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Smart dairy cattle farming: current tools, technologies, and future (Literature review)

Yousfi Maha [1, 2] and M'sadak Youssef [1]

maha.yousfi@wur.nl

1: University of Sousse, Higher Institute of Agronomic Sciences of Chott Mariem, P.O. Box No. 47, Sousse 4042, Tunisia
2: Wageningen University and Research, Agricultural Biosystem Engineering Group, Radix Droevendaalsesteeg, Building 107, 6708 PB Wageningen, Netherlands

Abstract- Since the 2000s, smart dairy cattle farming has experienced significant evolution. This development is driven by the availability of new technologies in microelectronics, computing, telecommunications, and nanotechnology, along with farmers' need for technological support to improve productivity, efficiency, and profitability. Smart farming enables continuous and real-time monitoring of animals and herd management. This article provides a concise review of the main research concerning technological advancements and innovative equipment introduced in dairy farms. It places special emphasis on the concepts of innovation and digital technologies, the types of sensors and data collected, and the integration of automation and robotics. Connected farming presents substantial opportunities. Various applications are reviewed including automated reproductive management, milking robots, and feeding robots. Currently, precision livestock farming tools offer clear benefits in terms of time savings and improved working conditions. However, these advantages have yet to be quantified using typical methods that assess the environmental, economic, and social sustainability of dairy cattle production. Further research is needed to evaluate the overall impact and sustainability of precision livestock farming.

Keywords: *D*airy cattle; precision livestock farming; digital technologies; automation; robotics; connectivity.

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Introduction

The dairy industry plays a significant role in global agriculture, employment, and economic development. Global milk production reached 950 million tons in 2023, presenting 1.3% increase from the previous year (FAO, 2023). With the global population projected to reach nearly 10 billion by 2050 (Willett et al., 2019), and dairy demand expected to rise by 4.9% in volume and 5.2% in value between 2019 and 2024 (FAO, 2021), dairy production is anticipated to grow by over 50% by 2050 (FAO, 2019) to meet these increasing needs. This underscores the importance of sustainable and high-quality production methods.

The digital revolution has influenced various sectors, including agriculture, leading to the rise of Precision Livestock Farming (PLF) which is a concept distinct from the broader field of Smart Farming. PLF includes advanced computing, sensor technology, and data-driven decision-making to enhance livestock management (Bao & Xie, 2022). The integration of Information and Communication Technologies (ICT) in PLF has significantly improved the collection and analysis of farm data, optimizing decision-making processes and facilitating early health intervention, reproductive management, feeding optimization and positive welfare (Gracia et al., 2020). Machine learning applications further enhance automation, ensuring greater efficiency, safety, and traceability in dairy production (Faverdin et al., 2020). These advancements contribute not only to improved productivity but also to reducing the environmental footprint and promoting animal welfare through real-time health and behavioral monitoring (Buller et al., 2020).

The historical development of PLF reflects a steady progression from mechanization to digitalization. While PLF as a concept was formally established in Great Britain in 1995 and later expanded in Belgium, its roots trace back to earlier work in automating livestock management (Mueret et al., 2013). The introduction of milking robots in the 1990s revolutionized dairy farming by enabling precise, individualized monitoring of systems to build the foundation for further sensor-based technologies in herd management. Over time, PLF evolved into a modular system where farmers could select and integrate specific technologies according to their needs, economic conditions, and farming strategies (Batte & Arnholt, 2023). The success of PLF today depends not only on technical advancements but also on the collaboration among farmers, technology providers, researchers, and agricultural advisors to ensure effective implementation and continuous improvement (Banhazi & Harmers, 2018).

Despite the advantages of smart dairy farming technologies, which improve productivity and animal welfare, their adoption faces challenges due to economic and infrastructural disparities. While developed countries benefit from advanced ICT infrastructure, in regions with limited access to technology, implementing PLF can be difficult, yet it remains crucial for advancing dairy production sustainably (Allain et al., 2015). Digital Agriculture emerged in the mid-2010s, employing advanced data sciences and technologies across all agricultural scales, seen as a means to enhance agricultural evolution and benefit farmers, consumers, and societies at large (Bellon-Maurel et al., 2022). PLF uses sophisticated technology to optimize dairy farming by monitoring and analyzing farm operations, ultimately improving animal health and productivity. Integrating digital technologies in PLF enhances efficiency and ensures sustainable farming practices, although widespread adoption remains a challenge.

This literature review examines the current tools and technologies in smart dairy farming, their potential to enhance productivity, sustainability, and animal welfare, as well as the challenges and perspectives of their implementation.

