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Evolution and use of Precision Livestock Farming (PLF) technologies in dairy cattle herd-health management

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Abstract

This literature review discusses the development and expansion of Precision Livestock Farming (PLF) and the rapid development of sensor technologies in recent decades. It provides an overview of the practical application of these technologies on dairy cattle farms. It presents the main functional elements of PLF, discussing both commercially available sensors and those that are still under development and require further research. It also discusses in detail the most important application areas, such as the automated monitoring of animal health and reproductive parameters, while addressing the potential limitations of PLF.

Absztrakt

Ez az irodalmi áttekintés a Precíziós Állattartás (Precision Livestock Farming, PLF) kialakulását és terjeszkedését, illetve a szenzortechnológiák elmúlt évtizedekben bekövetkezett rohamos fejlődését tárgyalja. Áttekintést ad ezen techniológiák tejtermelő szarvasmarha-telepeken történő gyakorlati alkalmazásáról. Bemutatja a PLF fő funkcionális elemeit, megvitatva mind a kereskedelmi forgalomban kapható érzékelőket, mind azokat, amelyek még fejlesztés alatt állnak és további kutatásokat igényelnek. Emellett részletesen tárgyalja a legfontosabb alkalmazási területeket, mint például az automatizált állategészségügyi és reproduktiós paraméterek megfigyelését, miközben kitér a PLF lehetséges korlátaira is.

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Abbreviation	Meaning
PLF	Precision Livestock Farming
ICT	Information and Communication Technology
IoT	Internet of Things
IoE	Internet of Everything
MM	Mathematical modelling
PSM	Precision System Models
DLF	Digital Livestock Farming
M&S	Modelling and Simulation
DES	Discrete Event Simulation
CS	Continuous Simulation
ABM	Agent-based Modelling
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
SML	Supervised Machine Learning
UML	Unsupervised Machine Learning
RML	Reinforcement Machine Learning
RFID	Radio Frequency Identification
RIR	Retinal Image Recognition
SARA	Subacute Ruminal Acidosis
BCS	Body Condition Scoring
ToF	Time of Flight
CV	Computer Vision
R-CNN	Region-based Convolutional Network
ResNet	Residual Network
YOLO	You Only Look Once
RH	Relative Humidity
CO_2	Carbon dioxide
NH_3	Ammonia
H_2S	Hydrogen sulfide
WS	Wind speed
SE	Solar radiation
N	Nitrogen
NO_3^-	Nitrate
N_2O	Nitrous oxide
GHG	Greenhouse gas
CH_4	Methane
CP	Crude Protein
SCC	Somatic Cell Count

EC	Electrical Conductivity
IRT	Infrared Thermography
FLIR	Forward-looking infrared
OST	Ocular Surface Temperature
USST	Udder Skin Surface Temperature
VFA	Volatile Fatty Acids
CRA	Clinical Ruminal Acidosis
SRA	Subclinical Ruminal Acidosis
RF-CHO	Rapidly Fermentable Carbohydrates
HC	High Concentrate
SCFA	Short-chain Fatty Acid
LPS	Lipopolysaccharides
BHB	Beta-hydroxybutyrate
SCK	Subclinical Ketosis
FPR	Milk-Fat-to-Protein ratio
DA	Displaced Abomasum
RDA	Right Displaced Abomasum
LDA	Left Displaced Abomasum
TNZ	Thermo-neutral Zone
THI	Temperature-Humidity Index
RT	Rectal Temperature
VT	Vaginal Temperature
ST	Skin Temperature
CL	Corpus Luteum
LH	Luteinising Hormone
FSH	Follicle Stimulating Hormone
E_2	Oestradiol
GnRH	Gonadotropin Releasing Hormone
IMAS	In-line Milk Analysing Systems
TBST	Tail Base Skin Temperature
rTBST	Residual Tail Base Skin Temperature
Trr	Reticulo-rumen Temperature
AMS	Automated Milking Systems
PMR	Partly Mixed Ration
NPN	Non-protein Nitrogen
AFS	Automatic Feeding System
TMR	Total Mixed Ration
NIRS	Near-infrared Spectroscopy
DM	Dry Matter
AMF	Automated Milk Feeders

1 Introduction

The demand for animal-derived products is increasing progressively which in turn leads to a need for expansion within the scope of livestock breeding for higher output. As a result of this it gets more and more difficult for farmers to provide sufficient herd-health management, using only traditional management methods such as the farmers observation, experience, and judgment. Therefore, Precision Livestock Farming (PLF) has been introduced to modern livestock farms to provide farmers with information on individual animals, by using real-time monitoring several features as biological indicators in order to help them with management decisions. PLF has evolved progressively over the last few years, expanding from the electronic milk meter which was the first significant implementation of PLF to include oestrus detection based on the monitoring of behavioural changes or disease detection via monitoring of rumination activity [1]. The Integration of PLF primarily involves sensor-based technologies, either attached to or implanted inside the animals. This allows for the collection of animal-related data, which are subsequently gathered and analysed through specialised software's. The algorithm is capable of issuing alerts to farmers regarding critical situations which require actions to be taken, such as artificial insemination in heat or the treatment of physical disorders. Consequently PLF presents numerous opportunities for the dairy farming sector, including the improvement of the overall animal production efficiency [2]. However, the rapid implementation of these advanced technologies into livestock farming also brings forth potential threats that could directly or indirectly harm animals. A significant concern revolves around the risk of technical failures within the PLF systems, particularly in farms heavily reliant on these technologies. Other risk factors include the harmful effects that might be caused by the exposure, adaptation or wearing of hardware components, poor external validation leading to inaccurate predictions as well as decisions along with the under- or overreliance on the technology, potentially resulting in the loss of essential animal husbandry skills. It is crucial to acknowledge and confront these potential threats in order to optimise PLF systems for the enhancement of animal welfare [3].

Literature Review

The current PLF research integrates different research perspectives including animal science, agricultural engineering, computer science, environmental science, and veterinary medicine. The veterinary medicine perspective, which will be highlighted in this paper, focuses on the early detection, diagnosis and prevention of diseases [1].

This review examines PLF-related literatures to provide an overview of the developments of PLF in dairy cattle herd health management and the PLF tools used. It aims to provide information about the monitoring of different parameters and interpretation of data for reproductive management such as oestrus detection, pregnancy detection and detecting the onset of calving, as well as the early detection and prevention of major health disorders occurring in dairy cattle, highlighting the use of rumination- and eating-time monitoring.

2 The Evolution of Precision Livestock Farming (PLF) and link to other sciences

2.1 The Concept of PLF

PLF defines the continuous automatic real-time monitoring of individual animals' health status, production, reproduction and animal welfare, as well as the environmental impact, aiming to enhance management practices in farms. The Objective is to establish an early warning system for farmers, enabling immediate action to be taken when necessary. It is based on the hypothesis that animals will exhibit behavioural changes as an initial response to conditions that are less-than-ideal, and these first signs should be detected by PLF sensor technologies [4]. Through the use of sensors, PLF incorporates the concept of precision agriculture into livestock systems and combines a set of technologies to improve both productivity and animal welfare [1]. Thus, maintaining a good animal health and welfare status may ultimately provide the best product quality over the long term. Technological advancements have progressed to the point, where accurate and cost-effective tools are now at our disposal [5]. Sensors have the capability to collect raw data, which, through algorithms or software's, is transformed into physiological and behavioural parameters. These parameters serve as predictor variables, particularly in diagnostic models for predicting physiological and health status such as oestrus, calving events, or illness. However, its objective extends beyond optimising detection alarm performances, to acquire big data of the physiological and health status, as well [1]. Parturition is considered one of the most critical stages within the cow's reproductive cycle, bearing significance due to the occurrence of numerous diseases during this period. The dry period and the first three to four weeks are considered the periparturient period. Understanding the complex interrelationship between periparturient diseases is essential for maintaining good animal health status and the management of this phase holds sway over future reproductive efficiency and productivity [6].

2.2 Industrial Revolution

Throughout the twentieth and twenty-first centuries, significant developments, including four technological revolutions from Industry 1.0 to 4.0 have unfolded. Industry 1.0, spanning the eighteenth to nineteenth century was characterised solely by the industrial goods market (simple market) considering the product volume, witnessing a shift from slow and small-scale production to industrialisation. With Industry 2.0 during the 1980s, there has been a substantial surge in volume and variety of industrial goods, introducing meaningful advancements like motorised vehicles and electronical devices. From the 1980s to the present, the Industry 3.0 has left a lasting impact on the electronics industry marked by a significant transition from analogue to digital technologies. This era also witnessed changes in designs of electronic products, transitioning from integral to modular, consequently leading to reduced average product life cycles. Lastly in 2011 the term Industry 4.0 originated in Germany and has rapidly disseminated throughout the world. This emerging framework places emphasis on the automation of factory processes, the integration of the internet into industrial operations, and the widespread adoption of Information and Communication Technology (ICT) to develop intelligent devices, machines and systems. Industry 4.0 is the outcome of the fourth industrial revolution and is characterised as a progression towards fully automated and interconnected industrial production. The Internet of Things (IoT) compromises a network of interconnected devices, capable of sensing, communicating and interacting with external and internal environments through embedded technology. This capability enables the creation of a smart connected environment which has the potential to enhance multiple aspects of our daily activities. In 1999 the Term was invented to describe a framework utilising data exchange to facilitate the interaction between the physical world and computers as well as sensors. The true birth of the Internet of things, also referred to as the Internet of Everything (IoE) occurred almost a decade later. During this phase, the approach expanded its scope to assess not only objects but also individuals and even animals. In PLF the IoT allows farmers to monitor livestock by using several sensors which can track multiple animal variables, including temperature, heart rate, rumination, and many others. As the IoT and the IoE have undergone substantial expansion, there has been a noticeable increase in data volume. Big Data and Cloud computing play vital roles in processing and storing these vast quantities of data by utilising applications that analyse and differentiate between important and less important data and therefore assist to reach conclusions [7].

2.3 Modelling-based methods to support decision-making

2.3.1 Mathematical modelling (MM)

The definition of MM varies according to different literatures, but it essentially converts real-life observations and perceptions into virtual representation through mathematical equations or formulas. Following that, stress and sensitivity analyses, with the use of independent data, are employed to evaluate and validate the model's behaviour and predictive accuracy. Problems are addressed through mathematization and the application of models with the results subsequently evaluated and aligned to real life processes [8, 9]. Mathematical models can be classified according to various criteria, such as optimization, application, time representation, time continuity, calculation mode, nature or space. One common distinction is between optimization methods, such as linear versus non-linear programming. Models can also be categorized by their application, whether they are descriptive or elucidative, focusing on explanation, or predictive and prescriptive, aimed at forecasting and decision-making. Another classification involves time representation, distinguishing between static or steady-state models and dynamic ones. Time continuity further categorises models into discrete versus continuous. Additionally, models vary by their calculation mode, being either deterministic or stochastic, with the latter incorporating probabilistic elements. The nature of the models can be empirical, based on observed data, or mechanistic, theoretical, or rational, grounded in fundamental principles. Lastly, models can be classified by spatial considerations, as either homogeneous or heterogeneous in nature. Their appropriate use is mostly determined based on the degree of the problems or systems uncertainty. Essentially the intended use of the models, such as describing, explaining and predicting behaviour can partially pre-establish the classification [9]. Modelling-based methods are getting more and more integrated, therefore it is essential to contextualise different types of models in PLF systems to be able to achieve model harmony. Model harmony implies that models have been developed, tested afterwards, and implemented in such a way that it maximizes the effectiveness of precision technologies in addressing challenges and meeting objectives, while also fostering scientific critique, dialogue and continuous refinement. This ongoing refinement is crucial for advancing precision system models (PSMs) and supporting the wider adoption of precision technologies in livestock farming. As PLF technologies and industrial applications have evolved, digital livestock farming (DLF) has been developed, which enables improved PSM applications. While the aim of PLF is the maximisation of data collection to improve efficiency and productivity, DLS focuses on inferring real-time data with the utilisation of predictive data modelling, based on artificial intelligence and machine learning. Therefore, it enables predictive ore even prescriptive capabilities, instead of just reactive ones. Generally these models can be valuable tools for predicting the outcome of various management strategies related to production and reproduction, which can aid in more informed and effective decision-making within livestock management [10].

2.3.2 Modelling and Simulation (M&S)

Simulation modelling aids in the decision-making process by transforming real-world problems into a computer-based environment, allowing for the imitation of real-world processes and operations, in order to understand them better. Traditionally expert knowledge was used and converted into dynamic models, but more recently, real-time data or observational datasets are used, and combined with the needed parameters, to extract models and generate simulations. The most commonly used M&S paradigms include discrete-event simulations (DES), continuous simulations (CS), also known as dynamic systems, as well as agent-based modelling (ABM).

DES models a system's operation as a discrete sequence of events occurring at specific points in time, with each event marking a change of state within the system. Traditionally, DES models are generated based on data from existing or previously tested systems (i.e. historical data), which can be enhanced with experimental rules and mathematical algorithms to predict system behaviours in advance. This can be used for instance to model the spread of disease, by simulating the diseases behaviour and aiding in making the best decision to prevent it from spreading further [11].

In contrast to DES, which tracks events at specific time points, CS models systems where changes occur continuously and gradually, rather than distinct events [12]. This approach analyses information feedback, which deals with the dynamic structure and feedback mechanisms between quantitative and qualitative factors within complex systems, enabling the recognition and solving of system issues. Often causal loop diagrams are used to help visualise the structure and behaviour of systems and to analyse it qualitatively. For a more detailed quantitative analysis, the causal loop diagram is converted into a stock and flow diagram, whereby the stock is defined as any accumulating or depleting entity (i.e. feed intake, milk production, GHG emission) and the flow is termed as the rate of change within a stock.

ABM is the third type of simulation model, which is popular for studying dynamic movement behaviours of systems. In a dairy herd for example, individual cows can be defined as agents and tracked through their lifespan, residing at different management options, such as calf, heifer and adult/milking. The model can then be applied to estimate critical points for management decisions, like the optimal time for insemination. The main goals of simulation approaches are to enhance animal welfare, reduce GHG emissions and maximise profitability [11].

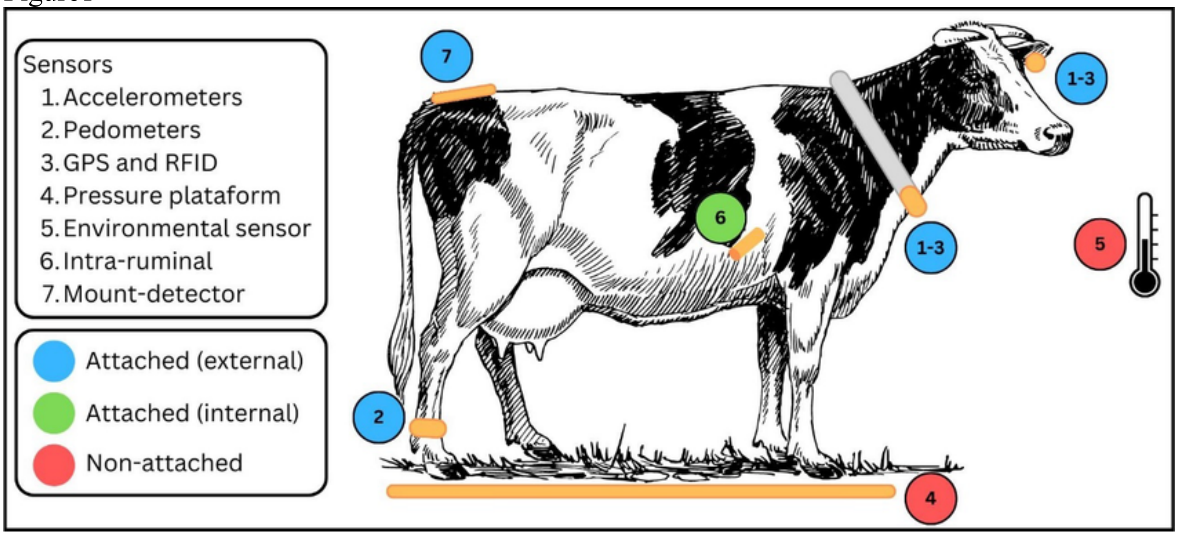
2.4 Artificial Intelligence and Machine learning

Artificial intelligence (AI) is defined as a field which combines computer science and large data sets, creating an intelligent system, which is able to perform tasks, typically requiring human intelligence [13]. AI has several subfields, such as machine learning (ML) and deep learning (DL), which enable automated decision-making, by solving complex problems without human supervision [14]. ML can be further divided into supervised, unsupervised and reinforced learning. In supervised machine learning (SML), the ML model uses datasets, which have already been labelled or classified by humans and learns to classify new datasets, based on these examples. Unsupervised machine learning (UML) on the other hand, uses unlabelled data, meaning the model has to find patterns and categorise the information by itself [15]. The third category, reinforcement machine learning (RML), can be defined as the active part of ML, where the model learns by interacting with its environment and receiving a feedback mechanism. In RML the agent makes decisions by exploring different actions in an environment and in turn receives feedback from the environment, which can be positive or negative, helping the agent to learn, which actions are beneficial, and which are not. Over time, the agent will develop a strategy or policy, guiding it to maximise long-term positive feedback [15, 16]. The use of AI and ML in animal production and reproduction management is not new, however, advancements in the recent years have significantly accelerated the development and application of AI in dairy farms management. AI technologies can address a range of critical tasks, such as monitoring animal health, optimizing milk production and enhancing reproductive management, as well as tracking animal behaviour, enabling the detection of early signs of illness and identifying environmental stressors. These innovations are potentially even more precise than humans, as they have the ability to process large amount of data in a quick and efficient manner, thereby supporting the sustainability and profitability of dairy operations [13].

