Suitability of digitally recorded data for automatic lameness detection on dairy farms

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AIC	Akaike information criterion
AMS	Automatic milking system
API	Application Programming Interface
AUC	Area under the curve
B	Bandage
BCS	Body condition score
BIC	Bayesian information criterion
BU	Bulb ulcer
CB	Claw block
CC	Corkscrew claws
CCC	Concordance correlation coefficient
CDF1	Commercial dairy farm 1
CDF2	Commercial dairy farm 2
CDF3	Commercial dairy farm 3
CDF4	Commercial dairy farm 4
CDF5	Commercial dairy farm 5
CI	95%-Confidence interval
Claw_health_status_c	Corrected claw health status
Claw_health_status_n	Normal claw health status
C_LMS	Corrected locomotion score
C_LMS2	Corrected locomotion score 2 (unsound)
C_LMS3	Corrected locomotion score 3 (lame)
CSH	Central sole haemorrhage
CSV	Comma-separated values
CTC	Chlortetracycline spray
CZC	Copper and zink chelate spray
DD	Digital dermatitis
DDM0	Digital dermatitis Stage M0
DDM1	Digital dermatitis Stage M1
DDM2	Digital dermatitis Stage M2
DDM3	Digital dermatitis Stage M3
DDM4	Digital dermatitis Stage M4

DDM4.1	Digital dermatitis Stage M4.1
DPP	Differential precision pedometer
DS	Double sole
ENET	Elastic net
ETN	Ear tag number
FCN	Farm cow number
GSC	Growth in the sole centre
HHE	Heel-horn erosion
HF	Horn fissure
ICC	Intraclass correlation coefficient
IH	Interdigital hyperplasia
IP	Interdigital phlegmon
IQR	Interquartile range
κ	Cohen’s kappa
κ_w	Quadratic weighted Cohen's kappa
LKV	Landeskuratorium der Erzeugerringe für tierische Veredelung in Bayern e.V.
LMS	Locomotion score
LMS1	Locomotion score 1 (sound)
LMS2	Locomotion score 2 (unsound)
LMS3	Locomotion score 3 (lame)
LRP	Long-range pedometer
LS	Lesion score
MDi	Mastitis-Detection-index
N	Number of observations
NA	Not available
NAS	Network attached storage
NTP	Network time protocol
OLU	Otherwise located ulcer
OR	Odds ratio
PA	Percentage of agreement
PLF	Precision livestock farming
ρ	Spearman's rank correlation coefficient

RF1	Research farm 1
RF2	Research farm 2
RF3	Research farm 3
RFID	Radio frequency identification
SAP	Salicylic acid paste
SAPO	Salicylic acid powder
SHD	Sole haemorrhage diffused form
SHC	Sole haemorrhage circumscribed form
SMOTE	Synthetic minority over-sampling technique
SN	Sensitivity
SP	Specificity
SQL	Structured query language
SU	Sole ulcer
THI	Temperature-Humidity-Index
TN	Toe necrosis
TU	Toe ulcer
TS	Thin sole
WLA	White line abscess
WLF	White line fissure

List of publications

Parts of this dissertation were published in the following studies and articles:

- Sauter, S., Hertle, S., Peis, R., Haidn, B. (2021). Demonstrationsprojekt 5: Vernetzte, tierindividuelle Sensorsysteme. LfL-Schriftenreihe, DigiMilch: Einblicke in die Zukunft der Milcherzeugung, Hrsg.: Bayerische Landesanstalt für Landwirtschaft (LfL), 64-68
- Hertle, S., Lorenzini, I.; Haidn, B. (2022). Kühen auf die Füße schau'n. Bayerisches Landwirtschaftliches Wochenblatt (BLW), 26, Bayerisches Landwirtschaftliches Wochenblatt (BLW), Hrsg.: DLV, 26-27
- Hertle, S., Lorenzini, I., Grimm, K., Haidn, B. (2022). Can a three-point locomotion scoring system reflect the actual claw health?. World Buiatrics Congress 2022 Abstract Book, 297-298
- Hertle, S., Sauter, S.; Lorenzini, I.; Haidn, B. (2022). Could digital technologies lead to improved lameness detection on dairy farms?. HAICTA Tagungsband, 10th, 2-3
- Boppel, M., Höcherl, S., Schneider, M., Thurner, S., Beckmann, S., Schäffler, M., Poteko, J., Wirsching, J., Harms, J., Sauter, S., Hertle, S., Haidn, B., Lorenzini, I. (2023). Experimentierfeld DigiMilch: Digitalisierung in der Prozesskette Milcherzeugung. Züchtungskunde, 95(5), 310-326
- Hertle, S., Lorenzini, I., Sauter, S., Haidn, B. (2024). Sensorgestützte Lahmheitserkennung bei Milchkühen: Entwicklung und Anwendung von Regressionsmodellen auf Basis von Aktivitätsdaten. KTBL-Tagungsband, 16. Tagung: Bau, Technik und Umwelt in der landwirtschaftlichen Nutztierhaltung 2024, Hrsg.: KTBL, 155-158
- Hertle, S., Lorenzini, I., Grimm, K., Haidn, B. (2024). A three-point locomotion score developed for practical relevance showing high validity and reliability. 22nd International Symposium and 14th International Conference on Lameness in Ruminants (*not yet published*)

I. Introduction

Cows, as prey animals, have an innate tendency to conceal signs of pain (Weary et al., 2006), which often leads to underdiagnosis of lameness, the most significant indicator of discomfort in the musculoskeletal system. Lameness, however, is not solely a clinical condition; it can profoundly affect a cow's overall well-being, influencing its natural behaviour, lifespan and productivity (Whay & Shearer, 2017). When a cow's ability to move freely is restricted, it impacts nearly every aspect of its daily life, from feeding and milking to social interactions. The wide-ranging consequences of lameness highlight the importance of early detection and intervention to ensure the overall health and welfare of the cow.

Digitalisation and automation are mentioned frequently as promising solutions to the numerous challenges emerging in agriculture. Farmers investing in new precision livestock farming technologies primarily aim to improve aspects like health monitoring, heat detection, animal welfare and labour management on their farms (Bianchi et al., 2022). At the same time, there remains a notable lack of awareness in this professional group regarding the potential for automated systems to effectively manage lameness detection (Bianchi et al., 2022), which would reduce the need to rely on error-prone, time-consuming manual observation (Schlageter-Tello et al., 2014).

The prevalence of lameness on farms tends to be consistently underestimated by farmers (Jensen et al., 2022; Laschinger et al., 2024), who are often oblivious to the far-reaching negative consequences of claw diseases (Van de Gucht et al., 2017). Jensen et al. (2022) noted that farmers who do not perceive lameness as a significant problem in their herd are less likely to consider investing in an automatic lameness detection system. Upon being educated on the matter, according to Van de Gucht et al. (2017), farmers begin to exhibit a discernible increase in interest towards integrating automatic lameness detection systems, reflecting a deeper understanding of the advantages these technologies can offer. In general, there is a preference by farmers for utilising indirect automatic lameness detection systems directly affixed to the animals over cameras or force plates (Van de Gucht et al., 2017). By making use of the sensor systems and their infrastructure already in operation, a monitoring framework can be implemented on farms, entailing minimal additional investment (Grimm et al., 2019). This comprehensive approach not only facilitates the observation of various health parameters but also allows for the integration of sophisticated algorithms and technologies to address specific challenges like the more complex, multifaceted lameness detection. The automation of the process can lead to a more consistent and objective monitoring of the animals' lameness status (Abdul Jabbar et al., 2017), thereby placing a stronger emphasis on the individual animal's welfare through the timely identification of claw issues.

There are currently no validated systems for indirect automatic lameness detection on the market. Consequently, two preceding studies at the Bavarian State Research Centre for Agriculture already focused on automatic lameness detection by using pedometer data in combination with performance parameters on Bavarian dairy farms. In this subsequent study, the behaviour, performance and claw health data of Simmental cows recorded by different animal-specific sensor systems on eight Bavarian dairy farms were used to validate the reference system for manual lameness detection and to determine which parameters from which commercially available sensor systems are best suited for automatic lameness detection and how they can be combined to accurately identify lame cows.

II. Review of Literature

1. Precision Livestock farming

Precision livestock farming (PLF) has gained increasing importance in recent years and the development is still on the rise. This process could be caused by a greater demand for animal products in general caused by a growing population (Ritchie et al., 2023) or by the improving economic situation in developing countries (Berckmans, 2017). Subsequently, to meet these needs and to stay profitable, farm sizes are growing and smaller agricultural family farms are replaced by fewer, larger-scale agribusinesses (Statistisches Bundesamt [Destatis], 2022). PLF, which is defined as a constant observation of the single animal and all its possible life influences by using digital technologies (Berckmans, 2017), is seen as a promising tool to facilitate the monitoring of larger herds while not losing sight of the individual animal. In PLF, sensors collect data on the animal, the herd or the environment, which are then analysed by algorithms and summarised for visualisation and final use by the farmer (Kleen & Guatteo, 2023). The focus of attention shifting towards the topic of animal welfare among the population (European Commission, Directorate-General for Health and Food Safety, 2016) might also be a reason for farmers to start investing in PLF technology. Getting real-time information from cameras, microphones or sensors on the current well-being, performance, reproduction values and environmental effects of the single animal (Berckmans, 2017) as well as performing continuous monitoring of the whole herd could lead to earlier detection of deviations and enable timely reactions (Džermeikaitė et al., 2023). The rising consciousness of the effects of climate change and the commitment to promote sustainability is an additional factor that should not be underestimated as a driving force for technologisation of farms (Singh, 2021). Better farm management due to PLF can significantly contribute to a longer life expectancy of animals (Singh, 2021), which may in turn lead to a more sustainable way of farming in the future.

