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Robotic Milking Systems: A Review

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Annotation: In dairy farming, robotic milking systems (RMS) replace manual labor with automatized, data-driven methods. This review focuses on the technological advancement, benefits, challenges, and future development of RMS in relation to milk production, animal welfare, and farm efficiency. RMS enables precision livestock management by integrating sensors, AI, and real-time analytics. This enables proactive health tracking and tailored cow management. The improved milk quality, more frequent milking, and lower labor costs are among the main advantages. Machine learning and system integration are needed to maximize sustainability and scalability. However, there are barriers to adoption, such as a high initial investment cost, technical complexity, and the need for skilled maintenance. RMS is ready to revolutionize how milk is produced as the dairy industry embraces Industry 4.0 by balancing environmental and ethical concerns with productivity.

Keywords: Cow welfare, Dairy farming, Environment, New system & Sensors.

1. Introduction

Robotic milking systems (RMS), or automatic milking systems (AMS), represent a fundamental shift in dairy farming, moving from traditional, labor-intensive milking parlors to automated, data-rich milk harvesting [1]. The way milk is produced has been revolutionized by these advancements [2]. In the beginning, only the mechanical efficiency of machines was prioritized while the automation of cleaning was ignored [3]. This evolution is driven by broad industry trends: the expansion of dairy farm sizes, a growing emphasis on labor savings, and increased focus on animal welfare [4, 5].

RMS generates vast volumes of data on milk yield, composition, and individual cow health, enabling a new paradigm of data-driven farm management known as precision livestock farming (PLF) [6]. This digitalization allows for the control of nutrient balance, performance monitoring, and health status evaluation tailored to an animal's physiological needs [7]. By integrating advanced data analysis capabilities, RMS empowers producers to make informed decisions based on real-time farm performance, significantly impacting productivity, animal welfare, and environmental sustainability [8].

This review will explore the components, benefits, and challenges of RMS, its impact on cattle welfare and behavior, its economic implications, and its role in promoting sustainable and data-driven dairy farming.

2. Literature Review

2.1. RMS Components and Operation

At its core, an RMS automates the multi-stage milking process, which includes teat cleaning, attachment of milking cups, milk extraction, and post-milking teat disinfection [9]. A typical system consists of a robotic arm equipped with sensors and actuators, a central control unit, and milk collection and storage components.

The robotic arm and its integrated sensors are responsible for identifying the teats, attaching the milking unit, tracking milk flow, and detaching the unit once milking is complete [10]. Advanced sensors monitor movement and vital signs to identify potential health issues [11]. Online sensors, often located outside the main milk flow, automatically analyze milk samples at regular intervals to monitor quality and composition [12].

This integration of sensors and data analytics enables the continuous monitoring of milk yield, quality, and cow health [13], forming a data pipeline that is central to RMS operation (Figure 1). The system's ability to extract real-time data from various sources, including the milker itself and wearable sensors, allows for the measurement of key parameters such as feeding frequency, intake, and time spent at feeding troughs [14, 15].