3 Introduction of the main functional elements of PLF

Robots and sensors are used for the purpose of data collection and production. Subsequently, algorithms analyse this data to generate relevant information and send out alarms, aiding farmers in their decision-making process [2]. A sensor is described as a device capable of detecting events or measuring changes in physical properties, converting them into usable signals for further analysis [17]. They can be categorised into three broad categories according to their relative position to the animal. The first one being "At cow" sensors which may be attached to the cow, inserted into the reproductive tract, or even swallowed and deposited into the reticulorumen. The second category, termed "Near cow" does not involve direct attachment to the cow, yet these sensors facilitate real-time interactions by observing, listening, weighing, or interrogating the cow itself or its immediate environment. "From cow" is the third category which utilises products derived from the cow, such as milk or bodily tissues and fluids, for the collection and analysis of data [18].

Figure1



Overview of sensor types and their positioning [19]

Table 1.

References	Involved Technologies	Parameters	Application
[20]	RFID technology	Sensor Identification	Identification and Tracking
[21]	Facial recognition technology	Biometric features	Identification
[22]	Accelerometers	Identification, Activity, Rumination time, Eating time, Lying and Standing time	Oestrus detection, Early disease detection
[23]	Pedometers	Step count, Activity	Oestrus detection
[24]	Pressure plates	Gait, Load differences between individual legs	Lameness detection
[17]	Microphones	Rumination time, Vocalisation	Oestrus detection, Early Disease detection
[25]	Reticulo-ruminal boluses	Rumination time, pH, temperature	Rumen health monitoring
[24, 26]	Camera-based systems	Body contours, dimensions, BCS, behaviour	Oestrus detection, Lameness monitoring
[27]	Barn environment monitoring sensors	Environmental parameters	Barn environment monitoring
[28]	CH4 Sniffer	Exhaled methane	Monitoring of GHG
[29]	Emission sensors (e.g. GreenFeed)	Methane and Carbon Dioxide Emission	Monitoring of GHG

Overview of the main PLF tools and their functions

3.1 Radio Frequency Identification (RFID) Technology

Identification systems have evolved rapidly in the recent years, transitioning from traditional visual identification methods to the current automated systems utilising RFID technologies. These advancements have facilitated their implementation into automation of milking and feeding processes [30]. The RFID system compromises three primary components: the Transponder, Trans-receiver/Reader, and Software. Transponders, acting as ID tags, consist of an antenna and a silicon chip, which holds a 12-digit number for animal identification along with a 3-digit country code. These tags are attached to animals, as ear tags, boluses, collars, or microchips and can be either active or a passive device. While passive transponders are activated by the reader, active devices possess their own power source, allowing for longer distance signal reception by the reader. However, the lifespan of active transponders is shorter compared to passive ones. Trans-receivers or readers are devices capable of sending signals to tags, facilitating the transfer of information stored. There are two main types of readers: Fixed RFID Readers and Portable/Handheld Readers. Fixed readers are stationed at specific locations where the farmer wishes to obtain the identification of animals on a regular basis. In dairy cattle farms, they are commonly placed at the entry and exit points of the milking parlour to record data of each dairy cows milking cycle. Conversely, Portable Readers feature built in screens which display the RFID number of the animal, allowing for identification in the field. Lastly the Software enables the storage of individual cows' data into a database, where data can be entered manually or automatically through electric devices [20]. The utilisation of RFID technologies for animal identification and monitoring of milking cycles can improve the quality of the milk yield in many ways. By accurately determining the entering sequence into the milking parlour and distinguishing among different categories such as age, health status and treatment status of animals, the system facilitates targeted management interventions. This approach also effectively prevents overcrowding at the entrance, thereby reducing stress levels and enhancing overall animal welfare. Additionally controlled monitoring of the feeding process is enabled, allowing for the optimization of the amount of concentrated feed given during milking for each individual cow and therefore maximising nutritional efficiency [30].

3.2 Biometric identification using facial recognition technology

Biometric methods are commonly used to for human identification and have the potential to identify dairy cows, using facial recognition. Recent studies suggest that specific facial features and unique skin textures are crucial biometric characteristics which can be utilised for animal identification via face imaging [21]. However, digital facial recognition in livestock faces several challenges, particularly due to poor image quality or low illumination, which are common issues in barn environments where animals are constantly in motion. Addressing these challenges, necessitate multidisciplinary research which integrate computer vision technology and patter recognition systems to develop effective solutions. Traditional animal identification methods, including ear-tags, microchips or tattoos are often subject to limitations such as the possibility of duplication, fraud or manipulation. Even RFID systems face challenges such as damaging or losing the device altogether. These issues could potentially be resolved through the adoption of biometric identification technology. Biometric characteristics-based recognition systems can use different characteristics to identify animals such as face image, muzzle point image pattern, iris pattern and retinal vascular pattern [31]. Muzzle point image pattern is often compared to human fingerprints due to its minutiae details, making it a highly potential identification method [32]. The muzzle pattern is characterised by a dense texture of grooves or valleys, referred to as beads, and ridges which are river-like structures. These features form a uniform pattern distributed across the skin surface of the animal's nose (muzzle point). Additionally muzzle point images consist of various colour attributes, including white skin grooves and black convex sectors, with the sectors being encircled by grooves. Furthermore, retinal image recognition (RIR) systems use unique pattern of retinal vessels as a biometric identifier for livestock. Similarly, iris biometric-based focuses on recognising the discriminatory features of the iris such as crypts, corona, furrow and rings. For image capturing, a digital camera with 30-megapixel resolution, is used and the images transferred to the cattle recognition system, which preprocesses the images and classifies the extracted features. The biometric identification system then extracts the biometric features to identify and verify the animals. Overall, computer vision technology is a promising research field, offering new opportunities for identifying different species and individuals, especially if its applicability is further expanded [31].

3.3 Accelerometers and Pedometers

Accelerometers are electronical sensors capable of measuring accelerations, as the name implies, by converting physical changes into voltage signal outputs in waveform. They come in various types, each determined by the number of axes they can measure. The Uni-axial accelerometer (1-Axis accelerometer) can be utilised where measuring acceleration along a single axis is sufficient, for instance the combination with microphones to discern chewing activities in cattle [17, 22]. Two-axial accelerometers are able to measure accelerations in two directions perpendicular to each other i.e. left and right or up and down [22]. On the other hand, a Triaxial Accelerometer can measure accelerations among 3 axes (x, y, z), providing a more comprehensive insight into motion, acceleration, and orientation in a three-dimensional way when a broader understanding is required [17]. Acceleration increases along either a single or multiple axes as the animal moves, which then can be translated into certain behaviours [33]. They are predominantly used to measure cows' daily activities which include walking, lying down, standing up, eating, and ruminating. In order to monitor various activities like this, these sensors could be attached to different parts of the body and can provide a wide range of information about the animals behaviour and physiological status, as well as any alterations in patterns, especially when combined with other sensors [22, 34]. The most frequently used wearable wireless single or even multiple biosensor systems in dairy cattle usually are mounted on the cow's neck using a special collar. Initially the main use of the neck collar was identification of cows for individual measurements with the use of RFID technology, later it was extended with heat detection function and most recently with control and measurements of the individual feed intake and rumination [35]. Collars for the use of oestrus detection have been available since the early 1980s. Early models utilised basic mechanisms like rolling balls or mercury tilt switches to record head movements. These devices were initially costly until the advent of integrated circuits featuring tri-axial accelerometers in the 1900s. With the introduction of affordable tri-axial accelerometers, as well as digital sensor processor chips, the collar has evolved into a versatile tool capable of not only detecting oestrus but also location, lying behaviour, lameness detection and with audio data collection, ruminating and eating behaviour [36]. Leg tags commonly feature triaxial accelerometers to track the activity levels of animals, including lying and standing time as well as counting the number of steps, aiding the farmer in the lameness detection while also providing information about the oestrus [35]. Moreover, tri-axial accelerometers can be attached to the tail, as to predict the onset of calving. Increased tail-rising activity is observed up to 24 hours prior to the onset of calving, with a further increase occurring a few hours before [37]. Pedometers, on the other hand, are devices which are strapped onto the legs of cows to measure their step count. In their traditional form, they used to contain an electrical switch which opened or closed with every movement, thereby adding a step count with each activation of the switch. This total count is transmitted to a central base station via telemetry whenever the cow is within a range of a receiver unit. Given that activity levels tend to increase during oestrus, pedometers serve as a valuable aid in oestrus detection [36].

3.4 Pressure Plates and Load cells

The objective of pressure plates is to analyse the distribution of weight across legs as the animal walks through the pressure-sensitive equipment. A common approach to lameness detection involves the utilisation of ground reaction systems equipped with load cells, such as the commercially available StepMetrix (Bou-Matic, Wisconsin, USA), which was introduced to the market in 2008. These load cells measure the forces exerted on the ground as the cow walks, as well as the distribution of individual limbs while the cow is standing. Lameness can then be identified by observing significant variability in weight distribution or weight-bearing across the limbs [38–40].

Another approach for cow lameness detection includes the assessment of stride-related data, which can be measured using pressure sensor systems like Gaitwise (Gaitwise, ILVO, Merelbeke, Belgium). Studies have shown that stride length (measured in meters) and duration (measured in seconds) can be used as indicators for lameness detection [24, 41]. Although the Gaitwise system (Gaitwise, ILVO, Merelbeke, Belgium) is not yet commercially available, research has demonstrated its potential for early lameness detection, with sensitivity rates ranging from 76-90% and specificity between 86-100%, depending on the severity of lameness, as the system has shown to be more accurate when detecting more severe cases of lameness [38]. However, the Gaitwise system (Gaitwise, ILVO, Merelbeke, Belgium) has some drawbacks in comparison to other imaging-based systems, including the larger space required for installation and higher system costs [24].

3.5 Microphones

Microphones are commonly used to detect and quantify jaw movements in cattle by distinguishing different sound patterns. When sounds pass through the flexible diaphragm within the microphone, they induce vibrations, the intensity, and frequencies of which are proportional to the output electrical signal. This enables the acoustic monitoring of jaw movements, allowing the differentiation of these into biting or chewing and consequently the differentiation between grazing or ruminating behaviour. The three primary types of jaw movements monitored include chew, bite, and chew-bite. It can discern between the distinct ripping produced during biting, from the grinding sound characteristic of chewing. The chew-bite in turn compromises a combination of both sounds. Rumination jaw movements on the other hand are more quiet and regular and can be described as a cyclic process that starts with the regurgitation of a bolus, followed by mastication with semi-circular movements of the jar and ending with pause before the start of the next mastication bout. [17]

3.6 Reticulo-Ruminal Boluses

The reticulo-ruminal boluses are orally inserted and positioned within the reticulo-rumen, utilising the measurement of rumen parameters such as temperature and pH or even motion activity, such as rumination. Historically, the utilisation of rumen bolus sensors for measurements emerged after the 2000s through experimental studies. The prevailing trend entails sensor fusion, wherein multiple sensors concurrently measure various parameters at the same time, subsequently aggregated by a data-processing system, which may give statements regarding animal health [25, 35]. Tools for ruminal pH measurements compromise a pH probe, a processing unit for recording the pH signal, a converter to transform the pH signal into radiofrequency and a receiver. Ruminal pH may also be an indicator of subacute rumen acidosis (SARA). However, its essential to consider the location of the bolus. Studies have shown that pH in the reticulum is higher than in the rumen. Therefore, the threshold for pH in case of SARA must be adjusted accordingly. However, due to the short lifespan of pH sensors, they find predominant use in research applications. Additionally, temperature measurements can give insight on the animal's physiological status. A decrease in temperature correlates with eating and drinking events, while an increase indicates elevated body temperature. Consequently temperature changes in the rumen can be used for early oestrus detection or indications for inflammatory conditions [25].

3.7 Camera-based systems and AI enhanced computer vision technology

3.7.1 Cameras

Cameras have evolved rapidly since their invention back in the 1800s, making it a tool which is small, portable, easy to handle and quite cheap, considering that one camera is able to observe multiple animals or even the whole herd. They are classified as non-invasive sensors that can monitor various cattle behaviours when placed around the animals' most frequently visited locations [22]. Image processing techniques, featuring 2D or 3D cameras, can offer a different approach for lameness detection, typically through analysis of back posture. However, due to significant variations among cows, a nuanced approach is required. What may signal lameness in one cow could be considered normal gait in another. As such, cow posture must be analysed individually to establish a baseline for comparison with each cow's normal posture. Evaluating the behaviour of cows could also be essential for lameness detection, as alterations in movement patterns or a decline in activity levels may indicate painful conditions affecting the limbs or claws [24].

An emerging trend over the last years has been the adoption of automated body condition scoring employing single or multiple depth cameras. Body Condition Scoring (BCS) holds significant importance as it serves as an indirect estimation tool for assessing fat reserves in dairy cows. During early lactation, cows typically experience a negative energy balance leading to a loss in body condition, which should be gradually regained by mid-lactation. Therefore, the continuous and accurate assessment of BCS is necessary for optimal milk production [26].Traditionally BCS has relied on visual observation and palpation, focusing on key anatomical points, such as the spinous and transverse processes of the lumbar vertebrae, the paralumbar fossa, the tail head, the tuber coxae and the ischial tuberosities. Through visual and physical inspections, estimations are made regarding the quantity of subcutaneous fat and muscle tissue under the skin. In underweight cows, these regions appear more angular due to protruding bones, while in overweight cows, these anatomical points exhibit a more rounded appearance [26, 42]. Numerous scales have been developed for evaluating the body condition of cows, with the prevalent method in Europe being the 1 to 5 scale, featuring intervals of 0.5 and 0.2. However, manual BCS is notably time-consuming and requires a proficient evaluator. As a result, alternative approaches using digital images have been developed to improve the assessment of BCS [43]. The most widely used methods for automated BCS uses 3D vision, providing detailed visualisation of the cow's contours. Depending on the specific features to be analysed, cameras are typically positioned above the cow for a top-down view to capture important characteristics such as the spine curvature, hips and pins. Alternatively, cameras can also be placed side-on to the cow, which also enables the visualisation of the spinal curvature, as well as the leg swing and the hoof placement. Among the most effective cameras for this purpose are Time of Flight (ToF) Cameras, which offer their own light source and deliver accurate real-time measurements with the necessary precision. Moreover, the utilisation of algorithms incorporating artificial intelligence (AI) has emerged as a progressing trend aimed at enhancing the accuracy of automated BCS [42].

3.7.2 Computer-vision technology

Computer vision (CV) is a branch of AI, which enables machines to interpret and extract relevant information through images, whether they are static pictures or frames within a video sequence. In livestock production, the adaptation of CV technology, is on the rise, primarily due to its capacity to gather real-time, accurate data, in a non-invasive way [13].