1.1 Opportunities and limitations in precision livestock farming

1.1.1 Opportunities

The implementation of digital technologies on farms could produce clear benefits for many farmers. The main advantage of applying sensors like ear tags, pedometers, boluses or collars is the earlier detection of health issues (Džermeikaitė et al., 2023). If behaviour or performance parameters of an animal differ from standard values, most systems generate an automatic warning message (Islam & Scott, 2021). The farmer can focus on these animals with a suspicion of illness and take action to prevent the illness from worsening. Difficult-to-detect processes like silent heats or subclinical mastitis can be uncovered by help of sensor systems and be promptly treated (Antanaitis et al., 2022; Hojo et al., 2018). Some sensors also recommend actions such as calculating the optimum interval for insemination after detecting a heat (Roelofs & Van Erp-van der Kooij, E., 2015). In sheep and pigs, animal-specific data is rare, while the primary focus is placed on changes affecting the whole herd, including applications like automatic weighing scales (González-García et al., 2018) or microphones detecting vocalisation (Hong et al., 2020).

PLF tools are not only helpful for the detection of diseases but also deliver data on productivity of the individual animals, which can lead to significant improvements in this area (Carillo & Abeni, 2020). Every milking, heat or feed intake can be detected, and different lists can provide insight into the history of reproduction, changes in weight or other performance parameters.

Herd management solutions offer various ways of displaying, including graphs or tables, and the capability of summarising large amounts of raw data to create reasonable and useful representations, which can supply farmers with useful information on their herd (Van Hertem et al., 2017). Management decisions such as culling can be made more confidently based on the information provided by sensor systems (Kleen & Guatteo, 2023).

Different stakeholders like veterinarians, claw trimmers or feeding consultants could get a first impression on the herd or specific animals by reviewing the sensor system data (Eastwood et al., 2016). This could enable an enhanced exchange of information between the different parties involved in the daily farming business and especially improve the integrated stock supervision (Kleen & Guatteo, 2023). In times of scarcity of qualified employees, PLF technologies could help to streamline farm working routines and processes (Gindele et al., 2016) or assist temporary staff in getting to know animals and farm operations. Data that can be transferred between different devices eases adding new information and checking specific animals even if the farmer is not physically near the barn (Islam & Scott, 2021). Documentation by sensor systems takes place 24 hours per day, giving the farmer an overview of events at all the times he normally could not fully focus on his animals (Buller et al., 2020).

A digital technology fully in place can also be a time-saving tool for farmers (Makinde et al., 2022). Collar tags blinking or sensor systems showing the location of the animal in the stable allow the farmer to easily locate the animal and find those cows who need intervention (Chapa et al., 2021). Smart gates divide the farm into different functional areas, giving the farmer a hint about which activity the cow is currently engaged in and can also be used to separate animals (Kuraloglu et al., 2023). Milking robots can contribute to more flexible work hours because presence at the farm is not set to two specific time slots a day for the milking process (Stræte et al., 2017). Driving the whole herd to the milking parlour as well as attaching milking utensils is also no longer necessary because cows enter the milking robot by themselves and get milked automatically. Automatic feeding systems, manure scrapers and other devices take over tasks for the farmer and accelerate the operating procedure (Da Borso et al., 2017; Garcia-Covarrubias et al., 2023).

In addition, the financial aspects of PLF should be considered. Although farmers need to invest in the technology first, several studies confirm there can be a financial profit by implementing PLF technologies on farms. Most of these studies examined the issue by creating models that simulate various baseline conditions to evaluate the possible effects on different farm environments. Pfeiffer et al. (2020) and Rutten et al. (2014) demonstrated by simulations that an activity recording sensor for heat detection would be a sound investment for most farmers. Crociati et al. (2021) investigated the financial advantages of an intravaginal calving alert sensor and showed a resulting increase of income by approximately 120 EUR per calving event. A cost-benefit analysis of an automated lameness detection system is considerably more complex, as it must account for not only system costs, performance and herd size, but also varying levels of lameness severity and different incidence rates (Kaniyamattam et al., 2020). Nevertheless, Kaniyamattam et al. (2020) were able to demonstrate that, with an assumed 10-year operational period, an automatic lameness detection system would prove financially beneficial for farmers in over 80% of the various scenarios considered. However, as most of the available studies focus on the profitability of heat detection, further research might be needed concerning cost-effectiveness of disease detection by sensor systems.

IoT and sensor technology will also be necessary to cope with the upcoming demands towards animal husbandry in the future. Climate change and animal welfare topics might lead to more extensive husbandry systems such as pasture grazing or free-range farming (Schulze et al., 2021). In these types of housing systems, building and repairing fences or driving animals from one pasture to another can be a time-consuming task. Virtual fencing, for example, uses GPS collars to track animals in set borders on pastures and can create a stimulus to steer them away from the border (Campbell et al., 2019). Installations like temperature- and humidity-controlled cow showers or ventilators might help cows to cope with heat stress in future climatic conditions (Ji et al., 2020; Legrand et al., 2011). Besides, digital technologies could minimise the environmental impact caused by cowshed emissions. Conditioning cows to use cow toilets could reduce ammonia emissions by directly collecting the urine (Galama et al., 2020).

1.1.2 Barriers

Even though automatisation and digitisation represent promising new developments in livestock farming, PLF is not free of risks and limitations. Initial investment costs are often high and there is no guarantee for farmers that the technologies will prove to be financially viable. Durability, maintenance or repair costs are only three out of many factors which might influence the profitability of a sensor system (Borchers & Bewley, 2015; Hartung et al., 2017).

In addition, it is difficult for farmers to find the best-fitting sensor technology for their farm due to a lack of unbiased information. Farmers place great value on independent advice and available on-site support (Borchers & Bewley, 2015) but often need to search for product descriptions like installation requirements by themselves or directly ask dealers of the specific company, which might lead to subjective consultations.

The starting situation of every farm, including animal population (Abeni et al., 2019; Van de Gucht et al., 2018), barn construction (Akinyemi et al., 2023), workforce (Abeni et al., 2019), wireless network connection (Akinyemi et al., 2023) and current disease prevalence (Van de Gucht et al., 2018), could influence the decision for the investment in a sensor system and its chances of success. The personal preferences of the farmer should also be considered in terms of sensor systems (Van de Gucht et al., 2017) or management applications and their availability on different devices. Assessing the individual circumstances of their farm can be challenging for farmers on their own, but in the end, it might be crucial for the benefit of sensor technologies.

Furthermore, potential time savings in the daily management routine should not be the driving force when deciding for or against digital technologies. Even if it could be a positive side effect, supervising sensor systems can take a lot of time (Hostiou et al., 2017), especially in the first period after installation. Some sensors need an initial behaviour learning phase (Hajnal et al., 2022), others demand time for the attachment to the animal (Yousefi et al., 2022) or require multiple manual data entries in the beginning (Daum et al., 2022). Getting used to the application might take a while and demand initial training of the farmer (Van Hertem et al., 2017). Power breakdowns, network issues or technical failures can never be ruled out completely and might cause production downtime or loss of data (Tuyttens et al., 2022). Representatives of the selling company might not always be reachable on short notice, thus it could be an advantage if farmers possess a certain degree of technical know-how to deal with such problems immediately (Hackfort, 2021). In summary, the way of working will differ after investing in a sensor system (Hostiou et al., 2017) and the farmer must be willing to face technological challenges.

PLF technologies might also directly influence the behaviour of cows or even cause damage, for example through an incorrectly attached sensor (Pfeiffer et al., 2021; Tuyttens et al., 2022).

The initial adaptation phase to new technologies on the farm can be difficult for some individuals and result in temporary discomfort (Tuyttens et al., 2022). The human-animal relationship could suffer from further technologisation of farms if the farmer exclusively focuses on alerts and sensor data (Hartung et al., 2017; Tuyttens et al., 2022). Digital technologies should never replace the direct contact with the animal but support the farmer in monitoring and management tasks while increasing the available time for the more animal-related activities (Hartung et al., 2017; Tuyttens et al., 2022).

Data sovereignty and security is also a topic that many farmers still feel insecure about, especially when it comes to sharing their data (Wiseman et al., 2019). The more digitised and technologised a farm is, the higher the risk of unauthorised access and data manipulations (Gupta et al., 2020; Kleen & Guatteo, 2023). Data protection is an important issue for farmers (Gupta et al., 2020), as in most cases the farm is not only a workplace, but also a home to them (Leshed et al., 2014). Data storage, for example in cloud-based solutions, and data exchange between different parties creates a risk of harmful interference from third parties (Gupta et al., 2020). Fears like constant surveillance and control by the government or distributors arising with further implementation of digital technology also need to be taken seriously (Tuyttens et al., 2022).

A further limitation of PLF is the lack of interconnectivity between most of the precision livestock technologies (Kleen & Guatteo, 2023). Communication between sensors of different manufacturers is rarely possible and often a separate herd management system is necessary to exchange data (Kleen & Guatteo, 2023). A uniform data standard is urgently needed (Bahlo et al., 2019) and although projects like iDDEN (iDDEN GmbH, 2023) work towards this goal, this process is still ongoing. Farmers tend to have a large number of different applications to manage all their on-farm technology and these separate systems each collect different parameters without comparing or combining their results to create alerts (Bahlo et al., 2019). Consequently, at this point it is still the farmer’s task to retrieve the available information, interpret the overall situation and draw conclusions.

1.2 Technical insights on sensor systems

1.2.1 Components and operation of a sensor system

A sensor system comprises various components (Figure 1), that are comprehensively described in the study by Hunter et al. (2010). It includes different sensing units like accelerometers or thermal sensors, whose characteristics are controlled by the microprocessor. After recording, the data is forwarded to an analogue-to-digital conversion unit, which translates the incoming analogue signals into discrete digital values. Depending on the employed sensor system, the data may be temporarily stored in a memory unit within the sensor system and is then wirelessly transmitted to external receivers via a communication tool. The necessary energy supply of the sensor system is provided by an internally integrated power unit, which may take the form of batteries, rechargeable batteries or self-sustaining power sources such as solar cells or piezoelectric systems. The receivers transmit the data to the management program associated with the sensor system on the computer or mobile device, where further processing algorithms extract useful information for the farmer, such as graphs, tables or notifications.