Precision livestock farming and digital tools used in dairy cattle farming

Information and Communication Technologies (ICT) have significantly advanced sensor technology, communications, and data processing, strengthening Precision Livestock Farming (PLF). PLF (Figure 1), distinct from the broader "Smart Farming" which encompasses all agricultural domains, utilizes advanced computing to enhance livestock management. According to Bao and Xie (2022), these digital technologies streamline the collection and analysis of data from sensors, databases, and monitoring systems, thereby improving decision-making processes.

García et al. (2020) found that these technologies provide farmers with timely and precise data on animal health, behavior, and performance, facilitating early health intervention, reproductive management, and feeding optimization. Machine learning applications in PLF enhance data processing, supporting operational automation while improving safety and traceability (Faverdin et al., 2020).

Digital tools in cattle farming improve productivity, reduce environmental impact, and promote animal welfare by enabling detailed monitoring of livestock conditions (Buller et al., 2020). Integrating these digital technologies involves systematically collecting data, which is then fed into information systems designed to optimize farm management and operations. Effective use of this data transforms it into actionable insights, advancing farm management practices and promoting efficiency and profitability (Banhazi and Black, 2009; Banhazi et al., 2012). The use of sensors and Information Technology in livestock management supports farmers in decision-making and reduces the physical demands of farm operations, thereby streamlining management processes and enhancing productivity (Hostiou et al., 2014). This comprehensive integration of technology in livestock farming not only improves immediate farm management but also paves the way for continuous improvement and sustainable practices within the agriculture industry.

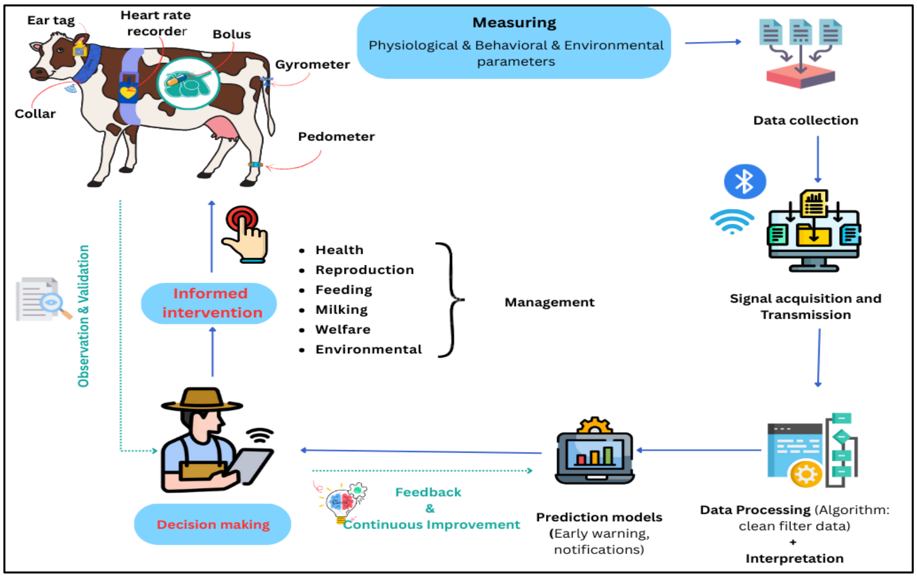

Figure 1. Illustration of the Precision Livestock Farming Workflow in Dairy Cattle

Milking robots represent a major advancement in the automation of dairy cattle farming. They do more than just mechanize the milking process; these sophisticated systems also provide precise and individualized management for each animal, including health monitoring and milk production optimization. By facilitating individual identification and continuous tracking, milking robots serves as a central pillar of Precision Livestock Farming.

Since the mid-2000s, the availability of sensors to assist in herd management has been increasing steadily. However, navigating the wide array of devices can be challenging (François, 2014). Today, a broader range of devices and measurements is becoming increasingly important in dairy cattle farming.

A wide range of sensors is available for various purposes in dairy farming. These sensors are used to identify animals, detect calving and estrus, monitor health disorders, and adjust feeding regimes. The Aspexit platform offers a Directory of Digital Tools used in agriculture, including livestock farming (Nicolas, 2022a). This Directory lists over 1,500 tools already referenced, dedicated to agricultural production, originating from more than 800 different French and European companies. In partnership with the Livestock Institute, Aspexit has integrated its database of sensors and robots in farming to enrich this.