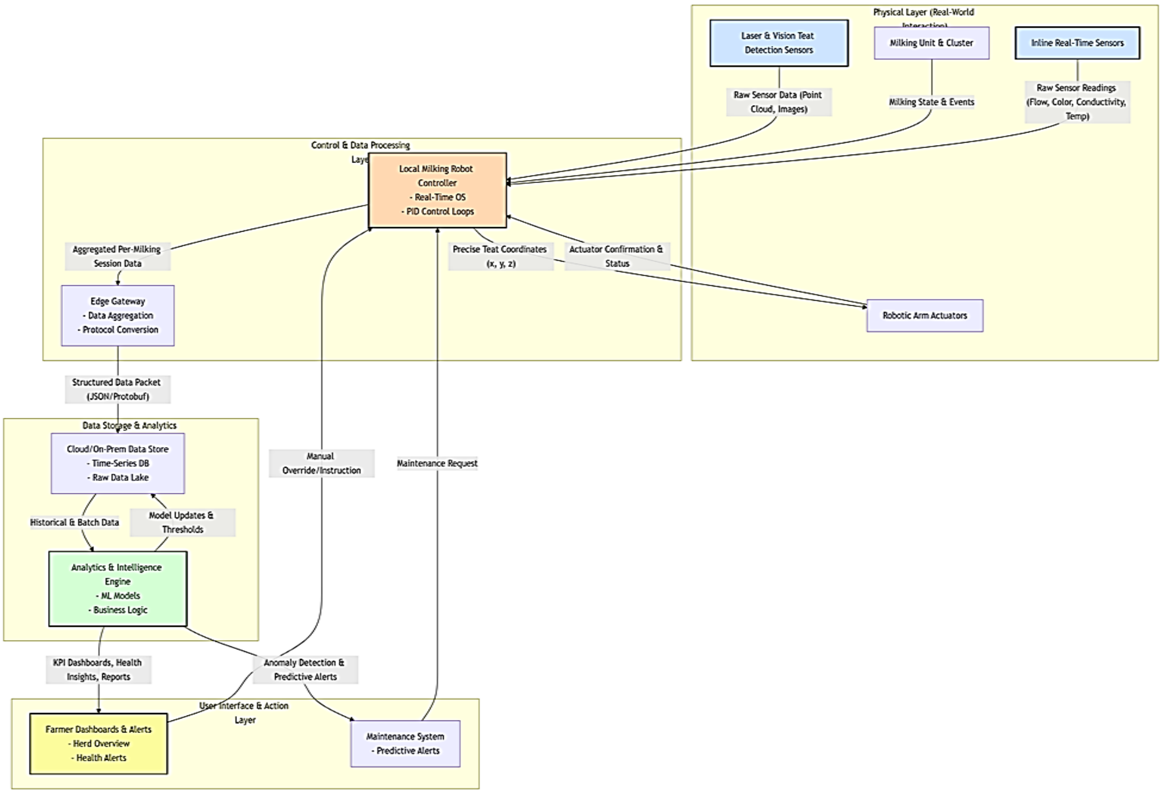

Figure 1: Schematic: Robotic Milking System (RMS) Data Flow Architecture

The development of the Canadian dairy industry from a traditional production model to a sustainable, data-driven one is represented in Figure 2. It presents the graphic case that using technology is the way to get past "policy and economic issues" and "pressure from international trade agreements." The industry can measure and lessen its environmental impact while simultaneously increasing productivity and economic resilience through AI-enhanced benchmarking, which will secure its success in a cutthroat and environmentally conscious global marketplace [16].