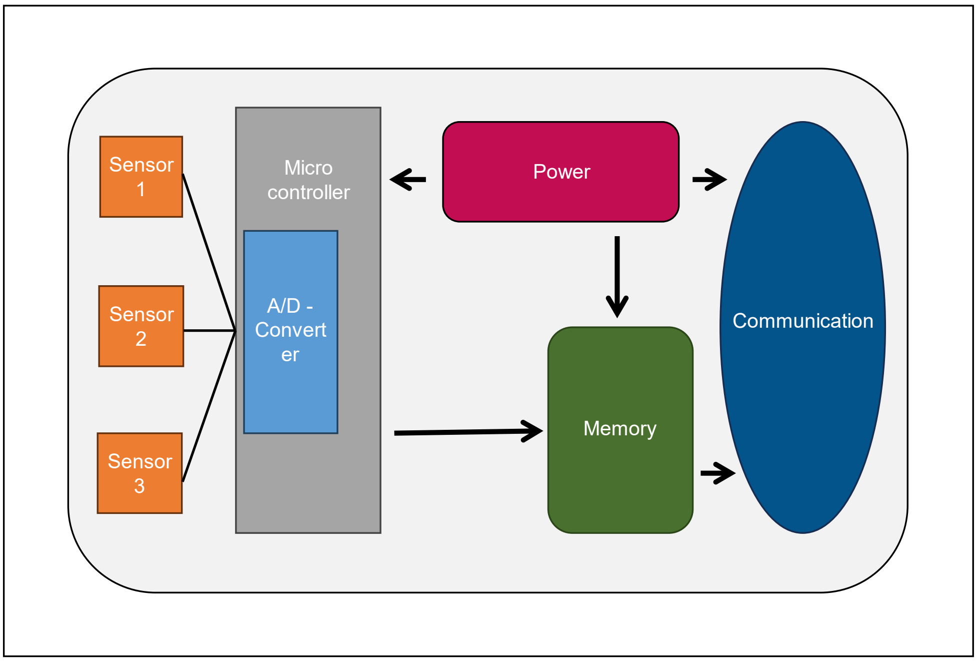


Figure 1: Schematic illustration of a sensor system, based on Hunter et al. (2010). Adapted from original with modifications

1.2.2 Categories of cow-attached sensor systems

Sensors attached directly to cows are already capable of monitoring a wide range of behavioural and physiological variables. These include parameters like feeding behaviour and quantity, grazing patterns, rumination, drinking behaviour and volume, pH levels, body temperature, activity, standing behaviour, oestrus signs, calving events, lying behaviour, respiratory rate or the cow's location within the barn. These parameters are monitored by a diverse array of sensor systems, a selection of which is depicted in Figure 2. The following section offers a general overview of the various sensor system classes, accompanied by validations of the systems utilised in this study.

1.2.2.1 Pedometers

General overview

Pedometers, initially designed for activity tracking purposes only, have evolved over the years into comprehensive recording devices capturing various behaviours. Some pedometers incorporate a three-dimensional accelerometer, enabling them to distinguish between different behaviours such as walking, standing or lying based on the direction of acceleration. If coupled with a magnetic field-inducing loop, they can also detect the cow’s presence at the feeding table (Lorenzini, Schindhelm et al., 2017).

Pedometers are typically attached to a cow's leg using a strap with pins or buckles, offering the advantage of easy removal when the cow leaves the farm and allowing for reattachment to another cow. However, proper attachment is not entirely straightforward, as tight fastening may constrict the leg, while loose installation makes the pedometer susceptible to the cow's movements, increasing the risk of detachment.

Proper orientation of the sensor on the cow's leg according to the label instructions is essential to avoid inaccuracies in recording lying times (Brehme et al., 2006). Additionally, the positioning of the sensor on the leg can significantly influence its accuracy, for example in detection of feeding behaviour (Greil, 2018).

Validation

Three different master's theses at the Institute for Agricultural Engineering and Animal Husbandry of the Bavarian State Research Centre for Agriculture were based on the work with the "Track a cow" pedometers by ENGS (ENGS Dairy Solutions, Rosh Pina, Israel). The first one focused on the validation of the recorded lying behaviour recorded by the pedometers and demonstrated that there was almost complete concordance between the visually observed and the automatically measured lying duration (Weingut, 2017). The examination of the lying events per hour showed a higher documentation of lying events by the pedometers than by the visual observer, but the concordance correlation coefficient (CCC) (0.8) could still be considered good (Weingut, 2017). Another thesis dealt with the validation of the feeding behaviour detected by ENGS pedometers and revealed there was a good concordance of the feeding duration between visual and automatic monitoring (0.9), but the pedometers often recorded one feed visit less than the observer (Greil, 2018). These discrepancies could be explained by the pedometer position, which led to errors when it was aligned parallel to the induction loop (Greil, 2018). In a more recent master's thesis, ENGS pedometers to detect heat events were combined with two induction loops to distinguish between grazing and stall periods of the cow (Wirsching, 2022). As the activity of cows on pasture is generally higher, the use of heat detection systems is often complicated by too many false heat alarms (Wirsching, 2022). Using pedometers, the cow's location, and an adapted algorithm, 67% of the cows, initially falsely identified as in heat, could be correctly recognised as not in heat (Wirsching, 2022).

Van Erp-van der Kooij, E. et al. (2016) validated the CowControl pedometers by Nedap Livestock Management (N.V. Nederlandsche Apparatenfabriek, Groenlo, the Netherlands) through comparison with live observation and video data and reported very high correlations for lying and standing. The standing-up frequency also corresponded to the video observation, but timing discrepancies of the leg tags led to poorer alignments. For walking, the CCC yielded only 0.45 and 0.5, which could also be explained by difficulties in observing this behaviour. Nielsen et al. (2018) evaluated these leg tags in the CowScout version supplied by GEA (GEA Group Aktiengesellschaft, Germany) and found similar results: nearly perfect accuracy for lying and standing, but shortcomings in step tracking.

Borchers et al. (2016) conducted a validation study, which included the AfiTag Plus pedometers by Lemmer-Fullwood (Lemmer-Fullwood GmbH, Lohmar, Germany) along with visual observation, revealing a high CCC of the lying behaviour exceeding 0.99. Henriksen and Munksgaard (2019) demonstrated the efficacy of accurately recording lying times and bouts of another pedometer by Lemmer-Fullwood, the AfiTag II, although variances were noted in pedometer readings among differently managed dry cows. Swartz et al. (2016) compared the measured step activity by AfiTag II pedometers in calves with video recordings and also noted a high correlation of 0.99.

1.2.2.2 Neck and noseband sensors

General overview

Noseband sensors can be integrated into a complete halter, while neck tags are mostly attached to a collar in various positions, for example snugly alongside the neck or hanging beneath it.

Neck tags, like pedometers, typically also contain an accelerometer, which distinguishes between different behaviours based on varying frequencies and directions. Vertical upward movements, for instance, can be interpreted as head bobbing during walking, while downward acceleration is more associated with feeding or grazing. Sensors with a microphone are able to identify the sound associated with regurgitation, which initiates rumination (Elischer et al., 2013). The audio recordings allow for the tracking of individual chewing cycles per bolus, the number of boli, and the duration of rumination (Elischer et al., 2013).

The noseband sensor comprises a pressure sensor, an accelerometer, and an oil-filled silicone tube within the halter, the latter of which directly detects pressure changes resulting from chewing movements (Kröger et al., 2016). This type of sensor is used mostly in research and is not meant for data collection on commercial dairy farms.

Some sensors use ultrawideband radio signals, which emit signals intercepted by receivers strategically positioned throughout the barn to calculate the cow's location (Frondelius, Van Weyenberg et al., 2022).

Like pedometers, neck tags and halters provide the convenience of easy transferability across different animals, but neck tags on a collar, in contrast to halter-attached sensors, are susceptible to data inaccuracies stemming from improper attachment, slipping or twisting of the collar.

Validation

Borchers et al. (2021) observed that the calculated mean difference for all behaviours recorded by the CowControl Necktag by Nedap aligned closely with the visually observed values, with feeding and rumination showing a strong correlation, while inactive time displayed a moderate correlation. High CCC (>0.89) were also reported by Van Erp-van der Kooij, E. et al. (2016) for all three behaviours.

No studies addressing the SCR (Allflex Livestock Intelligence, Dallas, USA) neck tags in the 5th generation could be found. The research of Schirmann et al. (2009) focused on the validation of a preceding SCR neck tag, comparing rumination data recorded by the system with visually documented observations and revealing a notably strong correlation (0.96). Elischer et al. (2013) found only a moderate correlation (0.61) between the walking behaviour recorded by the Qwes HR tag and visual observations.

No studies directly comparing the activity measurement of the DeLaval (DeLaval AB, Tumba, Sweden) activity meter neck tags with visual observation could be identified. Nonetheless, the study of Løvendahl and Chagunda (2010) on oestrus detection through the neckband sensors by DeLaval achieved a detection rate of 74.6%, with a daily error rate of 1.3%, employing a specific algorithm.

1.2.2.3 Boluses

General overview

According to Mottram et al. (2008), boluses were originally developed to enable continuous pH measurement without the need for specifically fistulated cows. They stated that due to the unique structure of the cow's rumen and reticulum, weighted objects like boluses can remain in the same location in the reticulum for the duration of the animal’s life. One problem that has been evident from the outset and continues to be found in newer bolus models is the difficulty in ensuring accurate pH measurements over an extended period of time (Mottram et al., 2008).

The boluses need to be resilient to rumen fluids, are orally administered and traverse the rumen until they reach their final position in the reticulum. Boluses with advanced features additionally integrate longer-lasting functions like a temperature-sensing unit to record the inner body temperature and the drink cycles and a three-dimensional accelerometer, allowing for the recording of supplementary parameters like activity or rumination. Early detection of oestrus, upcoming calving and diverse health issues can be enabled through these sensors.

A benefit of the system is that the bolus remains in the rumen, minimising the risk of loss compared to other sensor devices attached to the cow. Nevertheless, in case of malfunction, a replacement bolus is required and these boluses cannot be reused after the cow's death.