In the field of livestock farming, sensors play a crucial role by providing valuable data that can be used in two main ways, defining two major categories of application:

- **Decision Support Tools**: These devices provide information that helps farmers make informed decisions about their herd management. The data collected enable trend analysis, anomaly detection, and optimization of farming conditions to enhance animal health and productivity.
- **Automated Systems**: In this category, sensors are integrated into systems that automatically control equipment or processes based on the data received. These systems manage mechanisms such as ventilation, milking, or feeding systems without direct human intervention.

According to Nicolas (2022), sensors in farming serve various functions that improve efficiency and precision in livestock management. They can activate or control an automated system ensuring that farm operations run smoothly with minimal human intervention. Furthermore, sensors automate measurements that could be performed manually (milk meter, food intake weighing). In addition, they can measure parameters that are not detectable by the human eye or are difficult to measure manually (ruminal temperature, milk composition, cow activity, etc.).

Based on diverse technologies, these tools can measure various parameters. Physiological measurements focus on the animal itself (milk production, food consumption, body temperature). Biological parameters assess the animal's products (milk composition, physico-chemical characteristics of milk, etc.). Morphological assessments include Body condition score, measurements, and weight. Additionally Behavioral monitoring captures data on movement, activity, feeding behavior, and rumination. Integrating these sensor-based technologies offers precise monitoring of the livestock and improve the management of dairy cattle.

Digital technologies applied to dairy cattle farming

Digital technologies are radically transforming various aspects of dairy cattle farming. They enable more efficient resource management, improve genetic selection techniques, provide precise monitoring of herds, facilitate assisted reproduction, and enable early detection of health issues. These technologies offer considerable opportunities to increase sustainability, efficiency, and profitability on farms, while also enhancing the well-being of cows.

Genetic improvement

Genetic improvement in dairy cattle farming has seen significant progress due to the adoption of advanced digital technologies and precision breeding methods. Two principal tools in this field are Marker-Assisted Selection (MAS) and genomic selection. MAS allows for the identification of genetic markers linked to specific traits using high-throughput genotyping technologies that generate extensive genomic datasets. This technology provides fast and inexpensive sequencing of large populations. The datasets are processed using bioinformatics tools, based on sophisticated algorithms to detect genetic variations associated with desirable phenotypic traits. Machine learning (ML) and deep learning models, such as Random Forest (RF), Support Vector Machine (SVM), and Deep Neutral Genomic Prediction (DNNGP) (Chafai et al., 2023), refine genomic predictions by capturing complex genetic interactions and thus improve selection accuracy (Hayes et al., 2007). Furthermore, MAS offers user-friendly toolkits and visualization tools that make it easy for breeders to conduct genomic analyses and interpret results without requiring advanced programming expertise. The integration of multi-omics approaches combines genomic, phenotypic, and environmental data, to give a clear picture of trait heritability and performance. To manage these vast datasets, cloud computing, and big data platforms facilitate real-time storage, processing, and retrieval of genetic information. Moreover, automation and high-throughput phenotyping technologies, including digital imaging, sensor-based monitoring, and robotic systems, allow precise measurement of phenotypic traits, enhancing marker-trait associations(Chafai et al., 2023).

These markers act as indicators to determine the presence of these traits in animals. This method enables breeders to select animals based on their genetic potential for characteristics such as milk production, milk quality, disease resistance, and fertility. The application of these assisted selection techniques, supported by digital technologies contributes to more efficient resource management. By identifying the highest-performing animals and reducing inbreeding within the herd these methods have effectively identified and selected the best animals for milk production (Pszczola et al., 2011). It can achieve up to 38% higher genetic gains for traits like milk production when combined with pedigree data (Meuwissen, 2003).

Digital technologies and Precision Livestock Farming (PLF) have revolutionized the selection of dairy performance. Sensor based systems, such as RFID tags and automated milking technologies using robots, continuously monitor milk yield and composition (fat, protein), and health indicators like somatic cell counts. In addition, computer vision systems assess behavior and traits associated to health and welfare (Schaeffer, 2006; De Roos et al., 2008). The collected data is then integrated into breeding program to identify the highest-performing animals. Furthermore, these technologies allow the exploitation of genetic data to predict the future dairy performance of animals.

Advancements in high-throughput genotyping, such as SNP microarray and sequencing technologies, have further accelerated genomic selection (GS) by analysis of large scale genomic data. With this breeders can apply machine learning (ML) models, deep neural networks and gradient boosting to optimize genomic breeding values (GEBVs) and improve selection for complex traits such as feed efficiency and fertility (Hayes et al., 2007; Pszczola et al., 2011).