CV uses DL methods for target recognition, which can be divided into two main categories based on the detection stages. Two-stage object detectors extract regions from an image, that are likely to contain targets during the first stage and then identifies and localises the specific targets within the regions during the second stage [44]. This approach used in models like R-CNN (Region-based Convolutional Network), Fast R-CNN, Faster R-CNN, ResNet (Residual Networks) and RetinaNet, typically offers high accuracy. However, due to the complex architecture of the detectors, they require significant computational load, resulting in higher hardware demands and longer processing times. Therefore this approach is mainly applied in animal science [44, 45].

On the other hand, single stage models, such as the YOLO (You Only Look Once) series, have already proven effective as real-time object detection models, by monitoring feeding and other animal behaviours, across a variety of species, including cattle [45]. The accuracy and speed at which the model works, is the reason why it has become so popular and also how it got its name. It standardizes an input image to a uniform size and divides it into multiple grids. Each grid predicts the target category based on the grid where the centre of the target object is located, with the final detection results generated by the last convolutional layer. The core innovation of YOLO is transforming object detection as a regression problem, where the entire image serves as the input to a neural network that directly outputs both the bounding box location and object category [46].

In contrast to models, Digital Twins are a replica of real-world objects in digital form, updated in real-time through a continuous flow of data. Unlike static models, they are synchronized with their physical counterparts, capturing changes and enabling detailed monitoring and analysis. Although Digital Twin technology is still in its early stages with the application in livestock sectors, it has shown great potential in enhancing animal welfare and improving production. Advanced AI-driven smart camera systems monitor animals and farm activities 24/7, converting visual data for farmers to view as actionable insights, accessible on mobile or desktop devices. With facial recognition techniques, these systems can assess animals' mental and emotional states by analysing features like ear posture and the visibility of eye whites. Other applications of Digital Twins in PLF, include the detection of oestrus, GPS monitoring of grazing animals, while simultaneously observing grazing behaviours and patterns and even to better understand the development of cows from calves to adults. Although it has to be noted that there are several limitations when it comes to Digital Twins as well, such as the expensive investment of switching to a new system, unknown risks that might come with its implementation and lack of evidence it can even improve performance and profits. However, Digital Twins show great potential in revolutionising various aspects of PLF by combining the real-time monitoring via multiple sensors, big data, AI and ML, resulting in more accurate predictions, as well as mitigating negative animal behaviours, tracking and preventing the spread of diseases, improving animal comfort and reducing the costs of losses [47].

3.8 Automated barn environment monitoring systems

Although data integration offers significant advantages in farm applications, numerous existing systems monitor only a limited set of indicators, providing only a partial view of an animal's condition. Furthermore, up to this point there are no commercially available systems, which integrate barn environment measurements with cow-based data, despite the crucial role the barn environment plays in cows' welfare. A significant challenge in implementing data integration is the need for a complex system architecture capable of managing diverse data types from various sources and unifying them for processing. IoT technologies can facilitate the integration of data from various diverse sensors, which measure air quality, barn climate, water use and temperature, litter moisture content and temperature and cow behaviour, in order to present a real-time overview of the overall barn conditions as well as the state of individual cows to the farmer. Leliveld et al. (2024) have developed a prototype for an automated barn environment monitoring system, which simultaneously monitors cow behaviour. This system, known as GALA system, is capable of performing measurements at multiple locations, collecting and processing the data and analysing it before presenting the results to the farmer. External measurements taken outside of the barn include ambient temperature, relative humidity (RH), wind direction and speed, as well as rainfall. Inside of the barn the system also monitors ambient temperature, RH and wind speed and direction as well as black globe temperature, light intensity, water use and temperature, litter humidity and temperature, gaseous compounds such as CO_2, NH_3, H_2S and sound pressure levels. Additionally, cow behaviour is monitored using accelerometers. The system compromises four key elements: sensors, nodes, gateways and a cloud-based backend. This prototype was developed to provide an open framework for research and its design allows for customisation and fine-tuning before its implementation as a management tool on commercial farms [27].

3.8.1 Thermal parameters

Air temperature and air humidity are essential parameters for assessing thermal comfort in animals, largely because they are easy to measure in the field. Sensible heat loss occurs as the temperature gradient transfers from the animal's body to the ambient temperature. Key variables for calculating this transfer includes dry bulb temperature, wet bulb temperature, dew point temperature and relative humidity (RH). Commercial devices, like the Tinytag Plus 2 logger (Hasting Data Loggers, NWS, AUS) can accurately measure these parameters, facilitating practical monitoring in livestock environments [48, 49].

Air velocity or wind speed (WS) measures air movement/speed in the environment and plays a crucial role in heat transfer through convection and evaporation. In ventilation systems, WS is typically recorded as an average value across sections of the facility. Although air velocity can be measured through farm buildings, monitoring is often focused near exhaust fans in mechanically ventilated spaces. However, these measurements, which can be recorded with anemometers or hot-wire anemometers, are primarily used for research purposes rather than in routine farm applications [48].

Solar radiation (SR) is the primary contributor to heat transfer by radiation, particularly in open spaces. Evaluating the effectiveness of shade structures typically involves comparing solar radiation levels in areas with and without shading. Direct measurement of SR is commonly done using pyranometers, like the CS320 solar radiation sensor (Campbell Scientific Inc. Logan, UT, the USA), which has been applied by researchers to accurately assess solar exposure in livestock environments [48, 50].

Black globe temperature is an environmental parameter that reflects the combined effects of ambient temperature, wind and solar radiation on cows. It's measured with a matte black copper sphere, typically 12.5-15cm in diameter, with an internal temperature sensor. Today, commercial weather stations are available that integrate black globe temperature alongside other thermal indicators, offering a comprehensive overview of environmental conditions affecting livestock comfort and health.

Currently, measuring thermal parameters at the level of individual animals remains challenging due to variability in behaviours and postures, such as standing or lying in different parts of a barn. This variability emphasizes the need for further research to develop dependable methods for direct, single-animal thermal monitoring in livestock environments [48].

3.9 Emission Control

There are numerous concerns relating to the emissions coming from livestock farming, particularly their harmful effects on our ecosystem, biodiversity, as well as the potential risk they pose to human health. Nitrogen (N) losses produced by livestock farming contribute to various forms of pollution including Nitrate (NO_3^-) leaching and ammonia (NH_3) emissions from manure. Moreover, excess nitrate can result in production and release of nitrous oxide (N_2O). Additionally, livestock production significantly contributes to greenhouse gas (GHG) emissions, particularly methane (CH_4), which is produced during enteric fermentation, and both N_2O and CH_4 which are produced during manure management. The livestock sector alone is responsible for roughly 14.5% of the total anthropogenic GHG emissions and 64% of NH_3 emissions and has been defined as a major factor concerning climate change [51, 52]. To address this, various strategies have been proposed to reduce these emissions. Generally, a farm which is well-managed and employs effective measures for disease control, can significantly reduce its environmental impact. One of the most effective approaches to reduce methane emissions is by enhancing efficiency and productivity. Enhanced efficiency reduces methane emissions per unit of product while channelling more feed energy into valuable outputs like meat or milk. Selective breeding for animals with high performance and good feed conversion rate is seen as particularly beneficial in this regard. In dairy cows, it has shown that increased productivity results in a reduced requirement of feed per unit of product, which can be achieved with genetic selection and dietary improvements, leading to improved milk yield per cow.

Another strategy to reduce methane, as well as nitrous oxide (N_2O) emissions, which are lined to manure, is by enhancing the feed conversion efficiency. PLF systems can be used to monitor the overall animal health and feed intake, offering significant benefits for both efficiency and improving the environmental impact, by employing systems like precision feeding. By optimizing the formulation and delivery of feed, feed efficiency will be increased and simultaneously methane emissions reduced. The precise adjustment of feed rations to each animals' individual needs also minimises excess excretion of nutrients, in particular nitrogen and phosphorous. Additionally, the monitoring of animal health can facilitate early intervention and therefore reduce the reliance on antibiotic treatments, minimising the occurrence of pharmaceutical residues in water [51, 53–55].

An additional approach to limit nitrogen, phosphorous and ammonia excretions involves dietary manipulation. Modifying the diet can effectively manage both the composition and volume of manure, along with its related gaseous emissions, as well as CH_4 emissions produced by enteric fermentation. In dairy cattle, the reduction of N excretions can be accomplished by improving rumen protein metabolism, which in turn lowers the production of NH_3 and N_2O. Two strategies are recommended to achieve this: firstly, the reduction of the crude protein (CP) content within the diet from its original 17-18% to 14%, which is a common practice to reduce the N excretions while still upholding milk production, and secondly limiting ingested food meal digestion in the rumen. These approaches can reduce NH_3 emissions by as much as 70%. Another mitigation strategy involves enhancing the bioavailability of nutrients such as phosphorous through the addition of phytase to the diet. Techniques to reduce emissions in livestock housing primarily focusing on limiting the factors contributing to the release of gases, particularly NH_3 as well as CH_4 and N_2O to a lesser extent.

The production of these gases is also greatly influenced by housing features such as the type of floor, ventilation systems, temperature of the building and manure characteristics. Emission reduction from housing is primarily achieved through good management practice, including frequent manure removal and manure drying and maintaining optimal building conditions with proper ventilation, temperature and employing end-of-pipe technologies like air-scrubbing. Scraping systems when combined with improved floor designs, such as grooved floor, which promote quick urine removal to storage of slurry can achieve emission reductions of up to 40%. However, the effectiveness of this approach can be variable as some of the excretes may remain. Frequent washing of contaminated surfaces with water can reach more significant reduction in emissions, going as high as 90%, however this method increases both the consumption of water and manure volume generated [52, 56, 57].

Several advanced systems are available for monitoring methane emissions. One notable example is GreenFeed (GreenFeed, C-Lock Inc., South Dakota USA), which has been widely used for research purposes and is also commercially available. GreenFeed operates using a feed bait system to attract animals, where it measures methane emissions during digestion [29, 58]. In addition, sensors like CH4 sniffers and Zelp methane mitigation technologies (Zelp, London, UK) are also employed for methane monitoring. While CH4 sniffers detect methane emissions in real-time, Zelp mainly focuses on reducing emissions through wearable technologies designed for livestock, but both are valuable tools in emission research as well as reduction efforts [28, 59, 60].

3.10 Summary of PLF Tools in dairy cattle herd health management

PLF has advanced significantly within the last years, with a wide variety of sensors now available on the market, including RFID tags, accelerometers, pedometers, pressure plates, camera-based systems and automated milking systems [24, 35]. One of the most modern sensor systems used nowadays is the smart collar, which integrates multiple sensors, predominantly accelerometers, microphones and RFID tags and, is commonly implemented in dairy cattle farms, to monitor various physiological parameters [35]. The importance of PLF has also been proven regarding udder health management, reproductive management as well as detecting diseases, such as lameness, at an early stage to facilitate early intervention [24, 61, 62]. However, some PLF tools still remain in the developmental stage, such as the reticulo-rumen bolus, due to challenges ensuring biocompatibility, safety and longevity [25, 35]. Camera-based systems also face difficulties, including managing the large volume of data generated and maintaining high image quality, especially in barn conditions [22, 26]. Ongoing research aims to improve these technologies to enhance their accuracy and make them more reliable tools [22, 35].

4 Applied PLF

4.1 Automated health monitoring

4.1.1 Lameness

Lameness is clinically defined as the manifestation of painful conditions, primarily affecting the locomotor system, which can lead to deviations from the normal posture and gait, or even impaired movement. Claw lesions are the leading cause of lameness in dairy cattle and can be classified into two categories: infectious disorders, including digital or interdigital dermatitis, foot rot and heel erosions; and non-infectious disorders, such as sole ulcers, sole haemorrhages, white line disease or interdigital hyperplasia. Changes in locomotion due to pain are the most commonly used indicators for monitoring lameness, though alterations in general behaviour can also be indicative [63].

4.1.1.1 Lameness monitoring using load cells and pressure plates

Load cells or pressure plates are designed to assess how weight is distributed across an animal's legs as it walks over or stands on pressure-sensitive equipment. [24, 40]. Ground reaction systems containing load cells, measure the weight distribution across legs and utilise the principle that, weightbearing in lame cows is asymmetrical, for lameness detection. In case of lameness, less weight is placed on the affected limb and shifted more onto the contralateral limb. These devices can be employed to measure either dynamic forces during walking or static forces while standing. Systems measuring walking cows are frequently employed in research, studying gait characteristics and conditions which affect cow's ability to move and function. However, studies have evaluated the StepMetrix (Bou-Matic, Wisconsin, USA) system and sensitivity results have been consistently low, which might be explained by cows altering the transfer loads of the painful limbs during walking or standing.

On the other hand, systems designed to measure standing weight distribution tend to be easier to use and may require less space than those assessing walking forces, particularly when integrated into AMS, therefore they might have a bigger potential in being implemented on farms in the future. Although it has to be noted that even though the sensitivity was 100% , specificity was limited at 57.5% in case of measuring standing cows [32, 40].

The Gaitwise system (Gaitwise, ILVO, Merelbeke, Belgium) is used to detect lameness by analyzing gait-related variables, such as those that track locomotion characteristics and those measuring stance asymmetry, automatically after milking. Locomotion scoring variables include stride time and length, stance time, abduction and step overlap, while variables used for assessing asymmetry examines differences in step length, stance time or relative force between limbs.

A study by Van Nuffel et al. (2015) demonstrated that the results of the Gaitwise system (Gaitwise, ILVO, Merelbeke, Belgium) closely matched the scores given by observers, which evaluated cows walking over the pressure plates. Sensitivity and Specificity for detecting non-lame cows were 85% and 86%, 76% and 89% for mildly lame cows, and 90% and 100% for severely lame cows. Although recent research suggests using new variables to improve the detection of mildly lame cows, raising sensitivity and specificity to 88% and 87%. Overall, studies have shown that the accuracy of lameness detection highly depends on the variabls used and Gaitwise (Gaitwise, ILVO, Merelbeke, Belgium) shows a great potential as a future tool for lameness detection [40, 64].

4.1.1.2 Lameness monitoring using camera-based systems

The objective of visual technology is to mimic the visual observation of cow movement. Flower et al. (2005) conducted a study examining how hoof pathologies affect cow gait, by using motion sensors, attached to the cows, which analyses movement and compares them between lame and non-lame cows. In this study, healthy cows and cows with sole ulcers were filmed walking through a narrow walkway against a background. The findings revealed that cows with sole ulcers walked at a reduced speed and took shorter strides, highlighting the potential of this type of technology for detecting lameness associated with sole ulcers [38, 40].

Another promising approach for lameness detection involves assessing the back posture using 2D or 3D cameras. Viazzi et al. (2013) utilised ML to analyse variations in back postures, achieving high accuracy in their results. However, significant individual variations exist among cows, where what may be considered normal for one cow could indicate lameness for another. Therefore it's recommended to establish individual cow thresholds for comparison, rather than relying on a herd-level threshold [24, 38]

Herdvision (Agsenze, UK) is a commercially available video system, that employs a camera placed above the cow. This system monitors mobility for lameness detection, as well as BCS, with the data being transferred to the farmers mobile device [38, 65].

4.1.1.3 Lameness monitoring using accelerometers and pedometers

Accelerometers can measure behaviours which may be altered by lameness such as walking, lying, standing, eating and rumination time. Lying behaviour is frequently used as an indicator for lameness detection, as research shows that lame cows tend to lie down less frequently but for longer durations. There are also some indications of increased lying time during the day in case of lameness. Reduced eating time has also been related to lameness, showing a decreased time spent eating during the day, with shorter bouts and a slower reaction to feed being delivered. However, results of sensitivity and specificity don't show to exceed 90%. While rumination time is less effective for lameness detection, as both rumination and eating time are typically measured using neck-worn accelerometers, leg-worn devices have proven be more accurate for lameness detection [66]. Alsaaod et al. (2017) used two high frequency accelerometers, attached to each hindlimb, achieving 100% accuracy without false positives. However, this method is not widely adopted in practice. On commercial farms, accelerometers are usually low frequency and worn on a neck collar or a single limb, resulting in lower accuracy, when compared with multiple high frequency devices. Different studies have also shown variability in activity data between cows in a herd, suggesting that using individual cows baseline activity data to be more effective than comparing it to the herd averages for detecting lameness [38, 67].