Validation

A study regarding the validation of the recorded pH value and temperature by the bolus produced by smaXtec (smaXtec animal care GmbH, Graz, Austria) revealed that 94.7% of the boluses could adhere to the pH tolerance value of ±0.2 pH units and the measured temperatures were only slightly below the guaranteed accuracy by the manufacturer (Pfanzelt et al., 2021). Capuzzello et al. (2023) compared the rumen contractions recorded by the smaXtec bolus with those obtained via ultrasound and auscultation, which produced comparable results. Furthermore, a subsequent comparison of the rumination duration recorded by the bolus with that from a collar yielded a Pearson correlation coefficient of 0.72. Based on these findings, they concluded that the bolus is a reliable tool for recording daily rumination duration. Edwards et al. (2024) discovered a high Pearson correlation coefficient of 0.95 to 0.96 between the rumination time measured by the smaXtec bolus and that recorded by a neckband sensor and an ear tag. Although no studies directly comparing the activity recordings of the boluses with visual observations were found, Stein (2017) conducted an analysis focusing on heat detection based on smaXtec bolus activity measurement. They compared the heat events reported by the boluses with progesterone measurements in the cows' blood, revealing high precision (93%) and sensitivity (95%) (Stein, 2017).

1.2.2.4 Ear tags

Ear tags are affixed to the cow's ear and either need to be pierced independently or can be embedded within a radio frequency identification tag. In the case of the former, a significantly more invasive procedure is performed on the cow compared to, for example, attaching a neckband. Additionally, ear tags may tear off and become lost depending on the feeding grid or behaviour of the cow.

They commonly feature a triaxial accelerometer for recording feeding patterns, rumination, ear temperature or activity levels and, depending on the system, a positioning function may also be integrated (Zambelis et al., 2019).

1.2.2.5 Calving sensors

As described by Pfeiffer et al. (2021), calving sensors are attached to the cow a few days prior to the estimated calving date either directly with an integrated strap and ratchet or with adhesive tape. Tail movements are recorded, analysed and the farmer is notified a few hours before the impending calving. According to their examinations, the main challenge lies in the attachment process, as, depending on the method, there is a risk of causing pressure sores and swelling if the sensor is fixed too tightly. Conversely, if attached too loosely, sensors may easily fall off. Some animals may also require a short adjustment period to the sensors and technical issues such as insufficient battery power despite charging can complicate the process.

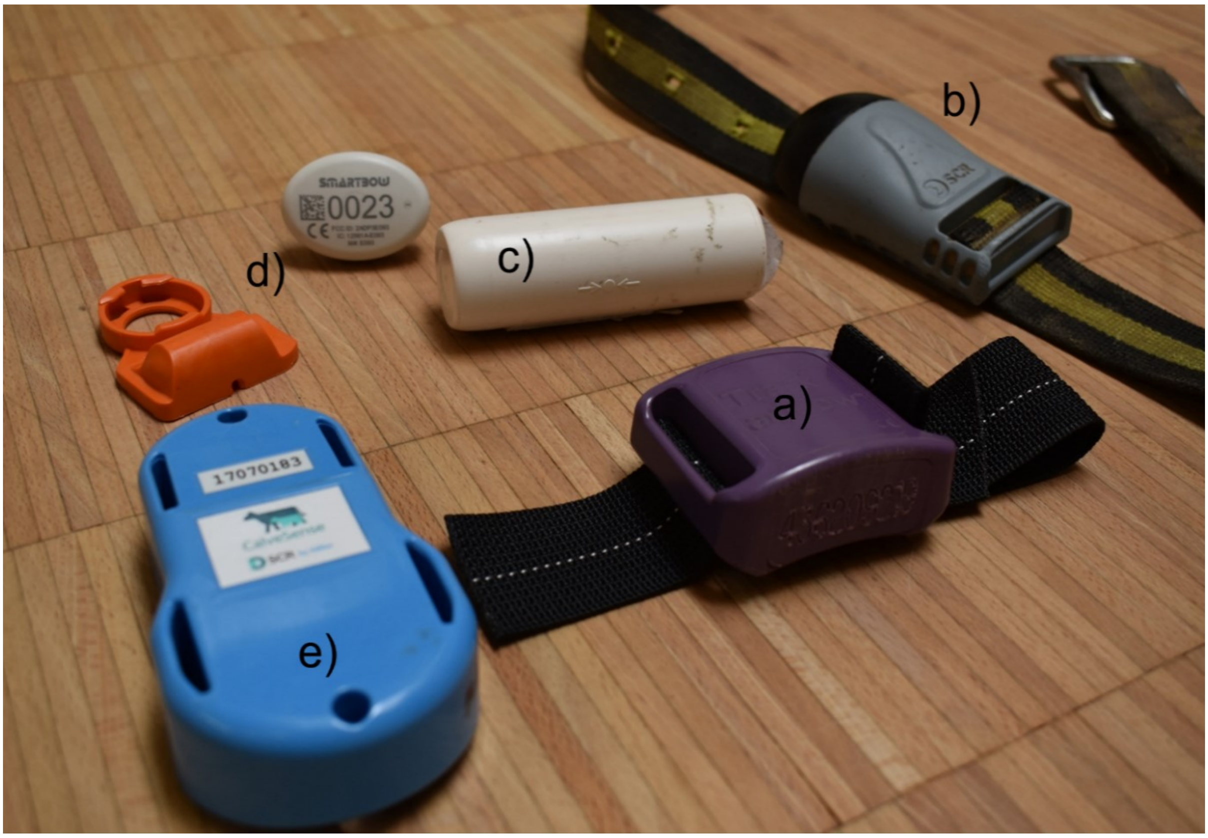


Figure 2: Examples of different sensor types (a) Pedometer, b) Neck tag, c) Bolus, d) Ear tags, e) Calving sensor)

1.2.3 Categories of non-wearable cow sensors

Even sensors not directly attached to the cow can significantly contribute to individual health monitoring. Depending on the manufacturer and model, milking systems can detect a variety of parameters beyond milk yield, including various milk components, somatic cell counts, conductivity, milk temperature, milk colour, the presence of blood or milk flow. Environmental sensors measure temperature and humidity, which are then used to calculate the Temperature-Humidity Index (THI). Body constitution sensors are used to assess the cow's stature through body condition scoring (BCS) and body weight.

1.2.3.1 Sensors for milk analysis in automatic milking systems

Modern milking systems can collect a broad range of cow-specific data. Although primarily used for mastitis detection, this data can also offer valuable insights into other health conditions. One of the often-measured parameters is electrical conductivity, which indicates ion content, influenced by levels of sodium, potassium or chloride. As explained by Hogeveen et al. (2010), during mastitis, the inflammation leads to changes in permeability of vessels in the udder and consequently to an ion imbalance. Higher ion concentrations in milk enhance its ability to conduct an induced electrical current and therefore the conductivity increases. To identify the affected quarter, the conductivity needs to be measured for each udder quarter individually.

Lely (Lely International N.V., Maassluis, the Netherlands) also records the milk temperature using a temperature sensor, which is particularly useful because an increase in temperature typically correlates with a rise in electrical conductivity (Kunes et al., 2021). Most robots also assess milk flow rates, which are mainly influenced by milking intervals and individual cow characteristics, but a heightened milk flow can also pose an increased risk of mastitis (Hogeveen et al., 2001).

Another key parameter associated with mastitis is the somatic cell count, as udder inflammation triggers the immune system, resulting in the migration of inflammatory cells into the udder and milk (Kunes et al., 2021). Sensor measurement methods can either rely on the viscosity similar to the California Mastitis Test (Hogeveen et al., 2010) or employ optical techniques such as flow cytometry or the Milk Leukocyte Differential Test, which can differentiate between various types of leukocytes (Kunes et al., 2021).

Some robots display the blood concentration or amount in the milk, while others report the milk colour. In this process, the milk is illuminated with light of the wavelengths red, green and blue and the transmission is measured (Song & Van der Tol, 2010). DeLaval also utilises the Mastitis-Detection-Index (MDi), which integrates three key parameters: conductivity, presence of blood in the milk and the interval between milkings. Cows showing an MDi of 1.4 or greater should be examined for udder health issues, while an MDi of 2.0 or more already indicates a critical risk (Bausewein et al., 2022).

The content of milk constituents, primarily fat, protein and lactose, can be measured using near-infrared spectroscopy, which involves the absorption or reflection of radiation at specific wavelengths by these components (Kunes et al., 2021). The fat-protein ratio is often analysed, as a fat-protein ratio below 1.2 indicates acidosis, while a value above 1.4 suggests a ketotic metabolic condition (Kunes et al., 2021).

The DeLaval Herd Navigator, as presented by Mazeris (2010), additionally measures urea, lactate dehydrogenase, beta-hydroxybutyrate and progesterone. Progesterone is used for cycle diagnosis in cows, aiding in the detection of oestrus, pregnancy and fertility issues. Beta-hydroxybutyrate and urea serve as indicators for ketosis and assist in dietary adjustments, while lactate dehydrogenase improves mastitis detection (Mazeris, 2010). The Herd Navigator samples cows based on biological models, testing them by using a dry stick approach, and the progesterone level is assessed with an immunoassay, while the other parameters are determined through colorimetry, ultimately generating a risk probability for each cow (Mazeris, 2010).

1.2.3.2 Environmental sensors

Environmental sensors also play a crucial role in monitoring and optimising the ambient conditions for dairy cows. Temperature and humidity sensors can help to monitor the in-barn climate and are often combined as the Temperature-Humidity-Index (THI) to estimate heat stress at the herd level. Weather sensors commonly record additional parameters such as rainfall or global radiation, which includes both direct sunlight and diffuse sky radiation, making it a valuable indicator of heat stress, particularly in pasture-based environments (Herbut et al., 2018). Conversely, sensor-measured wind speed can facilitate cooling through convection for cows located outside, but this benefit is absent in the barn, making the implementation of ventilators necessary (Herbut et al., 2018). Air quality sensors may detect levels of gases like ammonia and carbon dioxide, ensuring healthy air conditions, while light sensors capture different lux levels, enabling them to determine how long cows are subjected to daylight (Leliveld et al., 2024).