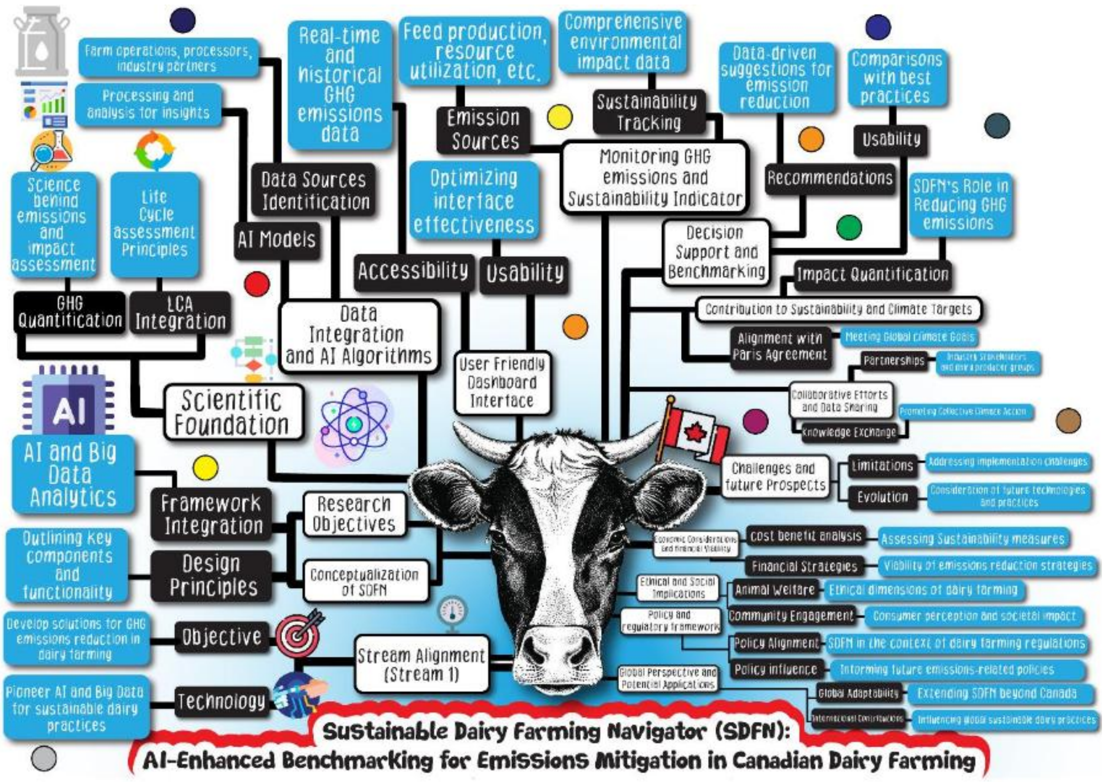

Figure 2. AI-Enhanced Benchmarking for Emissions in Canadian Dairy Farming [16].

2.2. Cow Traffic and Barn Design

The successful operation of an RMS relies on voluntary cow traffic, where cows choose to be milked according to their own needs and desires [17]. This voluntary access reduces stress and improves their overall quality of life. Barn design must facilitate this flow, with layouts typically falling into two categories: free traffic and guided traffic systems.

The choice between free and guided traffic, along with the potential need for fetching cows that do not present themselves for milking voluntarily, is a critical management consideration. The optimal system design and setup depend on several factors, including herd size, existing farm layout, and the farmer's specific management goals [12].

2.3. Performance vs. Conventional Milking

RMS offers several documented performance advantages over conventional milking. Because cows can be milked at any time, they are typically milked more frequently, which can increase individual milk yield and improve overall udder health [18].

A primary benefit is improved milk quality, achieved through consistent automated processes and real-time monitoring [19]. Regarding animal health, predictive analytics can be used for early detection of conditions like mastitis and lameness [20]. Studies also indicate improvements in teat condition due to standardized cleaning and attachment procedures.

However, for large herds, managing and controlling animals within an RMS environment can present challenges that may negatively affect health, reproductive performance, and farm income if not managed correctly [21]. The system's efficiency is also measured by box time (the time a cow spends in the milking station), which must be optimized for throughput.

2.4 Animal Welfare and Behavior

A significant welfare benefit of RMS is the reduction of stress by allowing cows to set their own milking schedule, reducing the need for human intervention and herding [17]. This change promotes more natural visit patterns and behaviors.

Continuous monitoring via sensors allows for proactive management of welfare issues. For instance, changes in movement data can indicate the onset of lameness, enabling early intervention [22]. The intersection of lameness and milking behavior is a critical area of study, as mobility issues can affect a cow's willingness to voluntarily present for milking. The overall impact on stress levels is generally positive, contingent on proper system management and barn design that minimizes competition and discomfort.

2.5. Labor and Economics

A primary driver of RMS adoption is labor substitution. By automating repetitive tasks, RMS reduces the physical burden on workers, particularly in large dairies, and decreases labor expenses, freeing up time for general farm management [23, 24].

The economic analysis, however, reveals a significant barrier: high initial investment costs (CAPEX) can be prohibitive for some farmers, especially those with smaller operations or limited access to capital [21]. The operational costs (OPEX) are also influenced by the need for specialized technical expertise for maintenance and repair.

The economic viability hinges on achieving a low annual milking cost per cow by efficiently utilizing labor to offset the capital investments [25]. Payback periods and return on investment are sensitive to variables such as local labor costs, herd size, and milk price. Larger herds can often distribute the high fixed costs more effectively, improving economic resilience.

2.6. Data and Analytics in RMS

RMS is a cornerstone of "Dairy 4.0," leveraging technologies like the Internet of Things (IoT), big data, and artificial intelligence (AI) to transform the industry [26]. The system functions as a data hub, enabling sensor fusion from various sources (e.g., milking, feeding, activity monitors) to create a holistic view of each animal [14].

Machine learning (ML) models are increasingly applied for anomaly detection (e.g., identifying deviations in milk composition that signal health issues) and predictive maintenance (e.g., forecasting mechanical failures before they occur) [20, 21]. The integration of AI-enhanced benchmarking, as explored in the Canadian context, can help measure and reduce environmental impact while boosting productivity [16]. Models like Adaptive Boosting (AdaBoost) and Random Forest have shown high accuracy in predicting complex outcomes like dairy emissions, demonstrating the power of these tools (Table 1) [15]. The combination of AI, ML, and automation significantly optimizes farming operations (Figure 3) [27].