Single-step GBLUP (Genomic Best Linear Unbiased Prediction) incorporates pedigree, genomic, and phenotypic data to refine predictions for milk production and longevity, whereas multi-omics approaches integrates metabolomic and proteomic profiles to enhance disease resistance selection. This capability allows for the selection of disease-resistant animals, reducing the prevalence of health issues, and contributing to the overall sustainability of the herd (Haile-Mariam et al., 2008).

Dairy cattle reproduction management

Detecting estrus in dairy cows in important for optimizing reproduction management, particularly to synchronize artificial inseminations, maximizing conception rates and reducing the intervals between calvings. Traditional methods rely on the observation of behavioral changes such as increased activity, such as the number of steps taken, the flehmen response, sniffing of the vulva of other cows, chin resting on the backs of peers, licking, and rubbing against peers (Roelofs et al., 2010).

To enhance accuracy and efficiency, various PLF technologies have been developed to automate estrus detection, primarily by monitoring movement patterns and activity changes (Table 1).

Table 1. Technologies developed for automated estrus detection based behavioral and physiological Indicators

Technologies	Function	References
Pedometers	Cow's limb mounted devices that count steps over time. Accuracy may be affected by lameness and breeding conditions.	Roelofs et al. (2010).
Accelerometers	Attached to the neck or limb to track 3D movement, number of steps and the duration of posture. Data is transmitted to the farmer at regular intervals wirelessly. The heat detection rates generally exceed 80%.	Alègre (2016) Allain et al. (2012a)
Thermo-boluses	Farmers use thermo-boluses to track cows body temperature, which slightly increases during estrus. These systems are more effective but more expensive than pedometers. Therefore, performance and costs must be considered when choosing the most suitable heat detection tool.	Allain et al., 2012a
HeatWatch 2® (CowChips):	Uses a pressure-sensitive radio transmitter on sacrum to detect mounting behavior lasting over 2 seconds. Detecting heat rates (<50% to >85%) are influenced by breed, flooring type and housing conditions. False alerts may occur from automatic brushes.	Roelofs et al. (2010); Saint-Dizier and Chastant-Maillard (2012); Chastant-Maillard and Saint-Dizier, (2016).
Video Surveillance Systems	Infrared cameras record all estrus behavior day and night, with a 82% heat detection rate. These systems are suitable only for indoor use. Image resolution may hinder cow identification.	Saint-Dizier and Chastant-Maillard (2012); (Hetreau et al., 2010)
Herd Navigator™:	Analyses progesterone in milk to detect estrus and reproductive anomalies with a 95% heat detection rate a 94% specificity. Also detects abnormal progesterone profiles, pregnancies and abortions and ketosis via beta-hydroxybutyrates (BHB) concentration in milk.	Asmussen, (2010); Saint-Dizier and Chastant-Maillard, (2012); Chastant-Maillard and Saint-Dizier, (2016).
AI-Endoscopy Integration for Heat Detection in Cows	Eye Breed combines AI and endoscopy for precise heat detection and insemination support. This smartphone-compatible device with an onboard camera enables real-time monitoring via the cow's genital apparatus (Figure 2).	(He et al., 2022)

