2025). Additionally, integrating phenotyping and genomics into these models has been shown to further enhance their performance, enabling even more accurate predictions (Džermeikaitė et al., 2023; Dorea, 2024). These diverse data types are increasingly captured and managed through advanced sensor technologies, such as 2- and 3-dimensional imaging systems (Viazzi et al., 2014; O'Mahony et al., 2019), as well as data-processing approaches, including autoencoders (Liseune et al., 2021; Lee et al., 2024), which enable the continuous collection and analysis of real-time data, including locomotion patterns, feed intake, and ambient conditions. The integration of these multisource data streams supports the development of sophisticated predictive health and surveillance models, as well as digital twins that enhance decision making and farm management (Neethirajan and Kemp, 2021; Thompson et al., 2021; Hostens, 2024). Digital twins are virtual representations of cows or herds. They can facilitate real-time monitoring and predictive analytics by simulating what the cow or herd would look like when their circumstances change, such as a new diet. They are already widely used in engineering, and their application in dairy farming could enhance herd management practices through modeling the effect of decisions on animal health and production (Petrov and Atanasova, 2021; Peladarinos et al., 2023).

The recent development of generative AI and large language models also has the potential to further accelerate optimized farm decision making and improved labor efficiency, as they can translate complex data and models to the language of the farmer and thereby enhance technology adoption (Jhajharia and Mathur, 2022; Liu et al., 2025). The effectiveness of these AI-driven decision support systems depends fundamentally on the quality and volume of data available from farm monitoring technologies. Automated health monitoring (**AHM**) technologies have emerged as critical data sources in modern dairy farming, utilizing wearable and nonwearable sensors to monitor behavioral, physiological, and productivity parameters. For instance, a study in Denmark (2008–2009) on 3 farms with more than 150 animals in lactation showed that AHM systems improve estrus detection rates (95%–97%) and consequently enhance reproductive performance, with conception rates increasing up to 50% compared with traditional methods (Blom and Ridder, 2010; Neethirajan et al., 2017). Furthermore, in Austria, it was demonstrated that an ear-attached accelerometer-based algorithm could accurately predict calving onset with a balanced accuracy of 74% 1 h before calving (Krieger et al., 2019). This methodology was further developed in another study, which predicted calving by detecting increased lying bouts and decreased rumination chews, achieving high accuracy within 3 h of calving (sensitivity = 88.9%, 85% and specificity = 93.3%, 74% for multiparous and primiparous cows, respectively; Zehner et al., 2017). Whereas these tools are frequently used in heat detection, the sheer volume of real-time data generated poses challenges for effective interpretation for more complex tasks. Here, ML algorithms play a crucial role, as they are capable of filtering and analyzing large datasets to, for instance, identify health disorders with high frequency and precision by incorporating diverse biodata and nonsensor information (Enrique and Bustos, 2022; Giordano, 2024; Perez and Giordano, 2025). These algorithms excel in identifying complex, nonlinear relationships within data, which is essential for diagnosing multifaceted health issues (Uzhinskiy, 2023). Machine learning applications also extend to production optimization; for instance, Liseune et al. (2021) developed a deep learning framework that enhances lactation curve predictions and forecast accuracy, particularly during the first 26 d of lactation, by leveraging historical milk yield data. However, challenges such as data heterogeneity and uneven disease incidence across farms necessitate advanced techniques such as hyperparameter tuning, data sampling, and novel model architectures to enhance adaptability and diagnostic accuracy across varying environments (Putatunda and Rama, 2018). Despite the successes of ML algorithms in identifying healthy cows, their effectiveness in detecting sick cows has been less pronounced (Giordano, 2024). A study showed that whereas some models, such as neural networks trained to detect diseases through milk mid-infrared spectrometry, achieve high specificity (e.g., 97%), their sensitivity in detecting illness can be limited (e.g., around 62%; Contla Hernández et al., 2021). Although a study by Simoni et al. (2024) showed that the use of a sensor-based system for detecting ketosis and hypocalcemia resulted in higher sensitivity (71%) than specificity (43%–48%). This performance was similar to those of the conventional diagnostic systems, indicating that the sensor-based approach did not significantly outperform conventional methods in terms of accuracy. However, van Leerdam et al. (2024) did find that a deep learning model outperformed traditional models while predicting the risk of hypocalcemia after calving, with an accuracy of 62%. This raises important questions about the practical deployment of such technologies in real-world farming environments. Addressing these challenges requires a dual focus: improving the data ecosystem and enhancing algorithmic reliability. A robust data collection system is crucial, ensuring diverse, high-quality datasets from commercial farms to train models that generalize well beyond controlled settings. Algorithm reliability may be improved by refining mathematical frameworks (e.g., calculus-based optimizations) and incorporating advanced techniques such as feature engineering and ensemble modeling (Du and Swamy, 2016; Monteiro et al., 2024). Progress in these areas, alongside fully AHM tools, is essential to bridge the performance gap between ML performance in simulation and commercial applications (Cravero et al., 2022).