A significant challenge in this domain is the lack of standardization and infrastructure barriers that prevent seamless data integration and analysis across the dairy sector [28].

Table 1: Predicting Dairy Emissions Using Machine Learning Models [15].

Model Name	**Description**	**Relevance to Dairy Emissions**	**Key Features**
Adaptive Boosting (AdaBoost)	An ensemble learning method that adjusts the weights of observations to focus on problematic instances. It builds a strong classifier by combining multiple weak classifiers.	Best performing model in the study, with 80% of predictions having a relative error below 12%. Highly accurate for dairy emissions predictions.	- Sequential learning: Focuses on errors of the previous learner. - Weight adjustment: Increases weights of misclassified observations. - Combines weak learners: Uses a weighted sum for final decision.
Random Forest	An ensemble learning method constructing multiple decision trees during training. Outputs the class that is the mode (classification) or mean prediction (regression) of the trees.	Outperforms several models like GammaGLM and k-NN. Robust against overfitting and provides a holistic view of feature importances.	- Bagging: Uses bootstrapped datasets for each tree. Feature randomness: Considers a random subset of features at each split. Aggregation: Combines predictions from all trees.
Linear Regression	A linear approach to model the relationship between a dependent variable and one or more independent variables.	Used as a benchmark in the study. Provides a baseline and is interpretable.	- Linearity: Assumes a linear relationship between predictors and response. - Coefficients: Indicates importance of each predictor.
Another benchmark Gamma A type of generalized linear model in the study. General model where the response Suitable for modeling Linear Models variable follows a Gamma positive continuous (Gamma distribution. variables, like GLM) emissions.			- Link function: Connects the linear predictor to the mean of the distribution function. - Flexibility: Can model different types of distributional data.
k-Nearest Neighbors (kNN)	Common baseline for A non-parametric, evaluating model supervised machine learning performance. Intuitive algorithm that classifies data but might not be as based on how its neighbors efficient on large are classified. datasets.		- Distance metric: Often uses Euclidean distance. Non-parametric: No assumptions about the functional form.

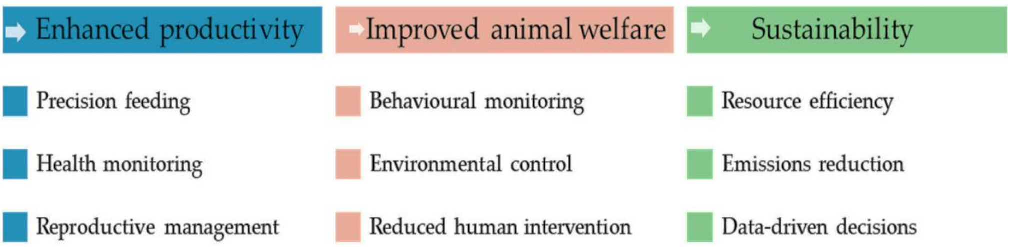

Figure 3. Shows the benefits of combining automation, machine learning (ML), and artificial intelligence (AI) to optimize different facets of farming operations [27].

2.7. Environmental Sustainability

RMS contributes to environmental sustainability primarily through increased efficiency and precision. The automated systems are designed to optimize resource use, leading to reductions in energy and water consumption compared to conventional parlors [26].

The precise application of detergents and teat dips minimizes chemical usage [9]. Furthermore, by improving overall herd health and productivity, RMS can help reduce the greenhouse gas emissions intensity per unit of milk produced. The ability to monitor and benchmark emissions through data analytics provides a pathway for the dairy industry to meet growing consumer demand for sustainable practices and reduce its ecological footprint [16, 29].

2.8. Adoption Barriers and Future Directions

Despite its advantages, RMS faces several adoption barriers. The high initial investment cost and technical complexity are the most significant hurdles [21]. The need for skilled maintenance and continuous monitoring requires a shift in farmer expertise from manual labor to data interpretation and technical management [22]. A lack of trust in data sharing and concerns about data privacy can also impede the wider adoption of these digital technologies [30].

Future trends will likely focus on advancements in sensor technology, data analysis, and system integration. Enhanced sensors will allow for even finer tracking of milk quality and cow health [31]. Integration with other farm management systems (e.g., automated feeding, manure handling) will create fully optimized, coordinated barn environments. The ultimate goal is the development of more robust and flexible robotic systems that pave the way for fully autonomous dairy farms [32].