1.2.3.3 Body constitution sensors

Alongside basic scaling systems, which can, for example, be integrated into milking robots, image recognition technology is often used to assess the body constitution of the cow through body condition score or body weight. Martins et al. (2020) investigated the potential applications of lateral and dorsal images from 3D cameras and found that they can already be effectively used to determine body weight, although there is still room for improvement in estimating BCS. DeLaval also offers a BCS camera that is mounted on the milking robot, capturing 3D videos as the cow passes through (Mullins et al., 2019). According to Mullins et al. (2019), this 3D technique enables the analysis of the BCS irrespective of the cow's movement speed. From these videos, an image is generated, and an algorithm analyses the surface profiles and fat coverage across various points on the cow's back, from the short ribs to the ischial tuberosity, ultimately producing a score ranging from 1 to 5. Mullins et al. (2019) discovered in their research that the system was effective in accurately identifying body condition scores between 3 and 3.75, but it struggled to classify animals that were above or below this range.

1.3 Areas of application in health monitoring of dairy cows

Utilisation of sensor systems has become common in many different fields for monitoring cows‘ health and reproduction. Beginning already in the 1980s (Hogeveen et al., 2010), significant efforts have been directed towards automating the detection of various health issues in cows.

Automatic heat detection using sensor systems can be encountered on many farms, as most sensors only use the cow‘s activity to create a heat alarm and many studies showed that sensors recording this parameter have high accuracy (LeRoy et al., 2018; Roelofs et al., 2017; Shahriar et al., 2016). Taking into account that activity is highly animal-related (Müller & Schrader, 2005), sensor system manufacturers often use the baseline activity of the individual cow to detect deviations (Schilkowsky et al., 2021). Sensors attached to the sacral area of the cow can determine mounting behaviour (Reith & Hoy, 2018), infrared thermography can identify changes in the surface temperature (Perez Marquez et al., 2021), microphones can recognise increased vocalisation (Röttgen et al., 2020) and temperature and conductivity sensors can detect vaginal deviances (Higaki et al., 2019). Another often used method is the regular measurement of progesterone concentration in milk, for example performed by the DeLaval Herd Navigator in the milking robot (Mazeris, 2010). New technologies like video analysis and image recognition could also efficiently support the farmer in detecting oestrus behaviours like the standing heat (Arago et al., 2020).

Calving events can be spotted by using different sensor technologies as well. Borchers et al. (2017) examined pedometers and collar tags recording activity, lying behaviour and rumination and proved that merging those parameters could enable a better calving prognosis. The combination of different sensor systems like accelerometers and localisation sensors is likely to improve the accuracy of prediction models (Benaissa et al., 2020). Reticulorumen boluses discern upcoming calving events 20 hours prior by noticing a drop of the inner body temperature (Kovács et al., 2017). Farmers could use this as a first alert to relocate the cow to the calving pen. Cows showing an earlier fall in reticulum temperature and a lower rumination time might be more prone to calving difficulties (Kovács et al., 2017). Higaki et al. (2020) created an effective calving detection model by using the tail skin temperature and machine learning processes. Intra-vaginal sensors are able to identify a sudden change in temperature and light gradient after being ejected from the vagina due to the progressing calving (Crociati et al., 2021). Some sensors can be attached to the cow’s tail, measure calving-related tail motions and send a message to the farmer a few hours before the calving event (Pfeiffer et al., 2021). Fixating these sensors at the tail without causing bruises or swelling and still preventing the loss of the sensor can be challenging for the farmer (Pfeiffer et al., 2021).

More complex clinical pictures are difficult to describe using sensors that record only one single parameter. The combined effect of multiple predictors is necessary to differentiate between diseases with similar symptoms. A well-known approach for detecting mastitis is the combination of different milk parameters recorded by automated milking systems. The selected thresholds and variables vary from one milking robot manufacturer to another (Bausewein et al., 2022) and include, for example, somatic cell count, conductivity, milk flow, blood, milk colour or milk temperature. Khatun et al. (2018) confirmed that integrating diverse factors measured by the milking robot in a regression model could lead to a noticeably improved identification of clinical mastitis. The cow’s behaviour can also be a mastitis indicator, as shown in the study by Antanaitis et al. (2022), where subclinical mastitis led to a decrease in rumination time, chews and drinking time. Steele et al. (2020) used milk parameters in combination with pedometer data and found dissimilarity in the behaviour and performance of cows with clinical mastitis caused by different pathogen types. Furthermore, GPS trackers can help to monitor the social behaviour of cows and therefore display the contact with mastitis pathogens by registering cow contacts, which enables a following ranking of the animals according to their mastitis risk (Feng et al., 2022).

Metabolic disorders arising often in dairy cows could be detected earlier with the help of different sensor systems. Acidosis is, for example, characterised by an imbalance in the acid-base status of the rumen, leading to a decrease in rumen pH (Jaramillo-López et al., 2017). Especially the chronic course of the disease without visible clinical signs, known as subacute ruminal acidosis, is often difficult to notice for the farmer (Studer et al., 2023). Boluses can continuously monitor the pH value and alert the farmer in case of a significant decrease (Studer et al., 2023). Deviations in the inner body temperature could also be an indication of a metabolic disease (Alzahal et al., 2011). Ketosis in cows is associated with higher ketone body values and a negative energy balance and often occurs in the first weeks after calving (Esposito et al., 2014). As the BCS of a cow is correlated with the risk of developing a ketosis (Rathbun et al., 2017), regularly monitoring its change with BCS cameras could enable earlier diagnoses. Milk components like an increased fat protein ratio (Kunes et al., 2021) or beta-hydroxybutyrate (Mazeris, 2010) could also be an indicator of a ketotic metabolic state. Antanaitis et al. (2020) proved that decreased rumination and drinking in cows can be detected several days before the clinical manifestation of the disease and Steensels et al. (2017) used a wearable sensor to create an efficient ketosis detection model consisting of a combination of rumination time, activity and milk yield.

Besides the most common production diseases, external influences on dairy cows, such as temperature and humidity, should also be mentioned. Hut et al. (2022) recently discovered that the impact of climate on behaviour parameters like eating or lying already starts at an average daily temperature of twelve degrees. Different cows might deal with higher temperatures in different ways depending on traits like breed and milk yield (Gantner et al., 2017) or individual factors like lactation stage or parity (Heinicke et al., 2019). Wearable sensors could help to increase the focus on the individual heat stress of the single animal instead of the whole herd. Ramón-Moragues et al. (2021) examined various behaviours under heat stress by using neck tag sensors and detected alterations in every monitored variable. Under heat load circumstances, the animals panted more and showed higher activity values, while their rumination, resting and feeding duration decreased (Ramón-Moragues et al., 2021). Ranzato et al. (2023) demonstrated that behavioural sensor data in combination with the cows‘ milk yield could be used to identify the animals more prone to suffering from discomfort in heat periods. Keeping track of the cows’ core or surface temperature could be another reasonable approach, despite the noticed time lapse between the increase of external temperatures and the cow‘s body temperature rise (Chung et al., 2023). Furthermore, as heat stress might influence the respiration rate (Gaughan et al., 2000), respiration-detecting sensors (Strutzke et al., 2019) or image recognition models (Wu et al., 2023), currently only employed for experimental purposes, could be further developed into practicable solutions.

A more detailed exploration of sensor systems applied in the field of lameness detection will be carried out in chapter 3.2.

2. Lameness

Characterising a deviation in gait resulting from pain-related, functional or structural disruptions within the musculoskeletal system, the term lameness involves the animal's response through the execution of specific unloading movements as a strategy to alleviate the associated discomfort (Baumgartner & Wittek, 2018). In dairy cows, lameness can be seen as an intricate and multifaceted condition, heightened by a variable time lag between the underlying causes and the manifestation of the symptom (Bell, 2015). Claw disorders and lameness are still reported as the third most common reason for culling of dairy cows, following reproduction issues and udder diseases (Heise et al., 2016; Kulkarni et al., 2023). As evident in Table 1, lameness continues to be a prevalent issue on dairy farms worldwide. Detected lameness prevalences over the past 10 years range from approximately 15% to 40%, indicating a persistent high level of claw disorders among dairy cows, irrespective of country or continent. This highlights claw health problems posing one of the greatest risks to the well-being of cows (Beusker, 2007) and substantially contributing to financial losses in livestock operations due to associated costs (Ózsvári, 2017).

Table 1: Lameness prevalences reported in different countries in recent years

Reference	Country	Years of study	Prevalence of lameness (median)
Griffiths et al. (2018)	England, Wales	2015-2016	31.6%
Weigele et al. (2018)	Switzerland	2015-2016	29.8%
Bran et al. (2019)	Brazil	2016	41.1%
O'Connor et al. (2020)	Ireland	2015	37.8%
(Van Huyssteen et al., 2020)	Canada	2018	20%
Sadiq et al. (2021)	Malaysia	2018-2019	36.9%
Sheferaw et al. (2021)	Ethiopia	2018-2019	14.1%
Jensen et al. (2022)	Germany	2016-2019	North: 23.1% East: 39.1% South: 23.2%
Matson et al. (2022)	Canada	2019	28.3%
Sahar et al. (2022)	Canada	2019-2020	31.8%
Salem et al. (2023)	Egypt	2022	43.1%

2.1 Anatomy of the claw

The digital end organ in cattle is constituted by the claws, comprising two main and two dewclaws on each limb (Mülling, 2006). The protective horn capsule surrounding the claw is shaped by keratinised skin and consists of the *epidermis*, *dermis* and subcutaneous layers (Mülling, 2006). Five distinct segments can be differentiated in the claw: the periople, coronary, wall, sole, and bulb segments, the latter playing a crucial role in load distribution (Geyer, 2008). At this particular site of the claw, the subcutaneous tissue is notably well-developed with fat deposits with a shock-absorbing function (Budras et al., 2005). The overlying *dermis* forms two layers, the inner *stratum reticulare*, which serves as a connection with the *periosteum* or *subcutis*, and the outer *stratum papillare*, which is linked with the *epidermis* by *laminae* in the wall segment and by *papillae* in the other areas (Mülling, 2006). The *epidermis* comprises cells undergoing keratinisation in an outward direction and relies solely on diffusion of nutrients through the vascular and neural plexuses of the underlying *dermis* (Mülling, 2006). A structure known as the white line represents a flexible connection between the hoof wall and sole, rendering it a susceptible area for microtrauma and the infiltration of infectious agents due to its composition of various types of horn (Mülling, 2006).