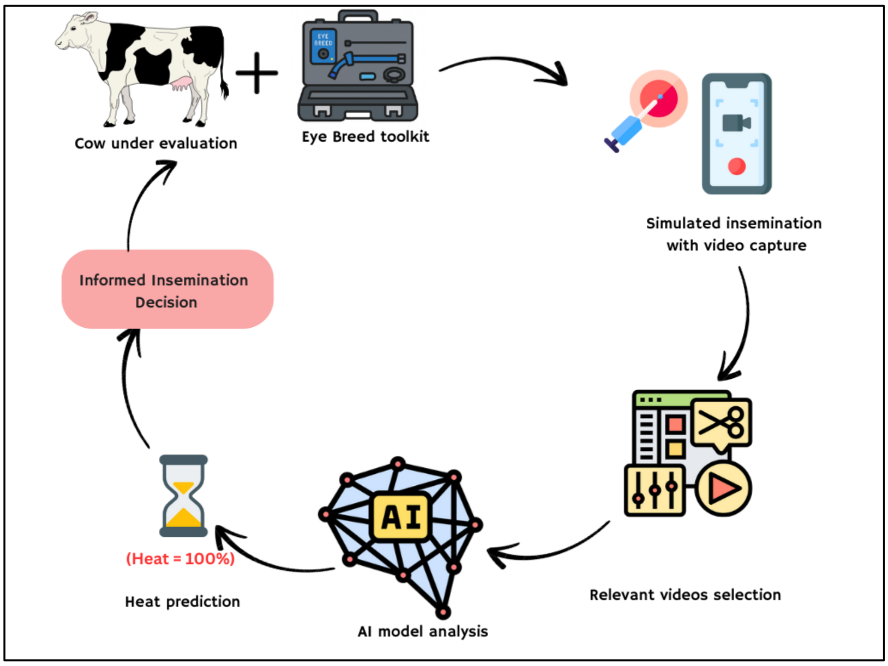

Figure 2. An overview of cow heat detection system using Eye Breed technology

Eye Breed quickly analyzes heat states using AI models that employ deep learning, specifically convolutional neural networks, to assess conditions in under 20 seconds (He et al., 2022). This technology not only enhances the accuracy of insemination timings but also positions Eye Breed as both a detector and an insemination implement, thereby streamlining reproductive management Allain et al. (2020).

Automated detection of calving in dairy cattle farming aims to optimize the use of the farmer's time and reduce the physical strain of labor by enabling them to anticipate and track calving events. Various systems have been developed to meet this need (Table 2).

Table 2. Evaluation of Calving Detection Technologies: Applications, Benefits, and Drawbacks

Technology	Function	Strengths	Limitations
Pedometer	Detects increased leg activity prior to calving	-High sensitivity and specificity (Disenhaus et al., 2010) -Early alerts to farmer	-Requires extra antennas -No data on labor stage or calf expulsion -Continuous monitoring still needed (Riaboff, 2020)
Tail-Mounted Accelerometer	Monitors tail lifting duration and activity level	-Simple -Low-cost -Sends alerts during prolonged tail lifting (Alègre, 2016)	-Possible time gap between alert and birth -Limited validation across conditions (Ouellet, 2015)
Pressure sensor	Detects abdominal and uterine contractions	-Non-invasive -Provides voice or light alerts based on contraction timing	-Difficult to install -Effectiveness varies -Needs further validation (Riaboff, 2020)

Overall, calving detection in dairy cattle benefits from various technologies such as pedometers and accelerometers, which measure cow activity to predict calving. However, these systems have limitations in accuracy and reliability, with detection rates often varying from 60% to 85%. Factors such as housing type and cow behavior can influence the outcomes. Research is needed to refine these tools and reduce false alarms, aiming to offer more precise and reliable methods for reproductive management (Sylvie Chastant, 2015).

Dairy production management

Milking Robot

The installation of a milking robot is part of a much broader process, ranging from feeding the animals to milk collection (Béguin et al., 2010). According to Bony and Pomiès (2002), although marketed robots have different operating systems, they all share several key components, including automatic identification, a milking booth, a teat cleaning system, a teat location system, a robotic arm, a milking system, a milk refrigeration and storage system, and a control station. Béguin et al. (2010) outline four types of management systems with different impacts on building layout and equipment level:

- In a free flow system, cows have free access to all stations in the building, including milking, feeding, and resting areas. The system is simple, easily adaptable in existing buildings, less costly due to fewer equipment needs, and less stressful for animals. However, it allows less optimized use of the robot, has a more difficult startup, and involves more challenging animal management (heifers, rejected cows, etc.).
- A guided flow system, with two guidance systems, one free controlled and the other pre-selection, organizes cow movement into a structured circuit following a specific order of resting, milking, and feeding. It allows easier startup and the possibility to combine with grazing. However, some cows may wait a long time in the waiting area, it can be more stressful for animals, and cleaning of the waiting area is required.
- A selective flow system limits access to the robot to only those cows that need to be milked, while a reverse selective flow system prioritizes feeding over milking, thereby optimizing the efficiency of milking time. These systems allow management of a high number of cows per stall and offer the possibility to combine with grazing. However, they are more costly, require more precise settings, and cleaning of the waiting area is required (Béguin et al., 2010)

In a robotic milking system, performance indicators vary depending on the type of flow. In free flow, the number of milkings and refusals are counted with a goal of four passages per cow per day. In forced flow, this target is five. In controlled free flow, the indicator is the number of times cows pass the smart gate (goal: six to eight). Finally, in the pre-selection system, the target remains the same (Journel, sd.).

The milking robot offers numerous advantages for farmers, meeting their expectations in terms of optimizing work time and reducing labor intensity. In addition to milking, the robot analyzes performance by recording various parameters and alerts the farmer to cows that require special monitoring in cases of heat or illness (Yousfi and M'Sadak, 2022). It thus becomes a valuable partner for the farmer.