Pedometers have been mostly employed to detect oestrus in cows, but recent studies have explored their potential for detecting lameness [38]. Research by Mazrier et al. (2006) used pedometers to measure the daily step count of cows over the duration of 10 days, where they found that 46% of cows that showed a reduced step count, developed lameness around 7-10 days later, while the other 54% were false positives. It's also important to note that a decreased step count may also be linked to other conditions such as mastitis or metabolic disorders, making it less specific for lameness detection. Mazrier et al (2006) used a reduction threshold of greater than 5% for predicting lameness but found that 92% of cows that developed signs of lameness had a step count reduction of greater than 15%, suggesting that it might be a more appropriate threshold for lameness detection. While the study focuses on predicting lameness in the future, it did not assess the detection of currently lame cows. However, identifying cows that may be at risk of developing lameness in the next 7-10 days could still be make it a valuable tool, giving farmers the possibility of early observation and intervention, if lameness does occur [23, 38].

4.1.2 Mastitis

Mastitis is defined as an inflammation of the mammary glands, caused by a variety of environmental or contagious pathogens, predominantly belonging to families of *Staphylococcaceae*, *Streptococcoaceae* or *Enterobacteriaceae*. It can be classified into clinical, subclinical or chronic forms [68, 69]. Clinical symptoms of inflammation include swelling, redness, heat and pain of the udder, which result from increased blood vessel permeability, allowing fluid and protein leakage, along with the action of immune-mediated inflammatory cells. In clinical mastitis, abnormalities in the mammary glands and milk are visibly noticeable, whereas subclinical mastitis requires diagnostic tests for detection. Although mortality rates for mastitis are low, the economic impact is significant, due to reduced milk production, the need for diagnostic tests, veterinary services, treatments and the disposal of contaminated milk. Additionally, mastitis poses a risk to animal welfare and public health [68].

4.1.2.1 Mastitis monitoring using AMS

AMS with fully automated in-line analysis equipment is one method to monitor the occurrence mastitis [70]. Somatic cell count (SCC) is the most commonly used indicator for assessing udder health in each quarter of individual cows during every milking session, as well as in bulk tanks. While SCC can partially monitor mastitis, newly developed sensors, such as the De Laval Online Cell Counter (DeLaval, Tumba, Sweden), have been specifically designed to monitor udder health, by facilitating repeated cell count measurements at cow level, which can be implemented in AMS. Additionally, continuous monitoring of EC using in-line sensors helps detect intramammary inflammation. However, the accuracy of results is variable, as the first collected milk, which is more sensitive for mastitis detection, may be altered by udder preparation and teat cleaning performed by AMS systems. Thus, it is recommended to monitor milk prior to teat cleaning [24, 71].

4.1.2.1.1 Somatic Cell Count measurement

SCC serves as a crucial and frequently employed indicator for udder health, consequently impacting milk quality and quantity. Somatic cells, predominantly leukocytes, proliferate in response to an infection, typically localised within the mammary glands. A healthy cow typically shows a SCC below 200.000 cells/ml, whereas a SCC surpassing 200.000 cells/ml strongly suggests the presence of mastitis [61, 72]. SCC can be directly measured in such a sensor system using fluorescence imaging, combined with automated stained cell nuclei counting. This method typically shows a good correlation with laboratory test results [73]. Online SCC measurements, such as the Online California Mastitis Test (O-CMT) are also becoming increasingly popular in AMS. This method involves mixing milk with a reagent, altering its viscosity. The resulting measurement is then converted into a value expressed in cells/ml. Although it's not as accurate as a laboratory SCC test, it offers a practical and useful tool for on-farm screening [74]. Another significant advantage of AMS is its ability to perform quarter milking, allowing for frequent SCC measurements of each quarter individually, as opposed to conventional systems, where all quarters are milked together. Moreover, using separate teat cups for each quarter helps minimise the risk of cross contaminations between quarters [75].

4.1.2.1.2 Conductivity sensors

Electrical conductivity (EC) measures a materials ability to conduct electric current. In milk, the ions are the primary components, which are responsible for conducting electricity. The sodium-potassium ratio in the mammary glands is regulated by the transport systems of the secretory cells, maintaining it at a ratio of 1:3 in milk, while in blood or extracellular fluid, it is around 30:1. Additionally, milk has a much lower chloride concentration compared to blood. When mastitis occurs, the permeability of blood capillaries increases, leasing to a higher concentration of ions in the milk, which in turn elevates the EC. This change in EC can effectively be measured by Conductivity sensors and used as an indicator for mastitis [76]. However, measuring EC in milk requires direct contact between the milk and the sensors electrodes, which is possible in theory but poses practical challenges for multiple reasons, such as the increased need for regular cleaning and maintenance of the sensors [77].

4.1.2.1.3 Capacitance sensors (Electrical Permittivity Threshold)

Capacitance is defined as the ability of a material to store electrical charge, which highly depends on the permittivity of the material. Capacitance sensors are made of two or more conductive plates, which are separated by an insulating material. The milk, which flows through acts as a dielectric material and consists of various components, such as water, fats, proteins and electrolytes, which can become polarized under an electric field. Multiple polarization mechanisms can occur, including ionic, dipolar, atomic or electronic polarization. During mastitis, the increased levels of SCC and altered electrolyte levels, disrupt the normal polarization processes of healthy milk, which results in measurable changes in capacitance, allowing for an early identification of mastitis [77]. GEA's DairyMilk 6580 (GEA Farmtechnologies GmBH, Böhnen Germany) is a commercially available sensors, which uses electric permittivity threshold (EPT) technology to measure SCC in milk, of each quarter, alerting farmers at early signs of mastitis and enabling early detection of disease [78].

4.1.2.2 Mastitis monitoring using infrared thermography

Infrared thermography (IRT) is a non-invasive method for detecting subclinical mastitis by accurately measuring temperature from a distance. However, its bias towards warmer temperatures, the time-consuming nature of the process and requirement for a skilled examiner make it unsuitable for automated disease detection [24, 70]. Some researchers have used forward-looking infrared (FLIR) methods to analyse the ocular surface temperature (OST), which shows correlation with rectal temperature, and udder skin surface temperature (USST) and have found that the USST was significantly higher than the OST in affected quarters [70].

4.1.3 Rumen health monitoring

Ruminal acidosis is a continuum of disorders, arising from ruminal dysbiosis and metabolic disturbances, varying in severity. The condition exhibits marked temporal dynamics, leading to varying concentrations of volatile fatty acids (VFA), ammonia, lactic acid and ruminal pH over time. Ruminal acidosis can be classified into clinical ruminal acidosis (CRA), subclinical ruminal acidosis (SRA) or subacute ruminal acidosis (SARA). CRA, poses a significant challenge for cattle and is mostly caused by a sudden, excessive intake of rapidly fermentable carbohydrates (RF-CHO) or a change of processing these RF-CHO. The course of disease shows rapid onset with marked clinical signs for a short duration of time. In dairy cows, SARA most commonly occurs, ranging from 10-26% of cows affected, during early lactation [79, 80]. This prevalence is linked to the high-concentrate (HC) diets commonly fed to dairy cows in modern intensive farming systems, particularly during the transition period, when cows experience various hormonal challenges as they enter the lactation period. The ratio of starch to fibrous carbohydrates plays an important role, as a shift to HC diets increases the rate of ruminal fermentation, leading to the production of short-chain fatty acids (SCFA), which cause the rumen pH to drop to a level <5.6. This drop in pH stimulates the lysis of Gram-negative bacteria, resulting in the accumulation of lipopolysaccharides (LPS), histamine and lactic acid. If the animal is not able to compensate for the resulting dysbiosis, SARA will develop. SARA poses a significant health and production challenge for ruminants, resulting in substantial economic losses for dairy herds, due to the reduced Dry Matter Intake (DMI) and milk production, as well as the losses caused by death or culling [81]. Although SARA is primarily associated with a change in ruminal pH, monitoring this parameter is often impractical due to the invasive nature of techniques like ruminal fluid sampling or high costs of ruminal boluses. Consequently, recent studies have focused on alternative methods, such as the monitoring of behavioural indicators like changes in feeding time, eating rate and rumination time, which can be particularly effective in detecting SARA episodes when combined with peripheral indicators, such as pH, urea or glucose, measured from bodily fluids or excretes [82].

4.1.3.1 Rumen health monitoring using accelerometers

When cows experience ruminal dysbiosis, they exhibit various behavioural changes, which can be monitored via accelerometers. Feeding behaviour is one of the earliest indicators to be altered during episodes of SARA. Cows experiencing SARA typically reduce their time spent eating but increasing their eating frequency, spreading smaller meals throughout the day. This shift likely occurs due to the discomfort caused by acid buildup in the rumen [82, 83]. Additionally, changes in rumen health significantly affect rumination time, which is closely linked to the digestion of fibrous content. When the ruminal pH drops during SARA, the activity of fibre-digesting bacteria is supressed, diminishing the cow’s ability to process and digest forage, resulting in decreased rumination time. Reduced rumination also lowers saliva production, which is supposed to act as a natural buffer. This creates a feedback loop, where the reduced rumination, exacerbates the acid buildup in the rumen, further worsening the condition [84, 85]. Moreover, cows suffering from SARA often show signs of lethargy and reduced activity. However, it can be challenging to differentiate, whether these behaviours result as a direct effect of SARA or are induced by dietary factors [82].

4.1.3.2 Rumen health monitoring using reticulo-ruminal boluses

The current diagnostic standard for detecting SARA is the measurement of pH of the ruminal juice, which can be done via rumenocentesis or oro-ruminal sampling. However, performing such methods is invasive and impractical. The suspicion of SARA usually rises if there are repeated prolonged periods where the ruminal pH drops between 5.2 and 6, but neither practical methods to measure this nor investigations on a herd level are available. Through technical advances and an increasing interest in the PLF sector, reticulo-ruminal boluses have been developed, which allow for the continuous monitoring of reticular pH. Although it has to be noted that it has mostly been used in research until now [86]. Studer et al. (2023) tried to suggest a herd level criterion, indicative of SARA but found no instances of three cows simultaneously exhibiting a drop in reticular pH <5.5. during a >3 hour interval, which reflects the hypothetical framework of their study, grounded in peer-reviewed literature, despite the data being collected from a population at risk. Denwood et. al. (2018) argued that the characterisation of continuous pH data should focus on deviations from expected rhythms, rather than solely relying on fixed pH thresholds. Additionally, there is a need for establishing pH thresholds and timeframes indicative of SARA that encompass both herd-level data and individual animal data, which should be studied further in future research [86, 87]. Studer et al. (2003) also suggested that with the advancing capabilities of future PLF systems, the data should ideally be combined with information from other monitoring systems (i.e. accelerometers, AMS), to assess both herd health and individual productivity [86].

4.1.4 Ketosis

Ketosis is a prevalent metabolic disorder in dairy cows, characterised by elevated blood ketone levels, typically occurring during early lactation. The transition period, spanning from 3 weeks before to 3 weeks post calving, is a critical time, when cows commonly face an energy deficit due to the increased nutrient demands of the growing foetus and development of mammary glands. Before parturition DMI decreases and the filled uterus compresses the rumen simultaneously, further contributing to this NEB. As a result of this, the body immobilizes fat reserves, causing an increase in blood ketone levels, primarily beta-hydroxybutyrate (BHB). Ketosis can be further classified into clinical and subclinical forms. Subclinical ketosis (SCK) is defined by blood BHB levels between 1.2 – 1.4 mmol without manifestations of clinical signs, while clinical ketosis is accompanied by clinical signs, such as reduced feed intake, weight loss and decreased milk production with BHB levels exceeding 3 mmol [88]. While clinical ketosis affects around 2-15% of cows within a herd, SCK is far more common, with prevalence rates reaching up to 40-60% in herds, which undergo regular testing. Furthermore, SCK, significantly increases the risk of developing postpartum diseases, such as metritis or abomasal displacement [89]. However, both clinical and subclinical ketosis can cause substantial economic losses, primarily attributed to the reduced milk production or failure of diseased animals to return to their normal production cycle after recovering. Thus, effective monitoring and management practices during the transition period are of essential to prevent the condition and maintaining good herd health [90].

4.1.4.1 Ketosis monitoring using accelerometers

Alterations in rumination, eating and locomotion behaviour are commonly observed in cows affected by ketosis and these changes can be monitored using accelerometers. Antanaitis et al. (2024) has found that cows with SCK show a significant reduction in rumination time by 17.5%, which may reflect an altered digestive process and potentially the decreased utilisation of nutrients [91]. Lei et al. (2021) has also demonstrated the value of monitoring rumination time for early and individual detection of ketosis. Their study revealed that cows with reduced rumination time in the week prior to parturition, are more prone to developing ketosis, while those still affected by reduced rumination time the week post parturition are at an increased risk of developing additional postpartum diseases alongside ketosis [88]. Antanaitis et al. (2024) observed that alterations in locomotion behaviour are good indicators for metabolic or intestinal diseases in cows, showing that those that are affected by SCK, exhibited a reduced walking time of 27.4% [91].

4.1.4.2 Ketosis monitoring using AMS

Ketosis in dairy cows can be detected through changes in milk composition, particularly the milk-fat-to-protein ratio (FPR), which can be measured with AMS. During phases of energy deficit, cows will mobilise fat reserves, resulting in increased fat and decreased protein levels in the milk [88]. Gross et al. (2011) found that an FPR above 1.35 often indicates SCK, as it reflects a state of insufficient energy intake [88, 92]. However, the accuracy of FPR for the detection of ketosis has been questioned, due to relatively low sensitivity and specificity levels of FPR thresholds, which could possibly be explained by infrequent or inconsistent calibrating of in-line sensors, necessary for accurate monitoring. Additionally, F:P ratios can be altered by other factors, such as breed, diet or other health disorders [93].

Blood BHB concentration measurement remains the gold standard for ketosis monitoring, with values above 1.2 mmol/l being indicative of ketosis. However, measuring BHB levels in milk is also commonly practiced and shows great correlations with the golden standard. Commercially available AMS, such as the DeLaval Herd Navigator (DeLaval, Tumba, Sweden), enable the automated and repeated milk sampling, offering a non-invasive method, which reflects BHB concentrations for a longer time, while also providing more insights on the onset and fluctuations of BHB levels, enhancing the detection without requiring more invasive blood samples [94].

In addition to milk composition data, AMS can track changes in milking frequency and milk yield, both of which decline as cows with ketosis show a reduced appetite and feed intake, resulting in a reduced milk production. This decline in milk production often precedes clinical symptoms, making it a valuable, early indicator for ketosis [95].

Overall, combining these parameters enhances diagnostic accuracy of ketosis and supports early intervention, thereby improving health outcomes for dairy herds [68, 88].

4.1.4.3 Ketosis monitoring using Time of Flight (ToF) cameras for BCS

ToF cameras are emerging as a valuable PLF tool for monitoring body condition score. BCS represents the energy reserves of a cow and is traditionally evaluated manually by assessing fat cover over specific anatomical landmarks. However, ToF cameras can automate this process by capturing depth images, which provide precise measurements of body shape and contour changes associated with fat and muscle distribution. This technology is particularly valuable in early lactation when energy demands peak and feed intake may not suffice, leading drop in BCS, which is a key indicator of NEB, making it an important factor in assessing ketosis risk in dairy cows [42, 96]. Gillund et al. (2001) studied the association between BCS around calving and the prevalence of ketosis and found that cows with a BCS >3.5 at calving faced a 2.5-fold higher risk of ketosis, compared with BCS <3.25. They also suggested that primiparous cows and those calving during summer showed the lowest risk of developing ketosis, while a multiparous winter-calving cow with a BCS >3.5 had up to an 18-fold greater risk. He also found that ketotic cows lost significantly more weight over a prolonged period of time, than healthy cows [97]. This approach is especially advantageous for large dairy herds, where manual BCS monitoring may be impractical. Continuous BCS monitoring with ToF cameras, therefore, provides a non-invasive and consistent method to identify cows at high risk for ketosis, enabling timely intervention and minimizing productivity losses [42, 96, 97].