2.9. Limitations of This Review

This review employed a broad literature search using Web of Science, Scopus, and Google Scholar databases to identify relevant studies on RMS, using terms such as “cow welfare,” “robotic milking systems,” and “precision dairy farming.” The focus was on peer-reviewed articles, conference papers, and industry reports from the last decade to capture the latest trends [26].

While the goal was a comprehensive synthesis, a formal meta-analysis was not feasible due to the heterogeneity of the available studies in terms of methodology, metrics reported, and regional context. The findings were aggregated to provide an overview of the current state of knowledge. Furthermore, the review primarily reflects technological and economic perspectives from developed dairy industries, which may not fully translate to all global contexts.

2.10 Future Work

It would be possible to significantly enhance the efficiency of the dairy industry by applying inexpensive domestic technologies [33]. Future trends in robotic milking systems will likely focus on further advancements and innovations in sensor technology, data analysis, and system integration.

Thanks to better sensors, it will be possible to track system performance and milk quality. Data analytics will be increasingly important to identify irregularities, anticipate problems, and optimise the milking schedule [31]. The integration with other farm management systems like feeding and herd health monitoring will further enhance the overall effectiveness and productivity of dairy operations. Widespread use of robotics and flexible robotic lines in the dairy industry should become a basis for the automation of technological processes [32].

Big data, machine learning, sensors and other digital technologies can improve sustainability and animal welfare in husbandry [34, 35]. In order for the novel technologies to be successfully integrated into farms, extensive training of farm workers is required so they can operate relevant equipment and interpret data [22]. Finally, it is crucial to address the lack of standardization and infrastructure barriers preventing data integration and analysis in the dairy sector to support milk yield [28, 36].

Motivated by Industry 4.0 By enhancing milk production and dairy product processing, "Dairy 4.0" technologies like robotics, artificial intelligence, the Internet of Things, and big data are continually transforming the dairy industry [26].

To enhance productivity and promptly respond to machine failures, the dairy sector is increasingly implementing IoT sensor technology for real-time monitoring [21].

Additionally, the dairy industry is under pressure from consumers’ desire for sustainability, necessitating innovations and regulatory measures to meet this demand [29].

By improving efficiency and accuracy in environmental management, the incorporation of Industry 4. Automation, data analysis, and IoT (Internet of Things) are some of the 4.0 technologies that are reshaping agribusinesses [37]. In light of the global quest for sustainability and responsible resource use, this technological convergence makes it easier to move toward economically and environmentally sound agricultural practices [38, 39].

3. Materials and Methods

This section describes the methodological framework employed for reviewing the body of existing literature on robotic milking systems. The following subheadings describe the research strategy, selection criteria, and method of data analysis employed in this study. To ensure that the latest technological trends and implementations in RMS were considered, the study focuses on peer-reviewed journal articles, conference papers, and industry reports published within the last ten years [26]. The goal was to find the relevant studies on the technological and operational, economic, and animal welfare aspects of robotic milking technologies. By integrating data from these sources, a thorough understanding of the RMS landscape was obtained, thereby providing a comprehensive insight into its intricate impacts on the dairy industry. In order to assist researchers, dairy farmers, and policymakers in making well-informed decisions, the study’s findings are synthesised to provide insights into trends and challenges in RMS usage. To ensure a high standard of evidence, the methodological strategies employed by the reviewed literature were scrutinized to evaluate the validity and robustness of the reported findings. Selection criteria focused on empirical studies assessing the performance of RMS, effects on animal health, labour efficiency, and economic viability. This meticulous selection process facilitated the identification of high-quality studies that directly addressed the review's objectives, thus enhancing the reliability and scholarly rigor of the synthesis

4. Results and Discussion

4.1. Results

Robotic milking systems offer a unique opportunity to upgrade dairy farms in terms of productivity, efficiency, and animal welfare [40]. In livestock farming, intelligent systemization (i.e., real-time monitoring, machine learning, and Internet of Things) is applied to improve animal health and maximize resource utilization for sustainable practice. Some of the process’s benefits include enhancing process safety, reducing pollution, saving energy, improving product quality, and increasing production efficiency.

More and more people see digital transformation in agriculture as the way to tackle several societal issues, such as feeding the growing world population, reducing farming's ecological footprint, and increasing food products' safety by improving traceability [41].

Digital agriculture enhances the understanding of the interactions between components of agricultural production systems by simultaneously considering human health, social, environmental, and sustainability aspects [42].