A robotic stall allows for the milking of 60 to 65 cows under optimal conditions. However, in predominantly free-stall French farms, one stall is needed for approximately 50 cows. Only farms with sufficient investment capacity, typically those with more than one hundred dairy cows, can afford this system (Veysset et al., 2001).

Automated Optimization of milk Quantity and Quality

Many dairy farms are equipped with milk meters to precisely measure the production of their cows. While monthly dairy monitoring was once customary, milk meters have been widely adopted, with 10% of farms equipped, according to a 2014 survey (Allain et al., 2015). Additionally, 13% of farms use milking robots, which have apparently become more common in recent years. Although production disturbances do not allow for the precise identification of underlying problems, they serve as good indicators of issues or deviations. New technologies have quickly found their place on farms, and they also provide new information that was not traditionally included in dairy farming practices (Faverdin et al., 2020).

The integration of Near-Infrared Spectroscopy (NIRS) in dairy operations allows for more effective management of dairy production. Using this tool, farmers can obtain instant information on milk composition, facilitating real-time decision-making regarding feeding, health, and reproduction of dairy cows (Evangelista et al., 2021). While NIRS technology is quick and easy to apply for evaluating milk quality, some issues have been reported, such as spectral distortions caused by the scattering of fat globules. By applying Principal Component Analysis to the near-infrared spectra, researchers have been able to assign specific wavelengths to fat, protein, and lactose, and to discriminate between samples (Mehrotra, 2000). A recent study by de la Roza-Delgado et al. (2017) on the use of portable NIRS instruments for *in situ* monitoring of cow milk composition indicators confirmed accurate calibration for fats and proteins but less precise calibration for non-fat solids (SNF). Meanwhile, Llano Suárez et al. (2018) explored the use of a portable NIRS instrument to monitor *in-situ* fatty acid profile of cow's milk. They found that this tool accurately measures variations in milk fatty acids, thus providing an opportunity to enhance nutritional monitoring of herds and optimize milk quality.

Feeding management

In animal feed management, a variety of tools ranging from automatic concentrate dispensers to feeding robots are sometimes integrated with milking robots. These techniques are used in both free-stall and grazing systems to optimize feeding efficiency and ensure proper nutrition for the animals.

Automatic Dispensers

Automated dispensing systems enable individualized feeding of cows based on their specific nutritional needs. They use sensors to measure each cow's food intake and automatically adjust the ration accordingly (Ferard et al., 2013). These systems reduce food competition among cows, ensuring that each animal receives its fair share of feed. The data collected, such as feed consumption and feeding behaviors, are used to adjust individual rations and optimize cow nutrition (Grothmann et al., 2010). Additionally, these systems quickly detect variations in food consumption, which can be an early indicator of health problems or changes in cow behavior (Grothmann et al., 2010). Farmers can receive alerts or automated reports on cows that exhibit abnormal feeding behaviors.

Feeding Robots

According to Bruel et al. (2020), feeding dairy herds involves several tasks that can be robotized. However, the robotization of feeding is not applicable in all situations and systems. Its cost-effectiveness is linked to significant time spent inside buildings, making it less suited for farms that prioritize grazing. Furthermore, like all robots, their usage saturation is also a key to profitability, and as such, it concerns mainly larger to very large farms. Nevertheless, some suppliers offer less complex options for medium-sized farms. The benefits and limitations of feeding robots are summarized in figure 3.