4.1.5 Metritis

Metritis is an inflammation of the uterine wall, affecting up to 40% of all dairy cows. This inflammation is often accompanied by an enlarged uterus and abnormal watery red to brownish and foul-smelling uterine discharge. The primary cause of metritis is bacterial contamination during or shortly after calving, when the cows' physical barriers in the reproductive tract are weakened, increasing susceptibility to ascending infections. Bacteria can enter the uterine lumen from the environment, skin or faeces of animals, which underscores the importance of hygiene conditions in the calving area. This in combination with the tissue damage and immune-suppression cows experience after calving, can increase the risk factor of developing an inflammation in the reproductive tract, especially the uterus [98]. Metritis can be classified into three grades based on severity. Grade 1, or clinical metritis, typically occurs within 21 days of calving and is marked by an enlarged uterus, reddish-brown, foul-smelling vaginal discharge, but without systemic signs. Grade 2, or acute puerperal metritis, also involves systemic clinical signs such as lethargy, fever, reduced feed intake, and decreased milk yield. Grade 3, or toxaemic metritis, is the most severe, with symptoms including recumbency and signs of toxaemia. Moreover, clinical endometritis, commonly occurs from 21 days post calving, mostly showing purulent uterine secretions and affecting up to 20% of dairy cows. Furthermore, pyometra, occurs between days 42 and 60 post calving and is marked by an accumulation of purulent discharge within the uterus, which can be asymptomatic at first but develop into toxaemia or septicaemia in severe cases. Early detection and treatment are crucial, as metritis can lead to significant economic losses due to reduced milk production, delayed return to oestrus, and increased culling rates [37, 98].

4.1.5.1 Metritis monitoring using accelerometers

Metritis is often associated with reduced activity, increased lying time, and altered eating behaviours due to discomfort and systemic illness in affected cows. Accelerometers, measure movement patterns and can detect significant deviations from baseline behaviours. For example, cows suffering from metritis may exhibit prolonged periods of inactivity or reduced rumination time. Stangaferro et al. (2016) investigated the efficacy of rumination and activity monitoring for identifying cows with metritis, revealing that although metritis typically leads to reduced rumination time and activity, the sensitivity of these indicators was only moderate. This means that while severe cases of metritis, especially those affecting the cow systemically, were more easily detected, milder cases often went unnoticed. This limitation is likely due to the varying impact of metritis severity on behaviour: systemic infections alter rumination and activity levels more drastically than infections confined to the uterus. Therefore, although rumination and activity monitoring alone may miss mild cases, it shows potential when used alongside traditional diagnostic methods, as it strengthens early detection capabilities and helps identify cows requiring closer monitoring [99, 100].

4.1.5.2 Metritis monitoring using temperature monitoring devices

Temperature data can serve as an early indicator of metritis, as one of the primary signs of the disease is fever, often accompanied by lethargy and decreased appetite. Non-invasive temperature monitoring systems, like reticulo-ruminal boluses, vaginal thermometers, and infrared thermography, have been used to continuously track temperature changes in cows, allowing for real-time detection of abnormalities. Studies indicate that cows with metritis often exhibit elevated body temperatures shortly after calving, typically within the first 10 days postpartum. Monitoring temperature trends with these devices provides an automated and effective way to identify cows at risk of metritis before symptoms worsen. Even though fever is a non-specific symptom that can indicate various pathological conditions, increased body temperature occurring in the first few days post calving is usually accompanying puerperal metritis. Therefore, regular body temperature monitoring could be integrated into farm management to aid early detection. However, there is no universally accepted temperature threshold for diagnosing puerperal metritis and proposed thresholds vary between studies. Although temperatures above 39.0°C are often considered abnormal, temperatures above 39.5°C appear more reliable for diagnosing metritis. However, despite its potential utility, body temperature alone is an unreliable diagnostic tool due to fluctuations influenced by factors such as health status, age, seasonal conditions, and diurnal variations, but it can be useful when assessing the severity of the disease [101].

4.1.5.3 Metritis monitoring using AMS

AMS have shown potential in detecting metritis in dairy cows through various milk and behavioural parameters. Changes in milk yield, conductivity, and composition, as well as milking frequency, can signal health issues, including metritis. Cows suffering from metritis often exhibit reduced milk production due to decreased appetite and metabolic disruptions, making sudden drops in yield a possible indicator of the disease. Additionally, increased somatic cell counts and changes in milk conductivity due to inflammation can serve as early warnings of uterine infections. Research by Stangaferro et al. (2016) highlights that cows with metritis tend to produce lower milk volumes in the days following calving, while Rutten et al. (2013) noted that fluctuations in milk conductivity and yield can be indicative of health disorders in the postpartum period. Combining AMS data with other health monitoring tools can improve the sensitivity and specificity of metritis detection, allowing for early intervention and reducing the economic impact associated with delayed treatment [100, 102].

4.1.6 Hypocalcaemia

Hypocalcaemia, commonly known as milk fever, is a metabolic disorder characterized by low blood calcium levels, typically occurring in dairy cows within the first few days post calving. This condition arises due to the high calcium demands for milk production, which often exceed the cow's capacity to mobilize calcium from bone stores or increase intestinal calcium absorption. Clinical hypocalcaemia presents with distinct symptoms such as muscle weakness, tremors, dilated pupils, lowered rectal temperature, and reduced ruminal contractions. The condition is typically classified into three progressive stages based on severity. In the first stage, the cow displays mild clinical signs but remains standing. The second stage is marked by sternal recumbency, where the cow can no longer stand but remains upright. In the third and most critical stage, the cow progresses to lateral recumbency, lying on its side and showing significant distress. Although these clinical signs of hypocalcaemia are well-documented, the precise blood calcium levels at which they manifest remain variable and are influenced by individual factors. Subclinical hypocalcaemia, a milder but much more common form of the disorder, can also impair immune function, increase the risk of other postpartum disorders, reduce productive performance and overall milk yield [103]. According to Reinhardt et al. (2011), approximately 25% of all dairy cows are affected by subclinical hypocalcaemia, with higher rates in older cows. Prevention and treatment methods include calcium supplementation, dietary adjustments before calving to lower calcium intake, and the use of anionic salts to improve calcium metabolism. Monitoring calcium levels and promptly treating deficiencies can significantly improve recovery and minimize the economic impact associated with milk fever [104, 105]. Although there is no automated hypocalcaemia monitoring sensor on the market yet, PLF can be used in the detection of animals believed to be affected by the disease and providing additional precious information for confirming the diseases.

4.1.6.1 Hypocalcaemia monitoring using accelerometers

Accelerometers can be valuable tools for monitoring hypocalcaemia, by detecting behavioural changes, which are indirectly associated with the disorder. A reduction in activity and increased lying times are common indicators for illness in general and are clinical signs of hypocalcaemia, attributed to muscle weakness and impaired motor function, resulting from low blood calcium levels, which results in cows being less mobile and more prone to lying down. Hendriks et al. (2020) found that cows with hypocalcaemia spent around 2.6 hours more lying down on the day post calving than normo-calcaemic cows. Only a limited number of studies have examined the relationship between blood Ca levels and cow activity, often showing varying results. However, a consistency is showing that cows with hypocalcaemia tend to exhibit reduced activity levels. The degree of this reduction typically correlates with the severity of the disorder, with more pronounced calcium deficiencies leading to greater declines in activity [106]. Reduced rumination time and DMI have also been suggested indicators for milk fever. Hypocalcaemia weakens smooth muscle contractions, which reduces rumen motility and passage rate of digesta through the digestive system. This decrease in rumination activity, along with a reduction in DMI, impairs overall digestive function. Early lactating cows rely on feed intake as their primary source of calcium and magnesium, so decreased DMI further exacerbates mineral deficiencies in the blood, worsening the effects of hypocalcaemia [107].

4.1.6.2 Hypocalcaemia monitoring using temperature monitoring devices

Decreased temperature is a common clinical sign associated with clinical hypocalcaemia in periparturient cows, with manual palpation of ear temperature being a common method for detective milk fever. However, ear skin temperature has not formally been validated as a reliable predictor of calcium status. Infrared thermography is a non-invasive technology, which has gained interest for veterinary diagnostics and was previously used to assess udder and hoof temperatures to identify subclinical mastitis and laminitis in cows, respectively showcasing its diagnostic potential. Temperature drops below baseline thresholds can indicate hypocalcaemia early, especially when paired with other data such as decreased rumination and activity [108, 109].

4.1.6.3 Hypocalcaemia monitoring by using AMS

AMS can support early detection of hypocalcaemia by continuously monitoring milk yield and composition, particularly focusing on reductions in milk output and changes in milk fat-to-protein ratio, which are often early indicators of calcium deficiency in dairy cows. Serrenho et al. (2021) found that cows with clinical hypocalcaemia typically yield 1.1 to 2.9 kg less milk per day for up to six weeks post-calving normo-calcaemic cows. However, studies assessing blood calcium levels shortly after calving came to different conclusions, showing a greater milk production in multiparous cows. This highlights the importance of studying the association between milk yield and milk fever in the transition period, since the mechanism to explain their relationship is not fully understood [103, 110]. Furthermore, hypocalcaemia reduces muscle contractility, including the sphincter muscles of the teat, thereby increasing the risk of developing mastitis. In addition to that, cows suffering from hypocalcaemia frequently lie down, which further increases the likelihood of pathogens entering through the open teat canal. Some studies have shown that the mastitis risk increases up to 8 times if cows develop hypocalcaemia. Therefore, a high prevalence of mastitis cases could possibly indicate hypocalcaemia within the herd [111].

4.1.7 Displacement of Abomasum

Displaced abomasum (DA) occurs when the abomasum expands with gas or fluid and shifts leftward or rightward, often trapped in its abnormal position by the descending rumen. Right Displaced Abomasum (RDA) frequently includes torsion, severely obstructing digesta flow and requiring immediate intervention. In contrast, Left Displaced Abomasum (LDA), which is more common, usually involves gas build-up with minimal torsion, allowing some digesta to pass, though reduced, leading to a more chronic state [112]. DA is frequently diagnosed by swinging and percussion auscultation, upon which sloshing and ping sounds can be heard [113]. Although there is no automated monitoring for abomasal displacement commercially available yet, the data generated by PLF sensors, as described in this review, can be used to support the diagnosis and confirm the disease.

4.1.7.1 Abomasal displacement monitoring using accelerometers

Cows affected by DA typically show a marked decrease in feeding and rumination time, reflecting the severity of the condition. For instance Kibar Kurt and Sarierler et al. (2022) found that cows with DA ruminate only around 200-300 minutes daily, compared to the approximately 500 minutes typical healthy cows [114]. Similarly, Stangaferro et al. (2016) observed a sharp decline in both activity and rumination time and found the highest sensitivity in detecting DA, in contrast to ketosis, which showed only moderate sensitivity. This difference in sensitivity is possibly explained due to the more disruptive impact of DA's on bovine health [115].

4.1.7.2 Abomasal displacement monitoring by using AMS

A sudden drop in milk yield, typically observed 4-5 days before DA diagnosis, shows a decline of about 1.2-4.4 kg/day. In addition, AMS detects alterations in milk temperature, which often deviate around 6 days prior to diagnosis, and an increase in milk conductivity, which is noticeable 1-3 days before clinical signs of DA occur. By analysing these parameters collectively, AMS can provide early indications of DA, allowing for prompt diagnosis and intervention, which could potentially reduce the severity of complications associated with the disorder [116].

4.1.8 Heat stress

Heat stress in dairy cows occurs when they cannot release excess heat without disrupting their body's thermal balance. This condition is often linked to environmental factors, such as high temperatures and humidity, or intense solar radiation exposure. In some cases, heat stress may also arise from the cow's internal heat production exceeding its capacity to dissipate it effectively. The thermo-neutral zone (TNZ) for dairy cows, is the temperature range in which heat production is minimized, allowing for maximum energy availability for milk production and spans from 5°C to 25°C. Beyond this range, cows may struggle to release or dissipate excess metabolic or absorbed heat, disrupting their thermal balance and compromising welfare. Heat stress elicits a variety of animal responses, which can be categorized into physiological, morphological, behavioural, metabolic, productive, and immune responses, each reflecting the cow's adaptation efforts to maintain comfort and productivity under thermal stress. Heat stress is one of the most extensively researched issues in the global dairy sector due to its widespread impact across various regions, drawing increasing attention from both researchers and farmers [117].

4.1.8.1 Heat stress monitoring using accelerometers

When a cow experiences heat stress, it's immediate coping response is to reduce DMI, limiting nutrient availability for milk synthesis [118]. This reduction in DMI lowers diet-induced thermogenesis, as consuming less feed minimises fermentation heat from the rumen. The decline in feed intake results from both discomfort of high temperatures, as well as the energy demands of sweat production, needed to cool the body [48, 117]. The duration of elevated temperatures is inversely related to DMI, showing that a brief, simulated heat wave can suppress feed intake as early as 1 day after temperature rises [118].

Additionally, numerous studies have shown that high temperatures reduce rumination time, with one study reporting a reduction of 2 minutes for each unit increase in daily maximum Temperature-Humidity Index (THI) above the threshold of 68. Similarly, an inverse relationship between rumination time and THI has been observed, with reduced rumination time noted during night-time under heat stress. During cooler hours, when heat stress subsides, cows tend to increase their rumination time. However, under prolonged heat, they may limit rumination even in cooler periods to reduce metabolic heat production [117, 119].

Standing and lying behaviours are also altered during heat stress, as they serve as adaptive mechanisms that facilitate effective body heat dissipation and reduce heat load from ground surfaces. High temperatures can result in prolonged standing, which may subsequently decrease milk production. By standing more frequently, cows can enhance their respiratory efficiency and better utilize their body surface area for efficient management of sensible and insensible heat loss, thereby minimising the amount of heat transferred from heat surfaces while lying down [48, 117].

4.1.8.2 Heat stress monitoring using temperature monitoring devices

Heat stress severely disrupts cows' normal thermal homeostasis, leading to altered body temperatures. When ambient temperatures exceed 30°C, cows experience significant difficulty in maintaining thermal regulation, resulting in marked increase in core, ocular and skin surface temperatures, which are clear indicators of their struggle to dissipate excess heat [117]. Rectal temperature (RT) indicates the core body temperature, closely linked to productive performance. While RT remains stable within the TNZ, it tends to increase with increasing ambient temperatures. Vaginal temperature (VT) is another method of assessing core temperature, conducted automatically with wireless sensors, such as the Star-Oddi's DST temperature loggers . However, these temperature loggers are primarily marketed for research purposes. Researchers have also explored skin temperature (ST), using infrared thermometers [48, 120].

4.1.8.3 Heat stress monitoring using AMS

Daily milk yield is a primary concern during heat stress, with research indicating that reduced milk production may also lead to decreased metabolic heat production. Numerous studies have demonstrated a negative correlation between milk production and THI, particularly when the daily average THI exceeds 68. Findings further support this relationship, showing that increased THI is associated with decreased milk production, especially in high-producing dairy cows. Additionally, both activity levels and milk yield decline in response to heat load, particularly 3-5 days following exposure. It can be inferred that the direct impact of heat stress on milk yield, suggests that a reduction in DMI accounts for approximately 30-50% of the overall decline in productivity [48, 117].

4.2 Automated reproductive monitoring

4.2.1 Oestrus Detection

4.2.1.1 Bovine oestrus cycle

The oestrus cycle typically spans 21 days in mature cows and 20 days in heifers, compromising four distinct phases: oestrus, metestrus, dioestrus and proestrus. Oestrus, lasting from 6 to 30 hours with an average of 20 hours, is characterised by the cow's display of sexual receptivity, indicated by standing behaviour to be mounted by the male. During this period there will be an increased cervical and vaginal mucus production, often observable as visible discharge from the vulva or trailing along the tail. Prior to oestrus, the corpus luteum (CL) will undergo luteolysis, resulting in minimal progesterone production. Concurrently, luteinising hormone (LH) experiences a sharp peak, triggering ovulation, while oestrogen levels decline from their preceding peak just before oestrus. Metestrus lasting 3 to 5 days, marks the period where the ovulation occurs, typically 10 to 15 hours after the cessation of oestrus. During this phase the CL undergoes early development. Some slight bloody discharge from the vulva, might be visible during this phase. Progesterone levels slightly increase during metestrus, but they remain low, due to the limited capacity of the relatively small CL to produce substantial amounts of progesterone at such an early stage of development. Dioestrus, the phase dominated by the CL, spans approximately 12 days. In the initial days of dioestrus, the CL increasingly produces progesterone, benefiting from its maturation and greater steroid production capacity. As dioestrus advances, progesterone levels in the blood plateau [121]. During proestrus, as the CL regresses and progesterone concentration decreases, a dominant follicle emerges from a group of antral follicles. This follicle undergoes maturation influenced by LH and follicle stimulating hormone (FSH). FSH holds significance in the initial stages of follicular development, while LH contributes to follicular growth. As the dominant follicle progresses towards a preovulatory size, it secretes an increasing amount of oestradiol (E2), which plays an important role in regulating oestrus through neuroendocrine mechanisms. E2 typically inhibits the secretion of gonadotropin releasing hormone (GnRH) from the hypothalamus and additionally the secretion of LH by the pituitary. However, in proestrus, increased E2 levels stimulate an increased GnRH secretion, and in conjunction with the direct effects of E2 on the pituitary, will trigger an LH surge, which in turn induces the ovulation [122].