These technologies encompass precise planning, sensors for animal health and welfare, drones and satellites for monitoring, and cloud data management. Food security and ecological stewardship are being advanced by agriculture's increased efficiency, sustainability, and resilience thanks to the technological convergence brought about by digital transformation. [43, 44, 45, 46].

The digital transformation of agriculture is considered key to enabling these transitions, which are interconnected and synergistic, contributing to the industry's sustainability [47, 48]. Policymakers, industry stakeholders, and researchers can benefit from this study's detailed analysis of digitalization in agriculture and its implications on sustainable crop production and food security [43].

Due to the anticipated increased food production with fewer inputs, digital technologies in agriculture are often regarded as a possible solution to world hunger and malnutrition [49].

By enhancing the use of resources and crop monitoring, precision agriculture, remote sensing, and data analytics promote environmental sustainability as well as economic profitability [50].

However, the widespread application of digital tools in agriculture poses social, ethical, and environmental concerns [51]. Careful consideration and proactive strategies are necessary to address the need for digital literacy and infrastructure, potential job displacement, data privacy issues, and the environmental impact of technology manufacturing and disposal [52].

Additionally, farming processes are being automated and improved due to the application of innovative technologies such as artificial intelligence, robotics, and the Internet of Things [53]. This entails activities related to planting, harvesting, and livestock management [54].

4.2. Discussion

To successfully implement and improve dairy production, farmers need to be well conversant with the modern techniques of dairy farming, as shown in the discussion on robotic milking systems [55]. To ensure the successful adoption of these technologies, it is vital to address concerns about the digital divide and ensure that all farmers have access to necessary tools and training [56]. The need for smart farming and modern agriculture, which requires farmers to be trained on how to analyze and interpret data and use digital tools in decision-making, is an example of the knowledge necessity [57].

Farmers need to be willing to share their data with other stakeholders, such as agribusinesses, for digital farming technologies to be widely adopted. However, lack of trust can impede data sharing [30]. It is essential to apply the responsible innovation approach to consider ethical issues smart farming poses. These include effects on labor, the well-being of animals, data safety, and privacy.

To increase the sustainability and efficiency of agricultural production, Agriculture 4.0 uses robotics, artificial intelligence, and the Internet of Things to automate processes [58]. Sustainable development is closely linked to the quality of life and well-being of farmers, urban-rural relationships, and the standard of living [59].

AI, IoT, drones, and renewable energy are employed in agriculture to build an automated real-time system supporting ethical and sustainable farming methods [60]. In order for farmers to optimize operations and access product markets, Agriculture 4. 0 needs digital platforms/tools and decision-making knowledge networks.

To ensure that all individuals can benefit from technology developments, converting to Agriculture 4.0 necessitates tackling issues like infrastructure constraints, gaps in digital literacy, and data privacy concerns.

Conclusions

This review has synthesized the current body of knowledge on Robotic Milking Systems (RMS), delineating their profound impact on the paradigm of modern dairy production. The analysis confirms that RMS represents a cornerstone of the Industry 4.0-driven transition to "Dairy 4.0," fundamentally shifting operations from labor-intensive routines to a data-centric, precision livestock farming (PLF) model. By integrating advanced sensors, artificial intelligence, and real-time analytics, RMS facilitates proactive herd management, leading to tangible improvements in milk yield, milk quality, and individual animal welfare through reduced stress and more natural milking schedules.

The adoption of this technology, however, is not without significant challenges. The high capital expenditure, technical complexity, and requisite shift in farmer expertise from manual labor to data interpretation and technical management present considerable barriers to widespread implementation, particularly for smaller operations. Furthermore, the full potential of RMS is contingent upon overcoming infrastructural and standardization hurdles that currently impede seamless data integration and analysis across the sector.

Looking forward, the future trajectory of RMS will be shaped by advancements in sensor fidelity, machine learning algorithms for predictive health and maintenance, and deeper integration with complementary systems such as automated feeding and manure management. To fully harness the benefits of RMS, future efforts must focus on developing more cost-effective solutions, establishing robust data standards, and providing comprehensive training for the next generation of dairy farmers. Ultimately, by balancing productivity gains with enhanced animal welfare and reduced environmental impact, RMS is poised to play a pivotal role in creating a more sustainable, efficient, and ethically responsible global dairy industry (26, 61, 62, 63, 64 and 65).

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