Building on these advances, the future of dairy farming is projected to advance with the help of ML, computer vision, and various sensor-based systems. The application of these technologies will enhance farm productivity, promote animal welfare, and enhance sustainable agriculture. Health monitoring systems now extend beyond milk composition analysis to more integrated systems that combine genomic data, environmental factors, and real-time phenotyping to generate predictive models for farm management (Radun et al., 2021; Cotticelli et al., 2023). This shift is indicative of a broader trend in agriculture where data-driven decision making becomes central to operational success (Tzachor et al., 2022; Abdul Ameer et al., 2024). In this context, dairy farming is expected to become even more data-driven and interconnected in the near future. The AI-driven phenotyping and health monitoring systems, augmented by real-time data from sensors, will become commonplace, allowing farmers, veterinarians, and other stakeholders to make more informed decisions, for example, about animal welfare and farm management. As farms become more automated, the farmer's role might require a shift from manual labor to include data management and oversight. Thus, new competencies will be needed, and training programs should be developed (Kosior, 2018; Radun et al., 2021; Wilgenbusch et al., 2022; Erdem and Ağır, 2024).

TECHNOLOGY ADOPTION, DATA INTEGRATION, AND CONNECTIVITY IN DAIRY FARMING: MULTILEVEL DRIVERS AND BARRIERS

The adoption of technology in dairy farming forms the foundation for enhancing productivity, animal welfare, and operational efficiency, whereas data integration and connectivity serve as critical components to synchronize and harmonize information across the supply chain for better-informed decision making. Stakeholders across the dairy industry are directing increasing attention toward the potential role of performance indicators, monitoring systems, and data-driven management practices in supporting productivity, efficiency, and sustainability. Rogers's diffusion theory explains that innovations spread through social systems based on factors such as perceived value and ease of integration (Rogers, 2003). Although sufficient awareness, information, and return on investment are key drivers of technology adoption, Ruzzante et al. (2021) highlighted that the adoption process is complex, with significant variability across contexts, leading to nonadoption, partial adoption, and disadoption based on specific technologies and local agricultural conditions.

Factors such as farmer education, household size, land tenure, and access to proper investment influence technology adoption. Kaushik and Rajwanshi (2023) identified 12 key enablers affecting technological adoption in dairy farms: affordability of adopting and maintaining technologies, awareness of available technologies, experience in the dairy business, ease of technology maintenance, the compatibility of technology with existing farming practices, managerial interest in technology adoption, availability of a trained workforce, ease of use, perceived usefulness of technology, competitive pressure, technology self-efficacy, and digital literacy. These enablers show that adoption depends on interacting economic, managerial, social, and technical dimensions: economic factors such as affordability and investment requirements, managerial and human capacity such as experience, managerial interest, availability of a trained workforce, digital literacy and technology self-efficacy, technological fit and usability such as compatibility, ease of use and ease of maintenance, and market or institutional pressures such as awareness and competitive pressure. However, the lack of government support, limited educational opportunities in dairy-based education, high costs, substantial investment requirements, and low acceptance by decision makers were the most significant barriers to technology adoption (Kaushik and Rajwanshi, 2023). In particular, the financial burden is compounded by the accumulation of multiple digital tools, each requiring subscriptions, maintenance, and training, which can exceed the value they provide. These barriers indicate that even when specific enablers are present, systemic constraints in policy, training, finance, and decision making can prevent technologies from moving from demonstration to routine use. Notably, these challenges are not universal. The USDA Economic Research Service reported a substantial increase in the adoption of digital agriculture technologies between 1996 and 2019, with automated guidance systems being implemented on over 50% of acreage for major crops such as corn, cotton, and soybeans (McFadden et al., 2023). These findings highlight the growing acceptance of agricultural technologies in certain contexts, dairy systems continue to face intertwined financial, educational, and policy barriers that slow the pace of adoption.