As described by Mülling (2005), the horn capsule of the claw encloses the distal part of the short pastern bone, the distal sesamoid bone, the claw joint along with its ligaments and the pedal bone. He noted that through its attachment to the pedal bone, the claw capsule serves as a support structure for the claw and transfers the forces exerted during weight-bearing evenly, including the sole and bulb part. The spreading of the claws after ground contact also contributes to shock absorption and aids the claws in distributing the forces exerted by the substantial body mass of the animal.

Compared to the hind claws, the front claws are set at a slightly steeper angle and exhibit a broader and more compact shape (Mülling, 2005). The greatest load on the hind limb claws is concentrated on the lateral claw, given its distinct prominence compared to its medial counterpart (Geyer, 2008).

2.2 Prevalent diseases of the claw

Insufficient horn wear and the ongoing horn growth alter the shape of the claw, complicating optimal load distribution and potentially leading to various claw disorders like sole ulcers or white line lesions (Mülling, 2006). Additionally, infectious processes may also contribute to the emergence of claw diseases like digital dermatitis or heel horn erosions.

2.2.1 Heel horn erosion

Heel horn erosion refers to V-shaped grooves that appear at the bulb and result from the dissolution of the soft bulb horn, which is particularly susceptible to softening due to moisture, ammonia and putrefaction processes (Kofler, 2014).

Since the lesions do not reach the *corium*, they do not cause lameness but contribute to the development of other hoof diseases such as digital dermatitis or sole ulcers (Nuss & Kofler, 2019). The causes for the formation include damp pasture or stall surfaces, ubiquitous putrefactive agents and excessive load on the bulbs due to insufficient claw trimming (Kofler, 2014).

2.2.2 Digital dermatitis

Digital dermatitis or "strawberry foot rot" refers to an inflammation of the skin above the soft bulb, potentially progressing to ulceration and extending into the interdigital space (Dirksen, 2006b). In rare cases, it may also manifest around the dewclaws or dorsally at the coronary band (Dirksen, 2006b).

According to Nuss et al. (2019), it is considered a multifactorial disease in which various conditions contribute to the infiltration of bacterial pathogens, such as the prevailing *treponema* and other secondary agents. They explained that prior damage is a required precondition for these pathogens to penetrate the skin, consisting, for example, in maceration and softening of the horn. This is caused by exposure to faeces and urine and thus ammonia, resulting in microfissures in the outer cutaneous barrier. Additional predisposing factors include unsanitary farm conditions in general, poorly designed cubicles, sharp edges, the acquisition of new animals as well as stress induced by overcrowding, poor nutrition, heat or other factors (Nuss et al., 2019).

Initially classified by Döpfer (1994), digital dermatitis can be categorised in different stages according to the visible defects, which are further elaborated in Table 2.

Table 2: Stages of digital dermatitis (Nuss et al., 2019)

Stage	Clinical appearance
M0	Healthy skin, without any visible lesions
M1	Small lesions (<2 cm) in the interdigital skin of the soft bulb
M2	Ulcerative, active and red-coloured erosions (>2 cm) above the bulb, often surrounded by protruding hairs (Figure 3)
M3	Healing defects, completely covered with crusts
M4	Chronic hyperkeratotic elevated lesions of brown colour (Figure 4)
M4.1	Chronic form with recurrent small erosions (M1)

Figure 3: Digital Dermatitis (Stage M2)

Figure 4: Digital Dermatitis (Stage M4)

While the M2 stage (Figure 3) is consistently associated with pain, M1 and M3 are notably less painful or entirely pain-free and in the chronic form M4 (Figure 4) cows often no longer exhibit lameness due to the absence of pain (Nuss et al., 2019). Despite potential lesion healing, *treponema* persist as cysts in the deeper layers of the skin, resulting in a latent infection of the animal (Nuss et al., 2019).

2.2.3 Sole haemorrhage

Sole haemorrhage refers to a reddish or yellowish discolouration of the horn on the sole, resulting from bleeding of the corium and the connective tissue (Kofler, 2014). Classification involves differentiating between diffuse, extensive (Figure 5) and localised, circumscribed (Figure 6) sole haemorrhages (ICAR Working Group on Functional Traits (ICAR WGFT) and International Claw Health Experts, 2015). The discolouration in the horn is caused by bleeding in the *corium* approximately six weeks prior to its appearance, given that the claw grows at a rate of approximately five millimetres per month (Kofler, 2014). The aetiology of the haemorrhage may stem from *corium* inflammation in the context of laminitis or traumatic incidents resulting from slipping, stepping on sharp edges or overloading (Kofler, 2014).

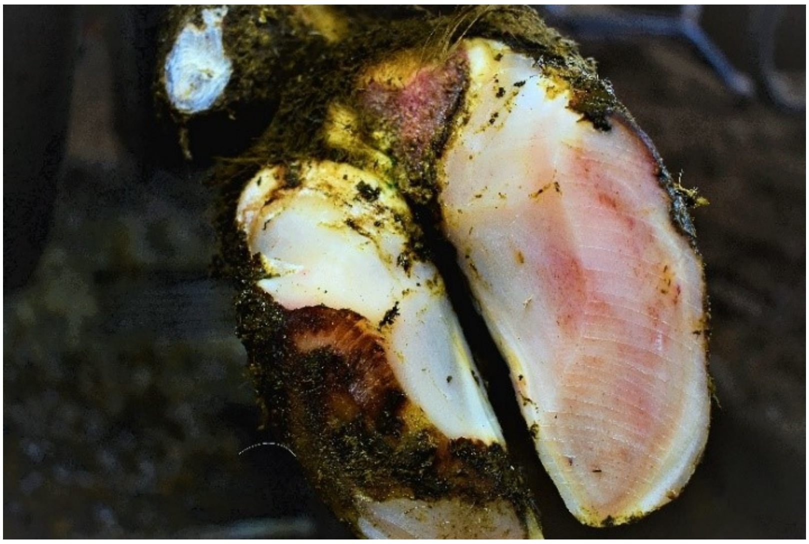


Figure 5: Diffuse sole haemorrhage

Figure 6: Circumscribed sole haemorrhage

2.2.4 Ulcers

Ulcers can develop in different locations on the claw, with the most common being the sole ulcer (Figure 7). This refers to a defect in the sole horn with exposed, inflamed corium at the transition of the hard to the soft bulb directly under the flexor tuberculum (Nuss & Kofler, 2019). On the one hand, this area is highly susceptible due to the varying hardness of horn types, making it prone to defects under load (Mülling, 2005). On the other hand, laminitis could lead to circulatory disturbances in the *corium*, eventually followed by sinking of the pedal bone along with the flexor tuberculum, which consequently compresses the *corium* (Nuss & Kofler, 2019). The compression leads to further undersupply and necrosis of the *corium,* causing a cessation of horn formation until ultimately the *corium* becomes exposed, inflamed and later granulates (Nuss & Kofler, 2019). The observation that the more heavily burdened outer hind claws exhibit this condition more often suggests that its development is influenced by factors beyond laminitis (Nuss & Kofler, 2019). This includes an excessive weight shift onto the bulbs due to overgrown claws, slippery flooring or structural aspects of the barn as well as changes in the bulb fat pad due to lactation stage or advanced age (Kofler, 2014). As previously indicated, ulcerations may also manifest in other, less frequent claw locations, including the toe or bulb (ICAR Working Group on Functional Traits (ICAR WGFT) and International Claw Health Experts, 2015).

Figure 7: Sole ulcer with Repiderma spray

2.2.5 White line disease

Flooring covered with a combination of faeces and urine contributes to a continual softening of the hoof horn, with the claw being particularly susceptible in the white line region due to its anatomical structure primarily composed of softer horn material (Nuss & Kofler, 2019). This maceration process facilitates the penetration of foreign bodies such as dirt or stones, leading to structural separations and the onset of a white line fissure (Figure 8) (Nuss & Kofler, 2019). Additionally, increased mechanical stress induced by sharp edges or tight turns in the stable along with laminitis or improper farm claw trimming can further predispose this area between the sole and wall to haemorrhaging and fissures (Kofler, 2014). Through this point of entry, pathogens can infiltrate the upper stratum of the *corium* and induce polymicrobial infections marked by inflammation, purulence and tissue liquefaction (Dirksen, 2006b). A white line abscess (Figure 9) forms, progresses and either eventually erupts externally through the coronary band or, less favourably, infiltrates deeper structures such as the claw joint (Nuss & Kofler, 2019).

Figure 8: White line fissure

Figure 9: White line abscess

2.2.6 Laminitis

Laminitis presents as a complex condition primarily attributed to circulatory disorders, leading to a diffuse, aseptic inflammation of the *corium* across multiple claws (Dirksen, 2006a). The aetiology primarily involves systemic disorders such as ruminal acidosis or occasionally overload conditions, leading to impairments in the suspensory apparatus of the claw (Nuss & Kofler, 2019). This cascade of events ultimately manifests in various laminitis symptoms, including white line fissures, sole haemorrhages or ulcers (Nuss & Kofler, 2019).

Both the rare acute laminitis, which is characterised by severe clinical symptoms, and the subacute or subclinical forms can transition into a chronic course with a risk of recurrence in the following manner described by Nuss and Kofler (2019). Toxins and other substances penetrate the *corium* in the acute phase and damage the capillary walls, which results in haemorrhages, circulatory disturbance, and the formation of inferior-quality horn. Ongoing nutrient deficiency subsequently loosens the suspension of the pedal bone. This can lead to its sinking or rotation and therefore further straining of the claw structures, causing contusions between the *corium* and the claw capsule. Hormonal changes around calving, leading to a relaxation of the connective tissue, along with less comfortable housing conditions for the cow, can also contribute to these processes.