4.2.1.2 Behavioural signs of oestrus

During oestrus, female cows exhibit behavioural changes driven by fluctuations in progesterone and oestrogen levels. The primary indicator of oestrus in dairy cattle manifests when the cow stands to be mounted. However, this behaviour is not shown by all cycling animals, some may only exhibit secondary signs, which vary in duration and intensity, such as increased activity, decreased feed and water intake, attempts to mount other cows, mucus discharge, sniffing other cows genitalia, vulva swelling and reddening, chin resting, back rubbing and increased vocalisation. Additionally, silent heat often occurs post-calving, further complicating oestrus detection [123, 124].

4.2.1.3 Oestrus detection using PLF tools

4.2.1.3.1 Oestrus detection using pressure detectors

Pressure-sensitive electronical devices are employed to identify the onset and duration of standing mounts which are accepted by cows in oestrus. These devices consist of a pressure sensitive transmitter embedded within a pouch adhered to the sacral region near the tail head. Activation is triggered when the sensor registers the pressure of the mounting animal's weight for a minimum duration of 2 seconds, thereby reducing the likelihood of a false positive results. Mounting attempts occur at a high frequency during oestrus, commencing up to 6 hours before and persisting for approximately 3 hours after standing oestrus. However, the average number of mounts seems to be lower in cows with a milk a production above the herd average than in cows with a lower milk yield. Additionally, it should be noted that research indicates that up to 40% of mounting events last for less than 2 seconds. The relevant data, including the cow's identification, date, time, number of mounting attempts and their duration, is sent to a receiver via radiofrequency and subsequently recorded by the management software. A specified algorithm can analyse each cow's mounting pattern and categorise a cow as "standing" when there have been three or more standing events within a four-hour period. Additionally, it generates various reports identifying cows classified as standing or suspected of standing, based on the number of mounts received within a four-hour timeframe. The integration of pressure sensing systems resulted in the detection of approximately 80% of ovulating cows, showcasing superior efficiency in oestrus detection compared to conventional visual observation [125, 126].

4.2.1.3.2 Oestrus detection using pedometers and accelerometers

Pedometers are used to measure cow's steps count, serving as an indicator of increased walking activity, particularly during proestrus and oestrus. However, as the raw count of movement lacks absolute significance, a comparative method is essential. This involves comparing the recorded count with a baseline expected from the cow when it is not in oestrus. Pedometer recordings revealed a diurnal rhythm in step counts, a crucial factor for algorithm development concerning within-cow comparisons [36, 125].

Accelerometers are combined with specially devised algorithms, which discern daily cow activity, from that associated with oestrus behaviour, based on deviations from the stored activity pattern. Upon cows surpassing a user-defined threshold, alerts are generated and received by herdsmen [125]. Cows appear to be approximately 2.3 to 6 times more active on the day of oestrus compared to the day prior, with walking time significantly increasing, commencing 8 hours before and persisting up to 5 hours after the onset of oestrus. Cows tend to show greater walking activity during night-time and early morning hours, posing a challenge for farmers relying solely on visual observation for oestrus detection. The number of lactations may also impact activity levels, with multiparous animals showing reduced intensity and peak activity as the lactation number increases. Additionally, high milk production negatively affects activity, as research indicates a 1.6% decrease in walking time for every 1kg increase in milk production. Further major factors influencing reproductive

efficiency are hot climatic conditions, which may reduce the oestrus duration and intensity, resulting in a large range of cycle length, that in turn contribute to lower oestrus detection and decreased pregnancy rates. Activity is generally lower during summer months, therefore cows exhibit only a slight increase in walking activity during that time [125, 127].
Moreover, during oestrus the rumination time is significantly shorter, where this decrease in RT was pronounced most in primiparous animals. However, research have shown that although cows which go in heat naturally exhibit a significant drop in rumination time, those whose oestrus was induced only showed minimal changes in rumination patterns [128–130].

4.2.1.3.3 Oestrus detection using camera-based systems

Video cameras offer an additional method of identifying cows standing to be mounted. The duration of cows showing standing oestrus can be compared with the average duration measured by pressure sensors. Ideally, cameras should be securely fixed to the upper corners of the barn at a height of approximately three meters and connected to a video management software to provide visualisation of the stored video sequences. However, the detection of this behaviour may be affected by camera resolution because low resolution can make it difficult to read the ear tags of animals, making cow identification challenging [125]. Using computer vision-based techniques in combination with artificial intelligence offers numerous advantages, since the cameras do not require direct contact with the animals and are able to simultaneously gather data from multiple animals at the same time. Therefore, it has the potential to reduce the cost per animal significantly. Various methods of video recording can be combined, including the length of an object within the camera frame or the height difference caused by the females mounting behaviour and the alignment of the fight line. Other methods involve the camera detecting one cow following another, where the length of two cows is visible for two seconds, followed by the mounting behaviour lasting for another two seconds or more, which is then interpreted as a sign of oestrus. The average time required for classical visual observation is around 40 minutes per day, whereas the time needed to analyse video sequences varied from 8 to 32 minutes. Investigations found that the efficiency of detection was higher with video recordings compared to the classical visual observation. Nevertheless, it must be noted that only cows showing obvious behavioural signs of oestrus can be detected in both cases [124].

4.2.1.3.4 Oestrus detection using microphones

The vocal behaviour of cattle is also affected by their reproductive status of animals, with an elevated rate of vocalisation observed near the onset of oestrus. Microphones, typically affixed to the animal's neck, are employed to record such vocalisations. These recordings are then transmitted to a receiver, which is connected to the management software, where a specialised algorithm will filter out those recordings surpassing a predetermined threshold, indicative of oestrus. However, it is important to note that individual variability in vocalisation rates may limit the practical applicability of this approach. Additionally, microphone based systems can be utilised to records the individual rumination time of cows, which shows a gradual decrease around the time of oestrus, starting around two days before its onset and showing the lowest activity on the day of oestrus [125].

4.2.1.3.5 Oestrus detection using temperature measurements

During oestrus, cows exhibit an increase in body temperature. Several methods are available to measure this temperature rise, including non-invasive techniques such as measuring the milk temperature within the milking system. The rise in milk temperature was considered significant, with deviations twice as high as those observed in the preceding five days. However, studies have reported a high rate of false positives or low sensitivity for this method. Additionally, the temperature increase may last only around nine hours, which may be shorter than the milking interval, complicating the use of milk temperature measurement for oestrus detection [36]. The integration of thermographic cameras could also prove beneficial in detecting oestrus, as cows may exhibit changes in body temperature during this period. Studies have indicated that a peak increase in vulvar temperature was observed 24-72 hours prior to ovulation, demonstrating a sensitivity of 75% and specificity of 57%. The temperature sensing camera captures images of the cow's hind region, including the vulval and anal areas, the posterior udder attachment, and the posterior udder lobes. However, this method has also been associated with a high number of false positives and negatives, making it unsuitable for the use of routine oestrus detection. Challenges in thermographic applications include addressing temperature variations unrelated to oestrus which can be influenced by factors such as the ambient temperature, humidity or skin moisture [36, 124]. More invasive methods include rectal and vaginal thermometry, where radio telemetric transmitters are inserted into the cow's vagina. According to studies, there is a slight decrease in temperature two days before the onset of oestrus, followed by a temperature increase during the LH peak. The temperature rise ranges from 0.4°C to 3.22°C, with an average of

0.48°C. The interval between the rise and temperature and the time of ovulation was found to be consistent, making this method a potentially reliable indicator of ovulation time and LH surge detection. However, environmental temperature, hyperthermia related to illness or other local or systemic inflammations may alter body temperature, increasing the chance of false positive results [125, 131].

4.2.2 Pregnancy detection

Accurately diagnosing pregnant or non-pregnant animals as early as possible after an artificial insemination is essential for maintaining high reproductive efficiency in dairy cattle management. Direct methods to diagnose pregnancies, such as transrectal ultrasound, can be used as early as 29 days post artificial insemination, while indirect methods, like measuring pregnancy-associated glycoprotein in blood or milk, can be performed accurately around 28 days post artificial insemination. Non-pregnant animals can be identified even earlier with the use of doppler ultrasound and progesterone measurements. However, these methods often yield a high number of false positives due to early pregnancy losses, necessitating follow up examinations to confirm pregnancies accurately. Additionally, the methods mentioned before are time-consuming, labour-intensive and require a considerable amount of animal handling, with laboratory tests often unavailable on site and taking several days to provide results. In this context, continuous monitoring of milk progesterone concentrations using automated in-milk analysers has introduced new opportunity for reproductive management [132].

4.2.2.1 Automated in-line milk progesterone analysis

Fully automated in-line progesterone analysers have recently become commercially available such as the DeLaval Herd Navigator (DeLaval, Tumba, Sweden) or the Milkalyser (Lely, Maassluis, Netherlands) [133, 134]. Although the initial installation requires a significant investment, these systems can be highly profitable for larger farms when compared to the manual measurement of progesterone levels. A sampler within the milking robot automatically collects milk samples from individual cows during milking, which are sent to the analyser, where progesterone concentration (P4c) is measured using a lateral flow immunoassay based dry-stick technique [135, 136]. The key features of in-line milk analysing systems (IMAS) in terms of reproductive management encompasses the monitoring of the returning luteal activity postpartum together with the progression of a subsequent luteal phase, detecting imminent oestrus once luteal phase has ended and determining an early pregnancy or non-pregnancy status, based on the dynamic changes in progesterone levels. A luteal phase was determined, when P4c levels increased to 5 ng/ml or higher until the subsequent P4c drop. Upon detecting a P4c decline, an oestrus notification was sent out by the IMAS software, recommending artificial insemination within the next 24 to 36 hours. If P4 levels remained above 5 ng/ml, which is considered the default cut-off point, by day 30 post-artificial insemination, a pregnancy notification is issued by the system and sampling frequency adjusted accordingly. However, if a P4c decline occurred, it indicated non-pregnancy and imminent oestrus. From day 30 on, pregnancy notifications were generated with each sampling, as a true pregnancy is expected to maintain P4 levels above the threshold. Sampling continued until day 55 post-artificial insemination, at which point it was automatically stopped. In conclusion, the IMAS demonstrated a high sensitivity of >95% though its specificity levels did not exceed 90% before 40 days post-artificial insemination, likely due to the early pregnancy losses. After day 40 post-artificial insemination, IMAS proved highly accurate in determining pregnancy status and could also identify non-pregnancy as soon as a decline in P4c was detected [132].

4.2.3 Prediction of the onset of calving

The main objective of accurately predicting the onset of calving is to ensure the appropriately timed calving assistance, which can reduce the incidence of dystocia (difficult or prolonged calving), stillbirth, various vaginal and uterine disorders. Dystocia and inappropriately timed (too late and too early) assistance can result in compromised animal welfare, milk production, fertility and a lower survival and growth rate of the calf. Therefore, maintaining good herd health management is crucial to optimize reproductive performance and the net return of the farm [37, 137].Traditional methods, including the evaluation of behavioural and external preparatory signs, are still commonly used in both large and small dairy farms [37]. However various sensors for the prediction of calving have been developed, which open new possibilities with the use of continuous monitoring via sensors [137].

4.2.3.1 Predicting the onset of calving by evaluating external preparatory clinical signs

Various clinical signs have been associated with an impending parturition, primarily involving changes in the udder, vulva and pelvic ligaments. Research has identified a general pattern for impending calving, starting with udder enlargement approximately 1-2 weeks before calving. Vulvar enlargement may also start around the same time but has shown the be more variable. Around 1-2 days before calving the udder becomes highly extended and the pelvic ligaments start to relax, which are highly indicative signs for calving. To predict either the calving event or no calving event within the next 12h, a parturition score (PS) has been developed. The PS evaluates 7 clinical signs including the relaxation of the broad pelvic ligaments, secretions of vaginal mucous, hyperplasia of the udder, oedema of the udder, filling of the teats, relaxation of the tail and oedema of the vulva. A PS of 4 points (0-3) were identified as a threshold enabling calving within the next 12h to be ruled out with a probability of 98.6% for cows and heifers, although the clinical signs were not as informative in heifers compared to cows [37].

4.2.3.2 Predicting the onset of calving via temperature measurements

Research has shown a decrease in rectal and vaginal temperature prior to calving ranging from 0.56 to 0.89°C. It was found that even cows showing external preparatory signs of parturition but still maintained a rectal temperature of above 38.8°C were unlikely to calve in the following 12 hours [37]. It must be noted that the body temperature follows a circadian rhythm in cattle, with the lowest temperature during the morning and the highest during late afternoon. However, this rhythm may be influenced by a variety of factors, such as unfavourable weather conditions, heat stress, cooling methods' efficiency or the frequency of the milking. Additionally, the animals' physiological status may also alter the diurnal pattern [138]. Recent developments have enabled the continuous monitoring of temperature using different temperature loggers, allowing for the prediction of calving 24 hours prior to parturition [37].

4.2.3.2.1 Vaginal Temperature (VT) and Rectal Temperature (RT)

Vaginal temperature in cows can be measured with the use of data loggers which are attached to a modified controlled internal drug release device without the use of progesterone. These are inserted around 6 days before the predicted parturition and expelled during parturition, resulting in a sudden temperature decrease. The time of calving for each cow is then determined by the time of the complete expulsion of loggers with the temperature data downloaded afterwards [139]. Additionally, rectal temperature was measured two to three times a day. One study showed that the VT decreased by around 0.2 to 0.3°C on the day of calving compared to 24 hours prior and 0.6 to 0.7°C compared to 48 hours before.

Similarly, RT decreased by 0.3 to 0.5°C from 24 hours prior and by 0.4 to 0.6°C from 48 hours before the time of delivery. Although, both VT and RT distinctively decrease prior to calving, they can't precisely determine the onset of calving. However, in addition to traditional signs, they can provide useful information about impending parturition [138].

4.2.3.2.2 Ventral Tail Base Skin Temperature (TBST)

TBST is defined as a peripheral temperature influenced by various factors such as core temperature, regulation of the peripheral blood system or environmental conditions, such as ambient temperature or humidity. There is a strong correlation between TBST and VT although TBST may be around 1.0°C lower during prepartum days. The pattern of change, timing and degree of decrease are almost identical in TBST and VT. Concurrently, residual TBST (rTBST = hourly TBST – mean TBST on previous 3 days during the same hours) exhibits a biphasic pattern while it decreases. Around 36 to 16 hours prior to calving a gradual temperature decrease occurs, which is independent of ambient temperature, while approximately 6 hours prior to until the calving this decrease becomes sharp and dependant on temperature. However, the accuracy of calving prediction shows a tendency to be lower in colder conditions. Furthermore, ventral TBST measurements have the advantage of being unaffected by different rearing conditions and allow continuous surface temperature monitoring without interruption. Therefore, they may be used to predict diseases that may be associated with a change in body temperature even after parturition [37].

4.2.3.2.3 Reticulo-Rumen Temperature

Reticulo-rumen temperature (Trr) can be a highly accurate indicator for predicting impending parturition within 24 hours, by detecting a drop in temperature of >0.2°C [140]. Sensors are administered orally and deposited into the reticulo-rumen to measure temperature hourly. A telemetric system is located within the maternity pen and equipped with antennas, providing a 90-meter reach capacity. Therefore, to record a sufficient amount of readings, the animal must be within the antenna's range at least 2 to 3 times daily. The readings are transmitted to a computer, where the Trr data is stored for later evaluation [37]. It has to be noted that water intake can highly influence the Trr, therefore only values above 37.7°C were used [141]. Microorganisms in the reticulo-rumen also generate heat, making the Trr approximately 0.5°C greater than the overall body temperature, which has to be taken into account [37]. Another study which explored the changes in rumination time and reticulo-ruminal characteristics has revealed differences in temperature drops between dystocia and eutocia. Eutocia, considered a normal calving, showed a pronounced temperature drop of around 0.48°C starting 24 hours before parturition. In contrast, dystocia, which required assistance by at least two people using considerable force, exhibited a temperature drop of around 0.23°C 32 hours before parturition. In both cases the temperature drop reached its lowest point around 16 hours before and showed a gradual increase until calving. Additionally, reticulo-rumen sensors have the advantage that they don't require constant manual checks or represent a high risk for developing lesions, compared to sensors inserted vaginally or rectally. In conclusion, since the temperature drop occurs approximately 12 hours earlier in dystotic cows compared to eutotic cows, Trr could serve as a potential indicator of dystocia. However, further studies are still necessary for better understanding of changes in peripartal rumination characteristics [141].