Along with this, widespread data adoption faces hurdles such as concerns over privacy, security, and data sharing, with many farmers reluctant to participate without guaranteed protection (Dagne, 2021). Many farmers are reluctant to engage with digital tools due to the lack of transparency regarding data control, as companies often embed data ownership clauses in End User License Agreements, which most farmers may not fully understand or read. This practice undermines trust and can discourage broader adoption of these technologies. To overcome this, it is essential that technology providers work closely with farmers to create data sharing agreements that are transparent and mutually beneficial. Building trust through clear communication, farmer involvement in decision making, and developing incentives for data sharing will be crucial to overcoming these barriers. Moreover, similar to approaches in retail and food service integration, as seen in companies such as Sysco, applying data sharing models in the dairy sector could increase profitability while also promoting sustainability and traceability to consumers, reinforcing the industry's commitment to quality and transparency (Diamond et al., 2014; Fowler, 2023; Taylor, 2024).

Beyond privacy and data sharing concerns, another critical challenge in technology adoption is the concept of "technology graveyards," which refers to technologies that failed to address practical farm needs and subsequently became obsolete (Bewley, 2024). These failures often stem from insufficient understanding of cow biology and farm realities, designing technologies unsuited for large animals or long-term farm use, and neglecting infrastructure needs, weather challenges, or rodent-related issues (Silvi et al., 2021; Bewley, 2024). Additional pitfalls include failure to address maintenance requirements, poor rural internet connectivity, overpromising on capabilities, and focusing more on the technology itself rather than the actionable information it provides; ongoing issues that still pose significant barriers to wider adoption (Eastwood and Dela Rue, 2020; Amare et al., 2021; Iwersen, 2024; Niles, 2024). This can be because a disconnect often exists between technology developers and the practical realities of dairy farming, with some making overly ambitious claims about product benefits without meaningful input from producers or on-farm validation. Low return on investment, poor accuracy in data collection or analysis, and lack of integration with other farm data sources further hinder successful technology adoption (Silvi et al., 2021). For instance, whereas PDF technologies have shown promise in improving individual cow management, their implementation on larger scales has been hampered by high initial costs and the need for specialized training (Borchers and Bewley, 2015; Gargiulo et al., 2018; Silvi et al., 2021). Moreover, the rapid pace of technological advancement can sometimes outstrip farmers' ability to fully integrate and use new systems, leading to underutilization or abandonment of potentially beneficial technologies (Eastwood et al., 2012; Tuyttens et al., 2022; Bewley, 2024).

Another growing concern is the accumulation of multiple digital tools, each requiring separate subscriptions, maintenance, and training. These systems often lack interoperability and include overlapping functions, making it difficult to maintain cost-efficiency. In addition to upfront costs, recurring fees and hidden expenses such as updates, calibration, and support contribute to a financial burden that can outweigh operational benefits. Most farms are not equipped to manage the economic and logistical demands of several parallel systems. It also calls for a shift from tool-centered designs to integrated farm-level ecosystems that focus on combining value rather than duplicating features. Lessons learned from these failures emphasize the importance of team expertise and the need for technologies that are both user-friendly and capable of integrating seamlessly into everyday farm operations (Mwalupaso et al., 2020). Successful adoption requires continuous validation and maintaining an economic balance between investment costs and potential returns (Bewley, 2024), with effective customer support and data standards playing a crucial role (Thompson et al., 2021).

This need for integration brings us to the pivotal role of data connectivity. Innovations such as sensor systems for monitoring cow health have shown great promise, yet they are still hampered by issues related to connectivity and system functionality (Bewley, 2024; Eastwood, 2024). To overcome these connectivity barriers, standardized data formats and protocols are essential, as they enable seamless communication across technology systems, simplification of tool integration, reduction of connectivity issues, and enhanced functionality, which together support greater adoption and improved return on investment. Implementing such standardized systems requires a robust technological infrastructure, including centralized computing resources, secure and comprehensive database systems, and standardized data formats for effective sharing and utilization of data in dairy farming. Several real-world initiatives exemplify how this infrastructure can be operationalized. A real-time, data-integrated, data-driven, continuous decision making engine such as the "Dairy Brain Initiative" (Cabrera et al., 2020) has been proposed to facilitate data sharing and utilization along with enhanced dairy farm decision making. Similarly, the "WALLeSmart" platform in Belgium, with its modular plugin architecture, has been reported to serve as both a hub and an application platform, enabling agricultural professionals and developers to build and run custom applications (Roukh et al., 2020; A. Roukh and S. Mahmoudi, University of Mons, Mons, Belgium, unpublished data). It also aggregates and processes diverse agricultural datasets to provide real-time insights and predictive analytics (Roukh et al., 2020; Roukh and Mahmoudi, 2025).