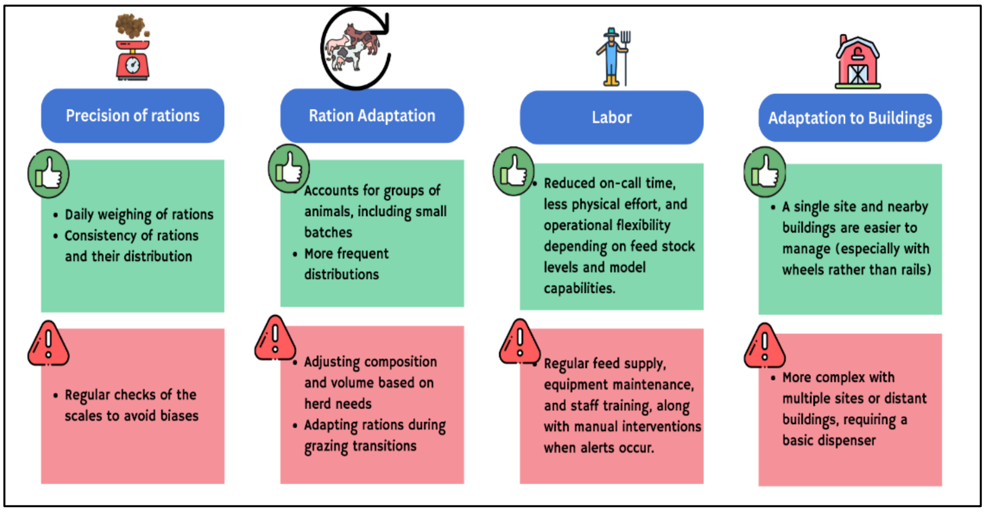

Figure 3. Characteristics of Robotic Feeding in Dairy Cattle: Advantages and Limitations

Measurement of Individual Food Intake

Managing dietary rations based on individual cow data is a key practice of Precision Livestock Farming (PLF) to optimize nutrition and cow health. A proposed solution involves using a camera equipped with depth recognition (Bezen et al., 2020): The camera is placed above the feeder at a height of 140 cm. To train the neural network to estimate the weight of the food before and after the cow has eaten, researchers take pictures of the feeder with different amounts of food and under various lighting conditions. A motion sensor is also installed to trigger the camera when the cow approaches the feeder and after the cow has left.

Optimization of Feeding Schedules

Optimizing feeding schedules is a key component of Precision Livestock Farming (PLF). This strategy determines the optimal times to feed cows, tailored to their individual needs and production goals. Automated feed distribution technologies facilitate scheduling personalized feeding times for each cow, based on precise measurements of their actual feeding behaviors and needs, provided by behavioral sensors. This approach not only improves operational efficiency but also contributes to tangible improvements in dairy production and animal welfare. By allowing farmers to precisely meet the nutritional needs of each cow, optimizing feeding schedules helps maximize farm performance while supporting sustainable agricultural practices (Shafiullah et al., 2019).

New Technologies to Facilitate Pasture Management

Recent advancements in measurement and communication technologies (smartphones and tablets equipped with Bluetooth, Wi-Fi, and GPS) open up new prospects for effective and precise management. In the medium term, remote sensing and the availability of high-resolution images, whether obtained by satellite or drone, offer new possibilities (Pottier et al., 2017).

Automation of Biomass Measurement

The height of the grass in pastures can be used to estimate available biomass and to derive most of the indicators that assist in managing grazing (Seuret et al., 2014). The electronic GrassHopper® herbometer (True North Technologies) is equipped with an integrated Global Positioning System (GPS) that allows for the geolocation of grass height measurements. The measurements and associated geographical coordinates are automatically transferred to a smartphone application via Bluetooth, enabling the farmer to visualize the measurements taken on their farm's paddocks in real-time (French et al., 2015).

The use of satellites is also expanding, as demonstrated by the product Pastures from Space®, which provides weekly information on grass growth at both regional and paddock scales by using both satellite-obtained biomass measurements and climatic data (Hills et al., 2016).

Recent technological advancements, particularly in terms of communication and information transfer, their commercial development, and accessibility, largely meet the expectations of farmers, not only in terms of labor but also in providing technical support (Pottier et al., 2017).

Virtual Fences

Virtual fences represent a major innovation in Precision Livestock Farming (PLF), especially regarding grazing. These modern systems do not use physical barriers to delineate the spaces allotted to animals. Instead, they employ advanced technologies to create invisible boundaries (Umstatter, 2011). Initially, virtual fence systems relied on the emission and reception of electromagnetic signals between a central device and a receiver worn by the animal (Brose, 1990). Over time, these technologies have evolved, particularly with the integration of GPS into devices worn by the animals, a significant advancement introduced by Marsh in 1999. These GPS devices allow for more precise control of animal movements: if an animal crosses the predefined boundaries, it receives a sound or electric stimulus to guide it back to the authorized area (Riaboff et al., 2020).

The eShepherd® system, marketed since 2016 by Agersens, is one of the first of its kind to be widely adopted. This system exemplifies the concept of pasture management via virtual fences, offering an efficient and less restrictive solution for farmers and animals. The operation of this system is detailed in Figure 4 below.