4.2.3.3 Predicting the onset of calving by detecting behavioural changes with the use of sensors

Prior to calving changes in behaviour can be seen, such as restlessness, lower feed intake and time spent ruminating, seeking isolation together with increased frequency of postural changes, tail raising and greater number of lying bouts, which all become more evident during the last hours prior to the time of delivery. Predicting behavioural changes only by visual observation can be challenging, as the observer must be present frequently which can cause discomfort for the periparturient animals and therefore interfere with the process of calving. Visual observation via the use of cameras placed within the maternity pen could be done, but this method is also time-consuming and not frequently used. A possible approach for detecting behavioural changes via video cameras could be by facilitating an algorithm for the automatic monitoring of activity and posture through online image analysis, which has become possible with the development by Lely Zeta (Lely, Maassluis, Netherlands). The most commonly used sensors in cattle herds are accelerometer, pedometers and microphones, which measure parameters such as standing and lying time, number of steps and lying bouts, as well as feeding and rumination time and tail raising activity or a combination of those to build a baseline. Deviations can be indicative of calving in the proceeding 6-12 hours. Authors have reported an increased frequency in standing and lying bouts as well as tail raising around 4 hours prior to calving in case of primiparous and 2 hours before in multiparous cows. Additionally, cows experiencing dystocia have been observed to show an increase in standing bouts 24 hours before delivery compared to eutotic cows. With the use of commercially available microphones, researchers have monitored chewing and observed a 70% decrease in rumination time within the last 24 hours before calving. Concurrently, eating time declined by approximately 66 minutes and DMI decreased by 56% during the final 6 hours prior to calving [137, 142]. Several tail-mounted accelerometers are also available on the market, but Moocall (Moocall Ltd., Dublin, Ireland) sensors were the only ones used for research. Two types of signals can be generated by these sensors, based on tail activity. An SMS type 1 alert is sent out if the sensor detects increased activity over the span of one hour. If this high activity persists in the consecutive hour an SMS type 2 alert is sent out, indicating that calving is imminent. While some reports seemed to be very promising at first, showing a sensitivity of 100% and a specificity of 95%, with the device being well tolerated. Other studies have shown a varying sensitivity from 19 to 75% and 63 to 96% specificity. Additionally, some sensors had to be removed all together due to the tail being swollen or painful or the cows dislodging the devices themselves by licking and chewing each other's tails. In some cases, this problem could be resolved by decreasing the original weight of the device from 133g to 50g and therefore decreasing the resulting oedema. Overall, Moocall sensors did not provide precise information about the exact calving time but could aid in optimizing work efficiency [37, 143].

4.3 Complex systems

4.3.1 Automated Milking Systems

The fundamental concept of AMS entails cows autonomously entering the milking box, thus enabling voluntary milking, without the need for human presence and at any stage of lactation [144]. The development of automatic milking began in the 1970s, driven by rising labour costs and the desire to maximise milk production. Between 1970 and 1990, numerous institutions conducted research to optimise teat positioning and created a device which automatically attached the milk clusters. Much of this innovation originated from a research institute in England, although several manufacturers such as DeLaval from Sweden and from other western European countries were working on AMS development simultaneously. In 1992 the first AMS was installed on a farm in the Netherlands, soon afterwards being adopted worldwide [145, 146].

AMS compromise a containment system, sensors, a robotic arm, a teat cleaning mechanism, a software interface, and milking equipment. The mechanical arm has various functions that may differ across AMS models. Typically, it initiates the milking process by detection of the udder and teats, followed by teat cleaning and disinfection, attachment of teat cups, detachment as the milk flow decreases and lastly post-disinfection. Concentrated feed serves as an incentive for cows to enter the AMS box, as palatable feed encourages more frequent visits, thereby potentially increasing the milk yield per AMS per day [144].

4.3.1.1 Traffic systems

Various cow traffic systems are used in AMS, namely the free cow flow and guided or forced cow flow systems. The free-flow system permits cows unrestricted access to any areas within the stall, apart from access gates at the AMS entrance. This configuration promotes enhanced animal welfare and facilitates optimal feed intake, as cows typically consume a higher dry matter content compared to the guided-flow system [144]. While this setup may result in fewer AMS visits, it might be preferred due to fact that it provides animals with a greater freedom of movement and therefore allows cows to synchronise their behaviour, which they commonly do within a herd [147]. Guided-flow systems, on the other hand, can be categorised into two types: feed-first and milk-first systems. In feed first guided-flow systems, cows can enter the feeding alley freely but must pass through the AMS box to get back to the resting area. Conversely, in milk-first system, cows need to reach the AMS box to be able to access the feeding alley but are unrestricted when returning to the resting area. In this system the frequency of milking events may be increased, potentially resulting in increased the milk yield. However, such advantages could be offset by a reduction in DMI, potentially predisposing cows to ruminal acidosis [144]. Although it should be noted that DMI and partly mixed ration (PMR) consumption results vary significantly across studies. While Bach et al. (2009) recorded no differences, Melin et al. (2007) reported a greater intake of concentrate intake and DMI in guided traffic systems. A possible explanation for this discrepancy is that in Bach et al.'s (2009) study, cows could access the PMR within the feeding area, whereas cows in the study of Melin et al. (2007) could only access forage and got water once they accessed the AMS [148]. Additionally, disadvantages may include queues forming at entrance gates to the AMS box, which could contribute to hoof disorders and other welfare issues, especially among more submissive animals [144]. Recent research has also been going into developing an intermediate traffic system, falling somewhere between free and guided traffic, to optimise both milking efficiency and animal welfare [147].

4.3.1.2 Milk quality parameters

Given the reduced interaction between farmers and cows facilitated by AMS, conducting milk analysis is imperative to uphold the quality of dairy products. Numerous milk parameters may serve as health indicators, including electrical conductivity, somatic cell count, urea content, milk fat, protein and lactose content, which can be detected by in-line analytical methods [61].

The milk fat content holds significant importance, influencing both the milk's flavour and visual characteristics. Serving as an indicator for milk quality, fat content correlates with the quantity and quality of feedstuffs, along with the stage of lactation. Reduced milk fat percentage is often linked to ruminal acidosis, wherein a decline in rumen pH elevates the concentration of free LPS within the rumen. This is accompanied by a translocation of LPS from the gut into the bloodstream, triggering an inflammatory response. However, the impact of high concentrate diets on LPS release, complicates it's utility as an indicator for ruminal acidosis [61, 149]. Furthermore, there is an increase in milk fat ratio when ketone bodies are utilised and transported to the mammary glands via the blood circulation for the formation and synthesis of milk. Additionally, the milk fat ratio also increases if cows experience fatty liver or ketosis [150].

Proteins constitute an important component of the milk, bearing significant economical and nutritional importance. Milk nitrogen compromises protein-nitrogen and non-protein nitrogen (NPN), with urea accounting for 50% of total NPN, while protein nitrogen compromises 80% casein and 20% whey proteins. Various factors such as illnesses i.e. mastitis can influence protein content, by an increase in capillary permeability [61].

FPR is also a useful diagnostic tool for detecting ketosis or acidosis. The optimal ratio is around 1.3 to 1.5. While in ketotic cows the milk fat content is increased (>4.5), the protein content is typically decreased (<3.2), therefore a FPR >1.5 can be an indication for ketosis. On the other hand, the milk fat content in cows with acidosis generally decreases, making a FPR <1.2 an indicator of SARA [150].

Understanding the correlation between intramammary infections and lactose concentrations is crucial for assessing milk parameters and milk quality. An inflammatory response can lead to epithelial damage around the alveoli, consequently leading to a disrupted equilibrium of the mammary blood barrier. To maintain osmotic balance certain minerals such as sodium and chloride come into play. Consequently, milk from cows affected by mastitis exhibits a lower concentration of lactose, a saltier tase and an increase in electrical conductivity [61].

Somatic cell count is a crucial indicator of udder health, whereas a SCC surpassing 200.000 cells/ml strongly suggests the presence of mastitis [61, 72].
Electrical conductivity (EC) measures the resistance of particulate matter to electric current flow, serving as an indicator of subclinical mastitis. The increased permeability between blood and milk compartments associated with mastitis can lead to an increase in Na^+ and Cl^- concentration in the milk, consequently affecting EC [72, 146]. These methods are fundamental for the development of in-line monitoring systems, designed to assess milk quality and mitigate the introduction of mastitic milk into the bulk tank. As a result they safeguard the interest of prospective consumers while also enhancing profits for producers [61].

4.3.1.3 Milking performance parameters

In Addition to milk quality parameters, farmers can monitor milking performance parameters, such as milk yield, milkings per cow per day, milking duration, flow and speed, which provides an opportunity to improve these factors and potentially increase profitability. Generally, farmers aim to decrease the duration of milking while maintaining a high milk yield, a goal which may be achieved by a greater milking speed. However, milking speed and duration are negatively correlated and selecting for fast milking cows can be risky and may result in udder damage or mastitis. Despite this, milking speed has been identified as a critical factor in enhancing milk production profitability and has been incorporated into numerous breeding programs as a selection criterion [151]. There are certain behavioural traits that cows should have, which can significantly influence the number of visits, attachment time, milking intervals and the overall milking efficiency. In case of AMS, cows need to be more independent and self-motivated to enter the milking robot. Social behaviour may result in competition at the entrance, leading to lower ranked cows spending more time in the waiting are and less time fulfilling other behavioural needs, which can in turn result in failed attachments or failed milking visits. Pain, discomfort or fear of humans can also cause stepping or kicking in the milking robot, leading to increased attachment time, incomplete milking or damage to the teat cups and cleaning devices. Additionally, nervous cows may experience elevated adrenaline levels, which inhibits the secretion of oxytocin, thus reducing or blocking milk ejection. Individual cows respond differently to handling and management, which may reflect underlying temperament traits and should be considered during breeding. Farmers prefer cows with “good temperament” meaning they are safe and easy to handle [152].

Table 2

References	Involved Technologies	Parameters	Application
[72]	Milk conductivity sensor	Electrical conductivity of milk	Early Mastitis detection
[74]	Sensors measuring SCC (with reagent)	Remains of cellular elements and cells	Early Mastitis detection
[72]	Sensors measuring SCC (without reagent)	Electric permittivity threshold	Early mastitis detection
[144]	Sensors measuring milk volume and contents	Fat, Protein, Lactose, LDH	Optimising milk quality and quantity, Early mastitis detection
[132]	Sensors measuring milk progesterone levels	Progesterone concentration in milk	Pregnancy detection

Overview of sensors built into the milking equipment

4.3.2 Automatic feeding systems and precision feeding

4.3.2.1 Automatic feeding systems

Automatic feeding systems (AFS) represents an advancement in Total Mixed Ration (TMR) preparation technology, offering various benefits in terms of workload reduction, improved animal nutrition and enhanced animal welfare. There is a broad selection of machinery on the market, providing farmers with the opportunity to choose one, which adapts best to the animals needs and unique constraints of the farming site. The AFS market is flourishing and currently offer three AFS types on the market which are defined by their automation levels. Stage I includes machinery which uses automation to shred, mix and distribute TMR, while still depending on a stationary mixer, that the operator fills with the necessary ingredients each day. In Stage II, TMR can either be stored within a mixing station or loaded into the stationary mixers automatically, using mechanical systems which load them into the auger-equipped wagons, where the TMR is mixed before it proceeds to ration distribution. Stage III represents full automation by employing mixing-distributing wagons who receive each ration component from the silos directly and deliver feed to animals without the need of human intervention [153]. AFS can be implemented with various technical approaches, including stationary systems like conveyor belts or even mobile systems like rail-guided, self-propelled or wheel-driven feeding-mixing wagons [153, 154]. However, studies and the experience of farmers prove the importance of considering both the feed delivery technology, as well as the organisational and structural aspects of the shed, when selecting an AFS. The chosen system should align with the farms specific requirements, ensuring to meet the needs of various animal groups, as well as supporting the operator's needs (providing efficient loading and unloading options and having an alternative method for feeding in case of any equipment failure). Generally, AFS's, are user-friendly and able to significantly reduce the workload, which is crucial for encouraging younger generations to engage in animal farming. However, farmers must still maintain good feeding practices, ensuring high quality of ingredients and effective management to achieve high quality feed and optimal animal production [153].

4.3.2.2 Precision nutrition and controlled feed intake

Accurately predicting the nutrient requirements of animals and acquiring knowledge of the feed ingredients nutrient content can be quite challenging for farmers. Precision feeding and precision animal nutrition aim to optimise the balance between nutrient demand and supply relative to animals. This approach targets animal performance, milk product characteristics and the environmental and economic outcomes of the farm [70]. Sensor technologies can be used at various steps to monitor and optimise nutritional processes. Firstly, the feed and consequently nutritional intake is largely determined by the quantity and quality of feed available. Various sensors and technologies can assess the volume and quality of feed by measuring the light reflectance, height, density and volume. Commonly used technologies to measure feed intake include electronic feeders, near-infrared spectroscopy (NIRS), monitoring feeding behaviour and weighing animals frequently. Although these technologies face limitations in extensive farming due to the grazing conditions, they prove more effective in intensive farming, where RFID systems and electronic feeders are employed. Once the RFID tag is read, a predetermined amount of feed is dispensed automatically. Electronic feeders then enable detailed monitoring of feeding behaviour such as the feeding time per day, number of meals, feeding rate and how the feed intake is distributed throughout the day [155]. A photogrammetry system has also been developed by Bloch et al. to evaluate the feed intake of individual cows using cameras and cheap equipment, which makes it user-friendly and simple. Deep-learning models and machine vision technology could also be incorporated into feed intake measurement [70]. NIRS is another potential technology, using analytical techniques to rapidly and accurately collect data on chemical-physical properties of TMR, faeces, milk and organic material and could potentially be used to determine the chemical composition of diets. Extensive research has also been conducted on using NIRS instruments to analyse faecal samples, focusing on determining the daily intake of pasture, it's chemical compositions and digestibility of the diet [70, 155]. NIRS calibrations have been used to predict several quality parameters such as CP and dry matter (DM) content in fresh grass and has shown a high accuracy to predict DM contents and moderate accuracy in case of CP content [70]. The Feed-Weigh Roughage Intake Control (Hokofarm Group, Enschede, Netherlands) offers a solution for individually monitoring feed intake. It uses an entry gate that grants entry to one animal at a time and opens once it reads the animals ID ear tag. Each feed bin visit is automatically recorded with a timestamp and the animals ID. The system simultaneously the feeds weight at the beginning and at the end of each visit, providing precise data on individual feed intake. Combined with intake prediction models, this system can be used in future research to estimate feed conversion ratios, which can then be utilised in breeding programs aimed at improving feed efficiency [156, 157].

Another solution for precise feeding is the use of concentrate feeding in AMS. If an AMS is implemented on a farm, cows will be provided with PMR at the feed bunk and concentrate by the AMS. The main goal of concentrate feeding in AMS is to motivate cows to enter the AMS voluntarily, while also meeting their nutrient requirements. A common strategy used when AMS are implemented on farms, is that there is a low concentrate level provided at calving, which is linearly increased until peak lactation. Afterwards, the supply of concentrates is increased as the milk yield also increases, followed by a reduced allowance once milk yield declines. Although AMS offers the possibility of increasing milking frequency and a more precise feeding of cows, there are multiple challenges that farmers are faced with. One being, that cows generally don't consume the whole amount of concentrate they are provided with, especially if the allowance is very high. Additionally, farms which offer a large allowance of concentrate via the AMS, often provide cows with a PMR of low nutrient density, which further compromises the supply of nutrients, if cows don't consume their allowance of concentrate. Furthermore, cows often face a time constraint, as the average time spent in the AMS may not be enough for cows to finish their whole allowance. Bach et al. (2017) have suggested restricting the amount of concentrate to below 3 to 4 kg/day to minimise nutrient intake variations and maximise the economic return. Additionally, other studies have emphasised the importance to consider how feeding strategies implemented with AMS can potentially alter the PMR consumption, to achieve great efficiency in milk production and high economic return [158, 159].