In parallel with connectivity, accurate and persistent animal ID supports traceability, herd management, and genetic improvement programs. Historically, management tags were farm-specific limiting their use for data exchange across systems. These issues have been addressed through international standards developed by ICAR, which certify radio frequency identification (**RFID**) and other ID devices in line with International Organization for Standardization guidelines, ensuring global interoperability and reliability (Rosati, 2011). Despite these efforts, many farm management systems still rely on internal, nonstandard IDs, often unique only within a specific farm or reused over time, hindering data integration and genetic evaluations. Although emerging biometric solutions such as muzzle prints and retinal imaging (Awad, 2016) may offer future improvements, the adoption of standardized animal ID systems remains essential for a fully interoperable farm data ecosystem.

Although some progress has been made, barriers to data utilization persist. Cabrera (2024) identified that data shared by companies in noninteractive formats (e.g., portable document format, emails) limits their analysis and integration, emphasizing the need for user-friendly API and direct computer access to fully use data. These technical barriers are compounded by a lack of professionals skilled in both animal science and data science, a gap that strategies such as creating combined majors and courses integrating digital agriculture and data management at the university level can mitigate. Additionally, precision agriculture, as highlighted by Lee et al. (2021), enables producers to respond more effectively to market fluctuations through advanced analytics, integration across vendor platforms remains a major obstacle. Proprietary data systems often retain information in silos, prioritizing vendor control over data portability and usability (Wolfert et al., 2017). Although initiatives such as the International Dairy Data Exchange Network aim to create shared infrastructure for data exchange (Reents and Pekeler, 2021), much of the industry still lacks open standards or incentives for vendors to enable full interoperability. This lack of cross-system integration further compounds existing delays, as Breunig (2024) notes, such as in real-time access to economic metrics such as IOFC, reducing the utility of analytics for decision making.

On an industry level, disparities between large and small dairy producers in accessing and utilizing data remain a significant challenge, further compounded by the lack of standardization (Lefebvre, 2024). Although standardization is essential, the trend of various companies using data from farmers and other stakeholders to monetize their insights raises ethical concerns, particularly around transparency and consent, as noted by Ryan et al. (2020). Beyond technical and talent gaps, van de Ree (2018) emphasized the growing need for legal frameworks around "data sovereignty" to ensure fair access to data while respecting the rights of data producers. These insights highlight the need for collaborative efforts in addressing both technical and governance challenges in data integration.

Educational integration of digital technologies is essential for preparing the next generation of farmers and other dairy professionals to tackle these issues. A survey by Weimar and coworkers in 2023 among veterinary and agriculture students about the readiness of the next generation to adopt digital technology (sensor technologies) suggested that incorporating such data-driven technologies and data analytics into curricula is vital to equipping students with relevant skills and knowledge to meet future industry demands and increase readiness to adopt (Baarbé et al., 2019; Iwersen, 2024). However, current readiness rates are estimated at only 20% to 30% (Iwersen, 2024; Niles, 2024), which, although acceptable given that not all trainees are expected to pursue careers in PLF or PDF, still underscores an opportunity to expand and enhance educational programs. Initiatives such as specialized master's programs in precision animal health could further address this gap by bridging veterinary medicine, animal husbandry, and production with modern, information-driven technologies (Amare et al., 2021; Iwersen, 2024; Niles, 2024). This approach aligns with broader recommendations to update educational curricula to meet the evolving demands of modern agriculture (Achuthan et al., 2020).

Looking ahead, the future of dairy technology will require deliberate consideration through a thoughtful, responsible approach. Concepts such as responsible innovation offer a framework that guides researchers, companies, and policymakers to anticipate, include, reflect on, and respond to technological developments, ensuring that these innovations align with societal values, ethical considerations, and long-term sustainability goals. Analyzing the reasons for not adopting such technologies is also important for motivating innovation in dairy farming.