2.2.7 Interdigital hyperplasia

Regular irritations in the interdigital space accompanied by inflammation of the skin can lead to tissue overgrowth, in the end resulting in the development of a bulge in this area (Geyer, 2008). Kofler (2014) explained that interdigital hyperplasia (Figure 10), also known as tyloma, progressively enlarges with persistent irritation, reaching a size that induces bruising during walking and cutaneous inflammation. Digital dermatitis lesions may also manifest on the hyperplastic growths and these hyperplasias, accompanied by a compromised skin barrier, are consequently associated with discomfort (Kofler, 2014). Splayed claws, whether genetically predisposed or arising from improper claw trimming or other claw disorders, can be conducive to the development of these growths (Kofler, 2014).

2.2.8 Double sole

After inflammation or bleeding of the *corium*, there can be a separation of horn layers on the sole, that causes the formation of a cavity (Nuss & Kofler, 2019). Moisture and pathogens infiltrate and decompose the horn, contributing to the formation of the double sole (Figure 11) (Nuss & Kofler, 2019).

The exudate leakage can be caused by secondary conditions associated with laminitis or by traumatically induced contusions and after the recovery of the *corium*, the characteristic inner horn layer forms beneath the cavity (Kofler, 2014).

Figure 10: Tyloma

Figure 11: Double sole with sole ulcer

2.2.9 Vertical horn fissure

This claw disease involves a separation of the horn, occurring dorsally, axially or abaxially on the claw (Kofler, 2014). It runs vertically and can either remain superficial or penetrate the *corium* and the cause for its formation can be injuries to the coronary band, poor-quality horn due to laminitis, nutritional deficiencies and dehydration or mechanical factors (Kofler, 2014).

2.2.10 Interdigital phlegmon

The interdigital phlegmon or foot rot is described as a symmetrical and distressing foot inflammation, often coupled with a foul odour (ICAR Working Group on Functional Traits (ICAR WGFT) and International Claw Health Experts, 2015). It manifests suddenly, coincides with acute lameness and advances with a diffuse purulent-necrotising effect deep into the subcutaneous tissues, extending towards the distal interphalangeal joint (Kofler, 2014). The affected animals present distinct clinical symptoms, including localised erythema, warmth and swelling in the coronary band region, accompanied by systemic indications such as pyrexia and a compromised general condition (Nuss et al., 2019).

Stones, rough edges, dirty walking surfaces or gaps may induce minor defects in the interdigital space and afterwards anaerobic bacteria, such as *Fusobacterium necrophorum*, can eventually penetrate the skin through these defects, triggering the inflammation (Kofler, 2014).

2.3 Causes for lameness in dairy cows

Several different factors can contribute to the development of lameness and can be categorised into factors originating from the individual animal, management conditions and environmental influences (Figure 12). The correlation of various factors makes it particularly challenging to identify the root causes of claw diseases, as, for instance, certain animal-specific factors may either promote lameness or have no impact, depending on the management practices implemented on each farm.

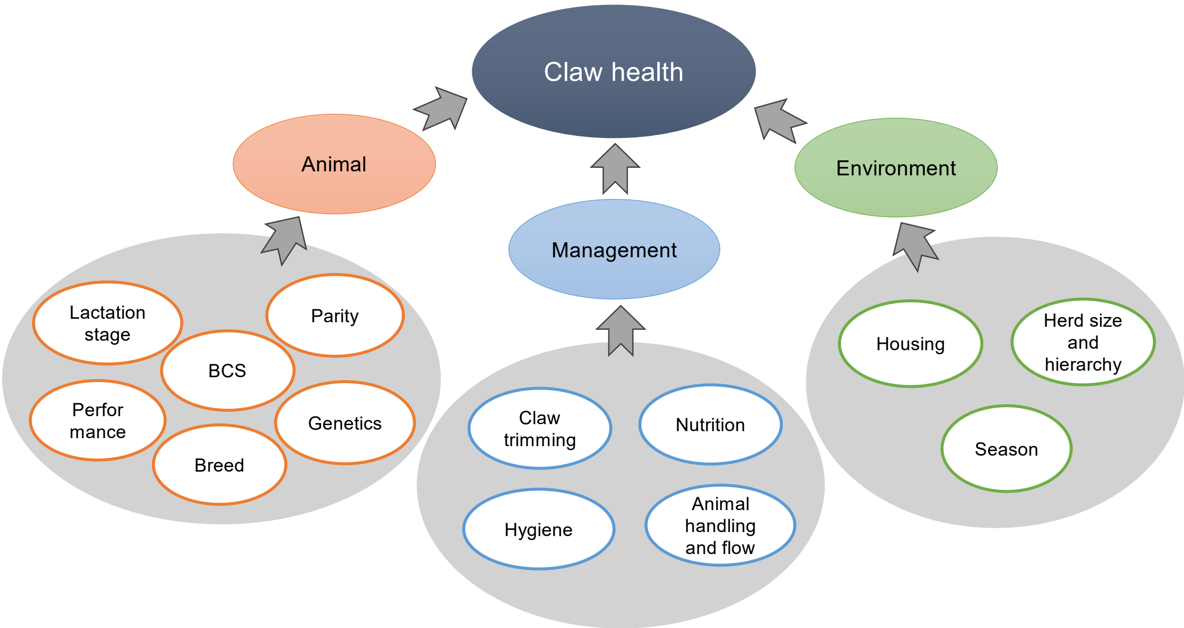


Figure 12: Factors influencing the development of claw lesions

2.3.1 Animal-related factors

2.3.1.1 Breed

Various cattle breeds may display distinct susceptibilities to claw diseases; for instance, research by Fürmann et al. (2024) revealed that the probability of dermatitis digitalis occurrence is five times higher in Holstein-Friesian herds, with individual Holstein cows facing a 63% elevated risk compared to other breeds. Baird et al. (2009) observed a higher incidence of white line defects in Holstein-Friesians compared to Norwegian cattle, while Lusa et al. (2020) documented a notably lower prevalence of foot issues in Jersey cows when compared to Holstein cows. Vlček et al. (2016) additionally reported that 45% of the Holstein cows in their study presented with claw lesions, whereas only 37% of the Simmental cows were affected. These differences between dual-purpose breeds and the dairy breed Holstein could be explained by the higher conversion of energy reserves in Holstein cows for the intense milk production, resulting in a more pronounced negative energy balance and a higher change of body condition (Gruber et al., 2014; Knob et al., 2021). Furthermore, the generally higher body weight and larger claw dimensions could lead to more frequent incidents of claw lesions in milk-orientated breeds such as Holstein or Brown Swiss (Lusa et al., 2020).

2.3.1.2 Genetics

Genetics can also be a significant element in the development of lameness. Numerous factors, including recovery from sole ulcers, exhibit inheritable traits (Barden et al., 2023), and the utilisation of genetic indices can facilitate the selection of appropriate animals for breeding, aiming to minimise the likelihood of lameness in progeny (Barden, Anagnostopoulos et al., 2022; Browne et al., 2022). Anatomical features such as the thickness of the digital cushion also have a hereditary component and can influence the development of claw diseases (Barden, Li et al., 2022).

2.3.1.3 Parity

The parity and consequently the age of cows can have a significant impact on the occurrence of lameness. The majority of studies indicate a higher likelihood of lameness with advancing parity (Lean et al., 2023; Pötzsch et al., 2003; Rittweg et al., 2023; Sheferaw et al., 2021). For instance, Lean et al. (2023) discovered that the risk of lameness in cows in the fifth lactation or beyond is more than five times higher than in animals during their first lactation. Furthermore, Pötzsch et al. (2003) could trace an increase in the amount of white line defects from 2% in the first lactation to nearly 50% in animals with five or more calvings.

Conversely, there is a significantly higher risk for cows in their first lactation compared to cows in the second or third lactation who have never experienced any claw issues (Thomas et al., 2023). Even though an increasing parity leads to a stronger asymmetry of partner claws, thereby favouring a rise in lameness cases, cows are also particularly prone to sole haemorrhages after the first calving (Sogstad et al., 2005). Capion et al. (2021) analysed records from Danish claw trimmers over a period of five years and identified varying trends depending on the claw lesion. While digital dermatitis manifested most frequently in heifers, the prevalence of the other three investigated claw diseases exhibited an upward trajectory with rising parity (Capion et al., 2021).

The structural alterations in the digital cushion may explain the increased vulnerability of heifers and cows in advanced lactation stages. In heifers, this cushion is predominantly constituted of lax connective tissue, which subsequently transforms into fat tissue and, as age progresses, undergoes a reconversion into more fibrous structures (Räber et al., 2004).

Age-related osseous modifications, particularly evident at the tuberculum flexorium, may also play a role in the heightened propensity of claw problems during the later stages of life (Tsuka et al., 2012).

2.3.1.4 Lactation stage

The relationship between days in milk and lameness varies across different studies. In the study of Rittweg et al. (2023), cows in mid-lactation exhibited a higher lameness likelihood, whereas the research of Sheferaw et al. (2021) indicates an increase in lameness with advancing gestation. Kulualp et al. (2021) determined that a more advanced lactation stage corresponds to a 2.2-fold higher risk of infectious claw diseases. O'Connor et al. (2020) observed that cows with over 120 days in milk exhibited elevated locomotion scores, but Sadiq et al. (2021) detected the preponderance of lameness within the first 120 days after calving. Van der Spek et al. (2015) found no overall difference in claw diseases between early and late lactation stages. However, in their study, sole haemorrhages occurred more frequently early in lactation, while white line defects were more common in the later period of lactation.

Bach et al. (2021) identified a reduction in the digital cushion during the weeks around calving, likely attributed to rotation and sinking of the pedal bone. These changes may arise from hormonal shifts during the calving period, leading to a loosening of the pedal bone attachment apparatus and contributing to claw lesions in early lactation (Bach et al., 2021). The development of claw diseases in the mid-lactation is likely already influenced by behavioural changes during the transition period, such as prolonged standing times or faster feed intake (Proudfoot et al., 2010).