4.3.2.3 Automated milk feeders

Traditionally dairy calves are separated from the dam during the first days of their life, after which they are fed with milk or milk replacer manually until they are weaned [160]. The amount calves are fed is typically limited to around 10% of their bodyweight to lower feed costs, increase the intake of calf starter and promote rumen development. However, when fed ad libitum, their intake averages closer to 20% of their bodyweight. Recent studies suggest that providing calves with a larger volume of milk or milk replacer can enhance animal welfare, health, feed efficiency and growth rates. While automated milk feeders (AMF) are not required to provide higher milk volumes, they enable smaller, more frequent meals throughout the day, improving digestion by raising ruminal pH and decreasing the risk abomasal ulcerations. Simultaneously the larger volume allows for a greater feed to growth conversion efficiency. In traditional systems, calves usually receive two larger meals per day, which can exceed the abomasum's capacity, potentially resulting in reticulo-ruminal milk overflow, also known as ruminal drinking. This can lead to bacterial fermentation and in severe cases following ruminal acidosis. Additionally, with AMFs, milk or milk replacer is dispensed through nipples, prolonging sucking time throughout the day, which aids in digestion and promotes satiety [161]. Most commonly calves are housed individually, as an attempt to reduce disease transmission and improve health management, by limiting contact with other herd mates. However, research shows that disease rates in group housing can be just as good as in individual housing. Additionally, housing calves together promotes social learning, and active behaviour such as playing and running, which are indicators of good welfare and can improve feed intake, as well as growth rates. AMFs are quite expensive, even if it is possible to feed up to 40 calves with one feeder, the recommended number is often reduced to minimise the risk of overcrowding or competition for access, which can cause stress. One key advantage of AMF is automated data collection, which help detect illness early on and enables prompt therapeutic intervention. AMFs also allow for individualised feeding protocols, offering controlled nutrition and medicine opportunities. However, more research is needed to be able to use these technologies to their full potential [160, 161].

5 Methods and Results

This thesis involved the extensive search for scientific literature across several databases, including "PubMed", "National Institutes of Health (NIH)", "Journal of Dairy Science", “Research Gate, “Science Direct” and “Web of Science”. The research strategy employed key terms such as “Precision livestock farming (PLF)”, “Automated health monitoring”, “Automated reproductive monitoring”, “Livestock monitoring”, “Rumination time”, “Dairy cattle herd health management”, which provided a diverse collection of published articles and books, relevant to the topic. A total of 162 references were analysed, with the majority sourced from “PubMed”, “National Institutes of Health (NIH)”, “Journal of Dairy Science” and “Research Gate”. The selected materials included 6 books, 2 graduate student theses, and about 154 published articles. The selection criteria prioritised literature written in English, which investigated the evolution and use of PLF in dairy cattle herd health management, specifically in health and reproductive monitoring. The objective was to critically evaluate and compare studies to provide a comprehensive overview of PLF’s evolution over the last decades, focussing on their functions and applications. The review also assessed which sensors are already commercially available versus those still in their research phase, as well as their respective advantages and disadvantages.

6 Discussion / Conclusion

This literature highlights the advancements in the field of PLF for dairy cattle herd health management. Over the past decades, PLF technologies have evolved from basic sensors to employing more complex, multi-sensory system, which enable the monitoring of multiple physiological and behavioural animal parameters in real-time. The global adoption of automation processes can be attributed to the development of Industry 4.0 during the industrial revolution [7]. By developing intelligent systems that can carry out tasks, which typically require human intelligence, on their own and may even be more exact than humans, the introduction of AI and ML has further revolutionised the field [13]. Additionally, by transforming real-world processes into mathematical equations or simulations, mathematical models and simulation models can aid in the decision-making process. This enables the predictions of diseases or reproductive status, allowing farmers to take proactive measures rather than reactive actions [10, 11].

Health monitoring remains a fundamental component of PLF, with a focus on the early detection of diseases such as lameness, mastitis, metritis, abomasal displacement and metabolic disorders. Rumination time, commonly monitored with the use of accelerometers, microphones or reticulo-rumen boluses, serves as a key indicator of health issues. Significant reductions in rumination time can be seen in rumen health disorders, ketosis, abomasal displacement and hypocalcaemia [91, 107, 115]. Although reduced rumination time may also indicate metritis, Stangaferro et al. (2016) only found moderate sensitivity, depending on the severity of the disease [100]. Rumination time may also be decreased in case of lameness, but the use of leg-worn accelerometers is more effective for lameness detection, rather than neck-worn devices used for monitoring rumination time [66]. Alterations in standing, lying and walking behaviour, often tracked using accelerometers or pedometers, can also provide valuable insights into health [23, 99]. O'leary et al. (2020) found that lame cows tend to lie down less frequently but for longer durations [66]. Similarly, Hendriks et al. (2020) showed that hypocalcaemic cows spend 2.6 hours more lying down post calving [106]. Heat stress on the other hand is often associated with prolonged standing, to minimise heat being transferred from surfaces while lying down [48]. Load cells and pressure plates are increasingly employed to monitor weight distribution and identify lameness through uneven weight-bearing patterns. While studies have demonstrated a high sensitivity of up to 100% when evaluating standing cows, the sensitivity for evaluating walking cows remained low, which may be explained by changes in weight bearing brought on by pain. Systems measuring standing weight distribution might also have a greater potential of being implemented on farms, as they don't require as much space and are easier to use [39, 40]. Van Nuffel et al. has demonstrated that the Gaitwise system can achieve high accuracy levels, however, the accuracy depends heavily on the variables used, with ongoing research suggesting refinements to improve detection, especially for mildly lame cows [40, 41]. Camera-based systems also play a role in lameness detection. Viazzi et al. (2023) assessed back posture of cows, with the use of 2D or 3D cameras, and achieved results with high accuracy. However, it has to be noted that individual back posture variations could pose a challenge in detecting lameness, highlighting the need for individual cow thresholds rather than a herd-level average [24]. ToF cameras, which enable continuous monitoring of BCS, have shown to be great tools for establishing cows with a high ketosis risk. Gillund et al. (2021) found a 2.5-fold higher risk of cows developing ketosis if they have a BCS >3.5 around calving [42, 97]. AMS have further advanced health monitoring, particularly for mastitis detection. Technologies such as SCC sensors, EC sensors and EPT sensors, built into milking equipment, alert farmers at early signs of mastitis, even at quarter level [75, 76, 78]. AMS can also monitor the milking performance, such as reduced milk yield, which often signals health issues, particularly post-partum diseases, such as metritis, ketosis and hypocalcaemia [95, 98, 100, 110].

Automated reproductive monitoring, specifically the detection of oestrus, pregnancies or calving, is another essential feature of PLF. Standing to be mounted, is one of the primary signs exhibited by cows in oestrus. Pressure detectors can detect a standing mount if they register the weight of a mounting animal for a minimum of 2 seconds. However, challenges arise as high-producing dairy cows, show less mount attempts. Additionally, 40% of mounts last less than 2 seconds, which make the detection harder. However, research has indicated that pressure sensing systems could detect around 80% of cows in oestrus with the use of specialised algorithms [125, 126]. Camera-based systems are another method of detecting cows standing to be mounted. However, this approach is heavily reliant on camera resolution, making identification of cows challenging [125]. Pedometers and Accelerometers are widely utilised to detect oestrus, as research indicates that cows exhibit a 2.3 to 6-fold increase in activity on the day of oestrus and a significantly increased walking time. However, this rise in activity can be greatly affected by environmental conditions, such as high ambient temperatures, which may reduce oestrus duration or even disrupt the cycle altogether [125, 127]. Additionally, rumination has been observed to decrease markedly during oestrus. It is important to note, however, that cows experiencing a natural heat show a pronounced drop in rumination time, compared to those undergoing induced heat, where changes are typically minimal [128, 129]. A rise in body temperature can also be an indication of oestrus, which can be measured with various technologies. A non-invasive approach to identifying an increase in body temperature, is the use of milk temperature sensors. Although it should be noted that, studies have revealed a high incidence of false positive results. Furthermore, the temperature rise may not remain as long as the milking interval, further complicating the detection [36]. Thermographic cameras, provide another non-invasive approach to capturing an increase in vulvar temperature. However, studies in this case have also reported a high incidence of false positive and negative results, which could be explained by temperature variations due to environmental factors [36, 124]. Although rectal and vaginal thermometry, are more invasive approaches, they are potentially more reliable [125, 131]. A notable advancement in PLF technologies, is the fully automated in-line progesterone analyser. While the initial installation of such systems requires a great investment, they can be highly profitable for large-scale farms. However, a follow up examination is required to confirm pregnancies, because this system often provides a false positive results, due to early pregnancy losses [132, 135]. Accurately predicting the onset of calving, is crucial for providing timely calving assistance. Continuous temperature monitoring via temperature loggers, is used to predict calving within the next 24 hours. Studies have shown a decrease in vaginal temperature by about 0.2 to 0.3°C and rectal temperature by 0.3 to 0.5°C 24 hours before the time of delivery. Although the temperature decrease by itself isn't enough to predict the exact onset of calving, it can be helpful together with traditional signs of parturition [138, 139]. A drop in reticulo-rumen temperature of >0.2°C can also be detected, via a reticulo-rumen bolus. Additionally, research indicates that cows experiencing eutocia exhibit a more pronounced temperature decline of around 0.48°C, compared to a milder drop of only 0.23°C, in cases of dystocia. This difference suggests that reticulo-rumen temperature changes could possibly serve as a potential indicator of dystocia, though further research is required for a better understanding [140, 141]. In the hours leading up to calving, cows exhibit various behavioural changes, which become more pronounced during the last hours prior to calving. While cameras are not commonly employed to monitor these behaviours, their integration combined with specialised algorithms holds potential for the future. More frequently tools such as accelerometers, pedometers and microphones are used to detect these changes. Notable signs include a remarkable decline in rumination time of around 70% 24 hours prior, an increase in standing and lying bouts 12 hours prior and an increase in tail raising activity around 4 hours prior to calving [137]. Tail-mounted accelerometers have also become commercially available, however, studies have shown variations in sensitivity and found that they did not provide precise information about the exact calving time [37].

Further limitations of PLF include the high investment costs which are required for installing and maintaining sensor technologies, particularly larger and more complex systems, such as the AMS. Technical failures also pose a great risk, especially if there is no backup plan available. Over- or under-reliance also poses a potential threat of PLF. Animal welfare can suffer when end-users either blindly trust or don't trust the alerts sent out by the PLF systems. For instance, poor accuracy and a high number of false alerts can lead farmers to disregard alerts altogether. Farmers, who are not yet familiar with these systems may also be overwhelmed with the vast amount of data and struggle to interpret the information, which can lead to suboptimal decision-making. Additionally, sensors which are directly implanted inside the animals or attached to them, can cause discomfort or harassment by other animals. There are also not many studies available on the long-term effects, caused by the exposure to PLF hardware. Furthermore, PLF may lead to further intensification, as studies have shown that the leading factor of adopting PLF tools on a farm is the large herd size, focusing on production efficiency, profitability and decreasing labour [3].

In conclusion, the evolution of PLF has significantly improved the management of dairy cattle herds. The advancements in sensor technologies, data analytics and AI have provided farmers with valuable tools, for monitoring, assessing and improving animal welfare, productivity and overall herd health. PLF systems allow for an early detection of health issues, optimisation of feeding practices and improvement of reproductive management, which results in more efficient and sustainable farming practices. Numerous studies mentioned above have achieved significant success with PLF technologies, while others have shown great potential. This thesis also highlights the importance of integrating multiple sensor-systems to enhance management practices. It also underscores the necessity for further research to overcome challenges, such as environmental factors affecting animal parameters, poor camera resolution and the complexities of integrating large volumes of data. Advances in AI and ML will also play an important role in future developments, enabling the development of algorithms which can further enhance automation programs. Additionally, installation costs, which may initially appear unprofitable to farmers, remain a key concern. However, educating farmers on the long-term profitability, as well as the improved animal welfare achievable through such systems, particularly for larger farms, is essential to drive adoption. With ongoing innovation between farmers, researchers and industry stakeholders, PLF will become an essential component of modern dairy farming.

7 Summary

The rising demand for animal-derived products, has made it increasingly difficult for farmers to manage herd-health, using only traditional methods. PLF has emerged as a transformative approach to modern livestock farming [1]. The technological revolutions from Industry 1.0 to 4.0 have enabled PLF to monitor livestock through various sensors, while tracking multiple animal variables [7]. Moreover, with the integration of artificial intelligence and machine learning, PLF can predict potential health and reproductive issues [13]. One of the primary goals of PLF is improving productivity, through better health management [2]. Various sensor systems are commercially available, including RFID tags, accelerometers, pedometers, pressure plates, load cells, camera-based systems and AMS [24, 35]. Neck collars, combining multiple sensors such as accelerometers, microphones and RFID tags, are commonly used on farms to monitor behavioural changes, including variations in eating and rumination time, lying and standing time and overall activity. These changes can serve as indicators of health or reproductive status. A decrease in rumination and eating time is commonly related to health issues, though it is important to distinguish from the drop in rumination time seen during oestrus or calving [33, 128, 129]. On the other hand, while decreased activity, is often related to illness, an increase in activity might also indicate restlessness, which is commonly associated with oestrus or calving [36, 139]. For detecting

conditions such as lameness, pressure plates or load cells are frequently used to monitor the weight distribution across legs [24]. Furthermore, sensors built into the milking equipment also have revolutionised both health and reproductive monitoring. The measurement of milk components, such as somatic cell count (SCC), electrical conductivity (EC) or electric permittivity threshold (EPT), are highly effective for mastitis detection [75, 76, 78]. Additionally, the monitoring of milking performance can also be a key indicator for health issues, as a sudden drop in milk yield often indicates disease, alerting farmer to potential issues before the occurrence of clinical signs [151]. This ability to detect health conditions early ensures that animals receive the necessary care before their welfare is severely impacted. Furthermore, reducing the need for manual checks minimises additional stress for cows, which further improves welfare [162]. Recent development in in-line progesterone analysis also supports reproductive health, enabling farmers to efficiently manage breeding an pregnancies, ultimately improving the herds overall productivity [135]. Lastly, PLF plays a significant role in environmental sustainability. By optimising animal health, productivity and emissions, farmers can reduce resource waste, improve their environmental impact, while increasing efficiency. Additionally, more efficient management practices can reduce the antibiotic usage, leading to less environmental contamination [29, 51, 53]. In conclusion, PLF offers numerous benefits for improving productivity, enhancing animal welfare and promoting environmental sustainability. The integration of PLF sensor systems combined with AI-driven technologies aids farmers in managing their herds more efficiently, ensuring better health, increasing profitability and reducing their environmental impact.

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INTERNATIONAL STUDY PROGRAMS
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Thesis progress report for veterinary students

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Thesis title: Evolution and use of Precision Livestock Farming (PLF) in dairy cattle and heard health A Literature Review

Consultation – 1st semester

	Timing			Topic / Remarks of the supervisor	Signature of the supervisor
	year	month	day		
1.	2023.	09.	08	Registration of thesis: Choose of topic. Deadlines	[signature]
2.	2023	10	06	Discussion of Table of Contents Introduction and literatures.	[signature]
3.	2024.	02.	08	Discussion of 1st Proposal of introduction and chapter 1	[signature]
4.	2024	04.	17.	Corrections of „PLF Tools" chapter	[signature]
5.	2024	07.	16.	Teams Meeting - Discussing Corrections	[signature]

Grade achieved at the end of the first semester: 4

Consultation – 2nd semester

	Timing			Topic / Remarks of the supervisor	Signature of the supervisor
	year	month	day		
1.	2024	09.	19.	Teams Meeting - Discussing Corrections (Repro. Management)	[signature]
2.	2024	09.	30.	Corrections on structure and copyright	[signature]
3.	2024	11.	05.	Corrections + Adding Table of PLF Tools	[signature]
4.	2024	11.	21.	Final corrections of „applied PLF" chapter	[signature]

5.	2024	11.	27.	Final Corrections of the Thesis	

Grade achieved at the end of the second semester: 5

The thesis meets the requirements of the Study and Examination Rules of the University and the Guide to Thesis Writing.

I accept the thesis and found suitable to defence,

signature of the supervisor

Signature of the student: ....

Signature of the secretary of the department: ....

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