In conclusion, although technology adoption and data integration across the dairy supply chain offer significant potential, overcoming challenges related to standardization, accessibility, and governance requires collaboration across academia, producers, technology providers, and processors. One significant challenge is the disparity in financial or technical resources, making it more difficult for small farmers to adopt advanced technologies compared with their larger counterparts. To address this, developing targeted funding programs and providing technical support for small- and medium-sized farms are essential. Continuous research and innovation, including the development of improved data sharing approaches, appropriate business models, and the creation of a digital workforce for industry, are necessary to realize the full benefits of integrated data systems. Promising business models might involve subscription-based services offering scalable access to data analytics and decision support tools, cooperative arrangements for shared data ownership and resource pooling, and flexible "technology-as-a-service" offerings that reduce upfront investment for farmers. As the industry evolves, effectively managing the complexities of technology adoption, data integration, and connectivity will be crucial for enhancing productivity, animal welfare, and overall farm and supply chain management.

SUSTAINABLE DATA STEWARDSHIP IN AGRICULTURE: GOVERNANCE, STANDARDIZATION, AND ETHICAL CONCERNS IN DATA UTILIZATION

The successful implementation of PDF is founded upon high data quality. Agreed-upon data standards and well-defined traits are essential for accurate data recording, as emphasized by Cabrera et al. (2020). As the animal agricultural sector increasingly relies on data-driven decision making, several critical aspects of sustainable data stewardship, particularly within the dairy industry, come to the forefront. For example, stakeholder collaboration in data recording standards ensures consistent, accurate, and accessible data across the livestock sector. Herdbooks, milk recording organizations, farm management software providers, and data exchange hubs play an important role in establishing these standards (Cabrera et al., 2020). These standards address trait definitions, measurement methods, and data exchange protocols, improving transparency, reusability, and benchmarking.

International standards, such as those established by organizations such as ICAR, play a crucial role in data standardization to ensure data consistency and reliability. The ICAR provides a platform for developing data standards and testing performance recording devices (ICAR, 2024). It offers certification for identification devices, such as ear tags and RFID, as well as milk meters, samplers, analyzers, DNA labs, and business processes such as herdbook and milk recordings through its Certificate of Quality (ICAR, 2024). The ICAR also focuses on developing guidelines and standards for animal identification, recording, and evaluation to ensure consistency and reliability across the dairy industry (ICAR, 2024). The evolution of these standards is essential to accommodate the formulation of new traits, such as feed intake and methane emissions. By enabling standardized data collection processes, ICAR facilitates the use of data to promote environmental stewardship and resource efficiency, aligning with global targets such as the United Nations' Sustainable Development Goals (12 and 13; Sachs et al., 2019) for responsible consumption and production, climate action, and industry commitments in the dairy industry (Wilgenbusch et al., 2022; van der Linde, 2024). Furthermore, by establishing standardized data practices, the reliability of the data improves, thus facilitating better benchmarking and overall quality enhancement across the agricultural sector (Duncan et al., 2022).

Another important concern in sustainable data stewardship is data ownership. The complexity of data ownership presents a significant challenge, especially concerning raw data generated from dairy operations. Whereas farmers typically own the raw data, extensive rights granted to companies to use and exploit these data under current contracts create a need for clearer regulations to protect agricultural data akin to protections in other sectors such as healthcare and finance (Janzen, 2024). Contractual boundaries in data usage among farmers, agricultural technology companies, and milk buyers further create challenges for data integration. These challenges highlight the critical need for well-defined ownership frameworks to ensure equitable data sharing and safeguard farmers' interests (Carbonell, 2016; Wiseman et al., 2019).

Although initiatives such as the Ag Data Transparent (Sanderson et al., 2018) certification represent steps toward transparency in data handling, emphasizing the importance of understanding contract terms and protecting data rights, significant challenges remain. Data ownership continues to be a critical issue within the agricultural scientific community. To promote data accessibility and transparency, journals such as the *Journal of Dairy Science* have adopted formal open science policies, encouraging researchers to share data associated with published articles (Kononoff, 2024). Additionally, broader concerns, including data normalization, intellectual property rights, and transparency in data handling, along with the growing role of AI, are driving a shift toward greater openness and standardization, aiming to regulate how agricultural data are shared, used, and protected (Carolan, 2017; Wolfert et al., 2017).