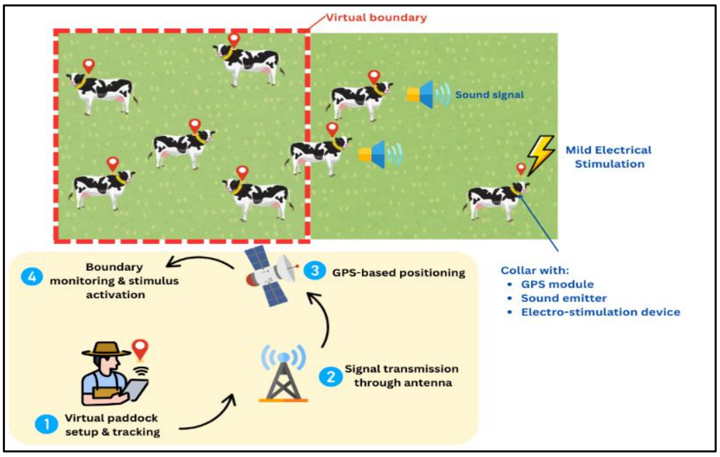

Figure 4. Principle of Virtual Fencing for Cattle

Health Management

Early Detection of Mastitis Assisted by AI Systems

In dairy cows, Ida® (Connecterra®, Netherlands) is one of the most used and advanced AI applications in Europe (Van Rossem, 2020). It uses a motion detector attached to a cow's neck to transmit its movements 24/7 to a program driven by algorithms for the early detection of pathologies, such as mastitis.
In addition to milking robots, several connected devices are available to quickly detect mastitis. The Online Cell Counter (OCC®) from DeLaval® is installed alongside the VMS® milking robot and counts the number of somatic cells from each cow (DeLaval, 2020). The Crystalab® from Fullwood® directly analyzes the content of fat, protein, and lactose in the milk collected by a milking robot to quickly detect the presence of mastitis, as well as potential ketosis or ruminal acidosis (Fullwood, 2020).

Monitoring Vital Signs of the Cow

Monitoring the vital signs of a cow is crucial for real-time assessment of the herd's health. A comprehensive system includes a body thermometer in the form of a bolus placed in the reticulum, an accelerometer, a GPS, and an environmental temperature and humidity sensor (Smith et al., 2006). This device can communicate with a base station via ZigBee. The data collected has shown that the recorded temperature is reliable, although water consumption by the cow causes a temporary drop in measured temperature. However, this feature also allows monitoring of the cow's drinking frequency. Furthermore, researchers have observed that a cow's heart rate is lower at night than during the day. Additionally, the respiratory rate can be monitored.

Monitoring Digestive System Parameters: Ruminal pH

Measuring ruminal pH is crucial for assessing the state of the digestive system and the digestion of food. A pH that is too low can lead to acidosis or sub-acidosis, while a pH that is too high can cause alkalosis. In both cases, digestion is disrupted, and the cow's milk production is compromised. However, continuously measuring the rumen pH is complex and requires the use of invasive methods such as the insertion of a trocar or, more permanently, the installation of a cannula. Despite the advancements in precision tools, the practical deployment on farms often faces hurdles such as high costs, complex integration with existing systems, and a lack of technical expertise among small to mid-sized farm operators.

Conclusion

The integration of digital technologies and artificial intelligence in dairy cattle farming is revolutionizing the industry, enhancing productivity while improving animal health and welfare. These innovations enable precise herd management, optimize nutrition, strengthen reproductive monitoring, and reduce the physical workload for farmers. As one of the most technologically advanced livestock sectors, dairy farming is leading in automation, with tools such as milking robots, automated feeders, and decision-support systems for detecting heat and calving.

Beyond daily operations, recent innovations in robotic milking and automated feeding pave the way for more integrated sensor systems that closely monitor animal welfare. Digital tools are also transforming pasture management through GPS collars, enabling precise traceability and optimized land use. However, despite their advantages, these technologies raise ethical and privacy concerns, particularly around data ownership and farmer autonomy. The cost of adoption can be expensive, especially for smaller farms, necessitating careful cost-benefit analyses and policies that ensure accessibility. Bridging the "digital divide" is crucial, particularly in regions where limited infrastructure restricts technological adoption.

As dairy farming moves toward a fully connected and data-driven future, training and demonstrations will be key to facilitating adoption. Networks like the Sm@rt Farming Network play an essential role in supporting farmers and promoting best practices. In Africa, digital agriculture offers a pathway for economic diversification and job creation, with growing research capabilities fostering technological innovation. However, ensuring equitable access to digital solutions requires investments in user-friendly technologies, tailored designs, and impact-driven research.

Ultimately, the digital transformation of dairy farming presents both opportunities and challenges. While it holds the potential to enhance sustainability and economic viability, its success depends on ethical governance, affordability, and equitable access to technology.

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