Effective data sharing is yet another critical aspect of sustainable data stewardship and is pivotal for advancing animal agricultural practices and fostering innovation. Successful data sharing relies on building trust among stakeholders and adopting standardized data formats, such as the Ag Data Application Programming Toolkit (**ADAPT**), to enhance data utilization and operational efficiency (Drape et al., 2021; Borrero and Mariscal, 2022). Building trust in data sharing relies on transparent processes, consistent interactions, and strong relationships among stakeholders to achieve economic, societal, and environmental benefits. The use of standardized tools such as ADAPT further supports these efforts by ensuring uniform data handling across the agri-food chain, enabling more efficient and impactful agricultural practices (Kemp, 2024). In this context, initiatives in agriculture such as AgGateway, driving digital connectivity in global agriculture and related industries, exemplify the transformative potential of data sharing by advocating for a value-driven approach that benefits economic, societal, and environmental outcomes (Craker et al., 2018; Kemp, 2024). As these data sharing practices improve, they contribute to better decision making and increased efficiencies within the agrifood system.

Along with data sharing, connectivity, and interoperability also play a pivotal role in maximizing the value of data contributing to sustainable data stewardship in dairy farming. National databases play a crucial role in managing high-frequency quality dairy data, capturing real-time information on traits such as milk yield and feed efficiency. The transition of national dairy phenotypic and genomic databases from USDA to the Council on Dairy Cattle Breeding (**CDCB**) has improved sustainability by reducing reliance on federal funding (Weigel, 2024). This move not only supports continued data collection but also enables the development of new genetic evaluations for economically and environmentally impactful traits, such as feed efficiency and methane emissions (Weigel, 2024).

Maintaining the long-term sustainability of these datasets remains uncertain due to increasing fragmentation, as proprietary data often resides within separate agricultural tech companies, and high-frequency data are generated by multiple, incompatible systems. This lack of integration limits interoperability, which is essential for advancing the dairy sector. Recent efforts by the CDCB have improved the responsiveness of national databases to industry needs. However, it is important to note that most of the data in CDCB's system is not owned by CDCB itself, and access decisions remain with the original data providers or contributors. Contributors such as farmers, breed associations, and genetics companies have invested decades in developing these resources and are understandably cautious about sharing them without clear benefits, which can make integration more difficult. Effective integration will require strong, mutually beneficial partnerships between technology providers, data contributors, and national platforms. Additionally, persistent challenges such as rural internet connectivity hinder the upload and synchronization of high-frequency data streams into centralized systems. These issues complicate the use of cloud-based platforms and slow progress toward standardizing and integrating diverse data sources (Kumar et al., 2024).

Integrating external data from incompatible systems often requires workarounds that present technical difficulties. As more agricultural technologies and data sources emerge, the process requires rigorous validation and alignment of data formats, units, and collection methods to ensure consistency, accuracy, and reliability. Without such efforts, the quality of data used for decision making could be compromised (Frandsen, 2015; Weigel, 2024). These developments along with the need for centralized data repositories or collection pools, not only underscore the broad impact of national databases on genetic evaluation and farm management but also emphasize the importance of effective data utilization to improve agricultural operations (Hutchins and Hueth, 2023).

At the same time, the rise in digitalization is creating greater cybersecurity issues within the agriculture sector because as it becomes more vulnerable to cyber threats. In the last 5 yr several prominent dairy processing companies have encountered cyberattacks which caused plant closures and disrupted dairy shipments leading to huge financial setbacks. This highlights an immediate necessity to safeguard the dairy sector against cybercriminals. The concept of "cyber bio-security," which integrates protections against both digital and biological threats, is becoming increasingly relevant (Duncan et al., 2019; Carneiro, 2024). Addressing these challenges requires robust cybersecurity measures, including comprehensive incident response strategies and regular system checks (Richardson et al., 2019). Cyber bio-security is essential in the dairy sector to prevent shortages, financial losses, and public health risks by ensuring data integrity, product safety, and regulatory compliance (Duncan et al., 2019). Key strategies, such as risk assessment, education, controlled access, regular system updates, data protection, and collaboration, all aimed at safeguarding farms and business operations from cyber-bio attacks are essential. In this scenario, collaborative efforts, such as those advocated by the Virginia Tech Center for Advanced Innovation in Agriculture, emphasize a holistic approach to cyber bio-security to safeguard agricultural data and ensure food system integrity (Drape et al., 2021; Nobles et al., 2022).

To unlock the potential of data in various formats, research and industry must develop frameworks for handling diverse data, addressing data heterogeneity through definitions and ontology mapping, and promoting evidence-based decision making. Applying the findable, accessible, interoperable, and reusable (**FAIR**) principles ensure data are more accessible, fostering collaboration between research institutions and the farming industry (Top et al., 2022; Hostens, 2024). These principles provide data originators and custodians with guidelines to ensure progressive data availability and reusability. "Findable" ensures data can be located through unique identifiers and rich metadata, whereas "Accessible" emphasizes clear retrieval protocols. "Interoperable" promotes the use of common standards for seamless integration across platforms, and "Reusable" focuses on providing licensing and provenance information to facilitate further use (Wilkinson et al., 2016; Ali and Dahlhaus, 2022). Moreover, insisting on data integration across different platforms, outside manufacturer-specific ecosystems, could foster competition among providers and potentially lower costs for farmers. Thus, sustainable data stewardship in dairy farming requires a multifaceted approach that balances the need for rapid innovation while maintaining with ethical and governance concerns. As data utilization grows, new collaboration between stakeholders and robust cybersecurity measures will be critical to maintaining the integrity and efficiency of the agrifood system.

CROSS-SECTOR LESSONS: DAIRY AND HEALTHCARE

The dairy industry has undergone a significant transformation in data collection, processing, analysis, and utilization, paralleling advancements seen in the healthcare sector. Just as data integration in healthcare has enhanced patient care and diagnostics, dairy farming has leveraged data to improve herd management, animal welfare, and productivity. In both industries, effective data management is crucial for optimizing outcomes and operational efficiency. In healthcare, the data lifecycle encompasses several critical stages, including data collection from diverse sources such as electronic health records (**EHR**), wearable devices, and patient surveys, followed by data cleaning, organization, analysis, and visualization to derive actionable insights (Tachinardi, 2024). Similarly, in the dairy sector, data are collected from multiple sources such as AMS and farm management software, enabling more impactful data analysis. However, a key challenge lies in integrating data across multiple platforms. Farmers often face constraints in having to use sensors and robots from the same manufacturer to ensure compatibility, which not only limits efficiency but also increases costs. Healthcare has shown that technologies such as extract, transform, load processes and AI play a central role in addressing these challenges by streamlining data management and enabling advanced analytics (Lavanya et al., 2023). A relevant example from healthcare is the implementation of EHR systems, which use standardized data exchange formats such as Health Level 7 and The Fast Health Interoperability Resources (Saripalle et al., 2019), enabling different software systems to communicate effectively (Ajami, 2016). Whereas healthcare is more advanced in data integration, security, and governance, the dairy industry's progress in real-time monitoring and predictive analytics offers valuable insights that could inspire similar applications in healthcare. By adopting collaborative approaches and leveraging best practices from each other, both sectors can further advance their respective fields, ultimately improving outcomes for patients and livestock alike.

RECOMMENDATIONS FOR INDUSTRY STAKEHOLDERS

As the dairy industry is now shifting its attention toward improving productivity, efficiency and environmental impact using data-driven technologies, PDF and AI have shown promising technologies. To maximize these benefits, the following recommendations are offered to address the identified gaps in the critical areas of data governance, technology adoption, and sustainable data stewardship.

1. Enhancing Data Standardization, Governance, and Integration

Addressing data governance challenges such as privacy, standardization, and interdisciplinary collaboration is critical for enabling resilient and sustainable dairy practices while promoting sustainable data stewardship. The industry must develop robust governance frameworks that standardize data formats (e.g., machine-readable, open-source standards) and ensure privacy protections. Adopting FAIR principles and evolving international standards (e.g., IDF, ICAR) will improve data reliability and collaboration. This includes creating user-friendly API and phasing out noninteractive formats such as PDF to enable direct data access, analysis, and integration. Legal frameworks should clarify data sovereignty to protect producers' rights while enabling fair access to data resources. Centralized databases, blockchain for transparent supply chain transactions, and standardized formats will improve interoperability and decision making across the industry. Also, addressing data heterogeneity through ontology mapping and robust cyber bio-security protocols will safeguard food systems.

2. Advancing Technology Adoption

The PLF adoption remains uneven, with underused tools and innovation uncertainty hindering progress. To address this, stakeholders must demonstrate practical integration of technologies through rigorous testing to validate economic benefits and through educational programs for the intended users to ensure correct application. Dedicated funding programs and partnerships with tech companies can reduce adoption barriers.

3. Application of Disruptive Technologies

Emerging tools such as AI, digital twins, IoT sensors, and drones can revolutionize practices such as milk quality analysis, lameness detection, and pasture management. Investments in affordable yet high-performance computer vision systems for farm monitoring, blockchain for traceability, and edge computing for real-time health monitoring will enhance efficiency. Newer technologies such as natural language processing can aggregate insights from unstructured data sources, such as veterinary reports, farmer notes, and social media discussions about animal health, while wearable biometrics improve welfare tracking, thereby supporting comprehensive herd management. However, challenges such as data heterogeneity and algorithm updates must be addressed to optimize new tools. Prioritizing novel technologies with a clear return on investment will accelerate adoption.

4. Maximizing the Value of Data

Real-time analytics and predictive maintenance algorithms can optimize herd health, resource allocation, and policymaking. Quantifying the financial effect of data-driven decisions (e.g., feed optimization, breeding strategies) will incentivize adoption. Integrating computer science into agricultural and veterinary education will equip future professionals with data skills, maximizing the value of the implementation of new technologies.

5. Investing in Data Infrastructure and Analytics

Building centralized, cloud-based platforms with edge computing capabilities to enable real-time processing and scalable analytics can be achieved through a collaborative approach involving technology providers, dairy industry consortia, research institutions, and government agencies. Recent frameworks propose integrated architectures combining edge computing, cloud intelligence, and federated learning to enable real-time farm-level processing while preserving data privacy through embeddings and secure model sharing (Hostens et al., 2025). Such systems represent the future of dairy data management, where individual farms can benefit from localized, autonomous decision support while simultaneously contributing to industry-wide knowledge advancement through coordinated research and commercial farm networks. Looking ahead, these proposed ecosystems could incorporate autonomous AI agents that manage multimodal data streams, select appropriate analytical models, and deliver context-aware recommendations to farmers, all while maintaining essential human oversight for critical operational decisions. Financing such infrastructure will remain a key challenge, so equitable investment models, including public-private partnerships, cooperative funding mechanisms, government grants, and industry consortia contributions, can support fair cost-sharing among farmers, industry, and government stakeholders while enabling farmers to benefit from both the technology and the decision making. Integrating diverse data sources (farms, processors, academia) into a unified ecosystem, alongside advanced visualization tools (e.g., interactive dashboards), will enhance decision making. Additionally, upgrading frameworks to address big data challenges and investing in predictive digital tools will drive productivity and resource optimization.

6. Building Collaboration and Empowering Stakeholders

Interdisciplinary partnerships among academia, industry, and policymakers are essential to address technical, ethical, and operational challenges. Annual innovation forums, hackathons, and certification programs in PLF technologies will bridge knowledge gaps. Continuous training, tailored resources, and awareness campaigns will improve the capacity of farmers, veterinarians, and other industry players in the use and implementation of new technologies in the production process and can help overcome resistance to innovation, ensuring equitable access to advancements across farm sizes.

CONCLUSIONS

The transformation of dairy farming through data-driven approaches is both inevitable and essential for addressing the complex challenges of modern agriculture. In this regard, the growing need to innovate, cooperate, and continuously learn is crucial for effectively managing the opportunities and challenges that arise from data integration and technology adoption. Central to this transformation are recurring concerns around data standardization, accessibility, and security; issues that must be resolved to enable the seamless and ethical use of digital tools in dairy operations. Moreover, interdisciplinary cooperation among academia, producers, and industry stakeholders is key to navigating the evolving landscape of dairy farming. In addition, the effective implementation of disruptive technologies such as AI and ML, coupled with robust data governance and sustainable stewardship, is vital for supporting more informed, real-time on-farm decision making. By improving data infrastructure, integrating educational programs, and promoting transparent data practices, the dairy industry will be better positioned to respond to modern challenges and move toward a more efficient and sustainable future. Thus, from enhancing data governance and infrastructure to embracing disruptive technologies and sustainable stewardship, this review highlights critical areas that require focused attention and development. Given these insights, it may be beneficial for industry stakeholders to act on these recommendations and adopt forward-thinking, innovative approaches to ensure long-term resilience and success in the dairy sector.

NOTES

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Nonstandard abbreviations used: ADAPT = Ag Data Application Programming Toolkit; AHM = automated health monitoring; AI = artificial intelligence; AMS = automated milking system; API = application programming interfaces; CDCB = Council on Dairy Cattle Breeding; EHR = electronic health record; FAIR = findable, accessible, interoperable, and reusable; FT-MIR = Fourier transform mid-infrared; ICAR = International Committee for Animal Recording; IDF = International Dairy Federation; IOFC = income over feed costs; IoT = Internet of Things; MIR = mid-infrared spectroscopy; ML = machine learning; PDF = precision dairy farming; PLF = precision livestock farming; PLS = partial least squares; RFI = residual feed intake; RFID = radio frequency identification.

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