Some hoof disorders, such as laminitis or digital dermatitis, demand a longer incubation period before becoming visually apparent (Zlatanović et al., 2021), which might be attributed to continuous microbial processes or the formation of substandard horn, and consequently these issues tend to manifest towards the latter part of lactation.

2.3.1.5 BCS

Green et al. (2014) provided evidence that a body condition score (BCS) below 2.5 contributes to the onset of claw diseases, predominantly arising from mechanical stress and suboptimal horn quality, while not correlating with the development of infectious claw problems. In the investigation of Rittweg et al. (2023) a low BCS also showed a pronounced correlation with the occurrence of lameness in the southern, northern and eastern regions of Germany. Randall et al. (2015) also recommend maintaining the BCS above 2.5 to prevent lameness and additionally highlight that a low body weight coupled with an advanced age at first calving might increase the susceptibility to recurrent lameness incidents. The reason could be a negative energy balance, which might lead to a fat mobilisation in the digital cushion and consequently result in the loss of its ability to distribute forces effectively (Newsome et al., 2017).

Some studies have identified an elevated lameness risk across all body condition scores outside the optimal range, also including animals with a higher BCS, which is potentially attributed to the increased load on the feet due to higher body weight (Kranepuhl et al., 2021; Ristevski et al., 2017).

2.3.1.6 Performance

The relationship between the performance of a dairy cow, specifically its milk yield, and lameness is inherently complex and multifaceted, making a straightforward description of cause and effect difficult. The breeding processes conducted with the aim of achieving ever higher milk yields naturally lead to increased strain on individual animals, consequently resulting in an elevated susceptibility to production-related diseases (Oltenacu & Broom, 2010). Archer et al. (2010) determined that lame cows on average presented a daily milk yield approximately 1-2 kg higher than non-lame cows. Rutherford et al. (2009) observed an elevated prevalence of lameness in herds with higher milk yields and O'Connor et al. (2020) identified a milk yield exceeding 6000 kg as a lameness risk factor.

However, there are also studies where high milk yield had no effect at all on the occurrence of lameness (Aeberhard et al., 2001; Haskell et al., 2006). Oehm et al. (2020) and Rittweg et al. (2023) moreover were able to demonstrate a protective effect of high milk yield in their research, as elevated milk production was associated with a reduced risk of lameness. This indicates that high milk production in cows does not necessarily have adverse effects on their health and well-being if appropriate management practices are applied (Trevisi et al., 2006). Furthermore, a correlation could be drawn between healthy cows and high performers, which in turn might explain a lower occurrence of lameness in these animals (Leblanc, 2010).

2.3.2 Management-related factors

2.3.2.1 Claw trimming

Lameness in cows is primarily attributed to claw issues, which often result from rare or improper claw trimming practices (Vidmar et al., 2021). Claw trimming is a proven method to reduce the pain of claw lesions through appropriate treatment, consequently leading to an improvement in gait (Passos et al., 2017). A distinction is made between functional claw trimming for the prevention of claw issues and corrective hoof care aimed at addressing pre-existing claw diseases (Vidmar et al., 2021). The former strives to maintain the optimal shape of the claw, enabling an even force distribution, while the latter serves to actively relieve affected areas and thereby promotes rapid healing (Vidmar et al., 2021). Leach et al. (2012) discovered that cows undergoing proper hoof treatment within the two days following lameness detection exhibit a reduced likelihood of developing severe claw issues and require subsequent treatments less often. Montgomery et al. (2012) observed the walking behaviour of cows before and seven days after claw trimming and noted that approximately half of the originally lame animals exhibited a normal gait again. Somers, Frankena et al. (2005) identified an extended interval of over 7 months between claw trimming sessions as a risk factor for digital dermatitis and also other studies highlighted the importance of a minimum of two hoof care appointments per year (Katsoulos & Christodoulopoulos, 2009; Manske et al., 2002).

2.3.2.2 Hygiene

Good hygiene, integral to the management of diseases caused by pathogens, can serve as a preventive measure against claw problems. In this context, primary consideration should be given to the walkways, as wet and soiled walkways predispose animals to slipping and, consequently, claw injuries (Rushen et al., 2004). Furthermore, the exposure to manure rapidly softens the hoof, making it noticeably more vulnerable to defects and bacterial penetration (Rushen et al., 2004). Thus, claw health is closely related to the regular removal of manure and can be enhanced by increasing the frequency of scraping (Chapinal et al., 2013). Route planning needs to be improved in using automatic scrapers, as the findings of Barker et al. (2010) suggest an increased incidence of lameness linked to these devices, possibly resulting from cows making abrupt evasive manoeuvres or stumbling directly over the robots. Besides the walkways, cows housed in farms with suboptimal cubicle cleanliness showed an up to 80-minute reduced lying duration per day compared to cows with clean cubicles and also had a 1.3-fold increased likelihood of lameness (Robles et al., 2021).

2.3.2.3 Nutrition

The condition of the claw horn can be affected by nutrition, especially when feeding an excess of rapidly fermentable carbohydrates and protein in silage or concentrates (Babintseva et al., 2020). This can result in compromised ruminal digestion and subsequent inflammatory processes, potentially contributing to the occurrence of claw lesions (Babintseva et al., 2020). The keratinisation process and the development of a solid hoof structure are significantly linked to the sufficient supply of amino acids, minerals, vitamins and fats (Mülling et al., 1999). Research demonstrated that administering biotin for a minimum of six months resulted in a 45% reduction of white line diseases in multiparous cows (Pötzsch et al., 2003). The addition of a copper sulphate manganese complex to the ration has an impact on hoof hardness, consequently enhancing the locomotion of lame cows (Zhao et al., 2015).

2.3.2.4 Animal handling and cow flow

The interaction between humans and animals, including the way cows are handled, may also play a role in the development of lameness. Through modelling, Rouha-Mülleder et al. (2009) showed that negative behaviours from the people responsible for herding, such as kicking or punishments, contribute to a higher lameness prevalence in herds, which could be explained by swift evasive movements and the resulting stumbling of the animal. Moreira et al. (2019) evaluated that a calm handling of cows could reduce the incidents of tyloma, while negative stimuli such as strikes might lead to an increase in sole haemorrhages.

According to Chesterton (2011), improving the flow of cows in daily management can be achieved by comprehending their behaviour and implementing reliable, systematic routines. Inadequate cow flow results in a more forceful herding approach to hasten the movement of cows and these actions might potentially result in claw lesions caused by injuries, as the cows can no longer position their feet of their own accord (Chesterton, 2011).

2.3.3 Environment related factors

2.3.3.1 Housing

Stall design, including the structuring of stalls, floors and other facilities, can significantly influence the lameness incidence in the herd. Cubicles measuring less than 171 cm in length (Oehm et al., 2020) and unbedded stalls only covered with mattresses (Salfer et al., 2018) may elevate the risk for lameness. Deep or sand bedding can be a mitigating factor for lameness, as lying on these is much more comfortable for the animals, and severely lame cows only increase their lying times on this kind of stall surface (Ito et al., 2010; Salfer et al., 2018). Studies observed diminished odds for lameness in the presence of shallow curb heights (King et al., 2016) and larger cubicle widths (Lardy et al., 2021). Besides the dimensions, the construction of the stall can also play a part in lesion development, as for example restrictive neck rails on one hand improve cubicle hygiene, but on the other hand discourage cows from standing in the stall, thus reducing the drying time of claws (Bernardi et al., 2009).

An optimal stocking density should not be underestimated as a determinant, as overcrowding might reduce lying and rumination time of the individual and antagonistic social interaction at the feeding table may become more common (Krawczel et al., 2012). It is thus advisable to maintain a minimum 1:1 ratio for both feeding and resting spaces on farms (Arbeitsgruppe Rinderhaltung, 2007).

Slatted floors being more slippery and uneven than solid concrete floors tend to heighten the occurrence of claw health issues (Rouha-Mülleder et al., 2009). Cows overall exhibit a slower and more cautious gait on the slatted concrete floor, a situation that could be improved by installing rubber mats (Telezhenko & Bergsten, 2005). Cows prefer to walk on softer and more flexible surfaces, resembling their natural walking terrain, ultimately resulting in a more regular locomotion (Telezhenko & Bergsten, 2005). De Andrade Kogima et al. (2022) proved that cows housed under nearly natural, pasture-based conditions showed the fewest lameness cases, followed by compost-bedded and free-stall cows. Incorporating sand-bedded areas can also be beneficial for joint and claw health (Upadhyay et al., 2023).

2.3.3.2 Herd size and hierarchy

Regarding herd size, studies yield varying results on lameness prevalence: larger herds may benefit from higher professionalism and personnel explicitly dedicated to claw health (Chapinal et al., 2013), whereas in smaller herds more time can be dedicated to individual animal care (Broom, 2013; Sjöström et al., 2018).

Due to displacement, cows with a lower rank in the herd hierarchy exhibit shorter lying times and tend to spend more time standing half in the stalls when compared to higher-ranking animals (Galindo & Broom, 2000). This results in a greater incidence of lameness and higher culling rates among these individuals (Galindo & Broom, 2000).

2.3.3.3 Season

Several studies identify summer as the season with the highest lameness prevalence, attributing it to wet conditions and increased humidity due to cow cooling facilities such as ventilators or cow showers (Ali et al., 2021; Sanders et al., 2009). Furthermore, heightened periods of heat stress during the summer can induce behavioural alterations, such as prolonged standing times, subsequently intensifying strain on the hoof horn and predisposing to lesions (Cook et al., 2007). Olechnowicz and Jaskowski (2015) focused on tie-stalls and observed an accumulation of claw issues in the winter, likely attributed to the seasonal variation in housing conditions, specifically the access to pastures during the summertime.

2.4 Effects of lameness on behaviour, physiology and performance

Several studies have explored the diverse effects of lameness events on different aspects of behaviour and performance, as illustrated in Table 3. Depending on the circumstances, cows may experience varied responses to claw diseases, which will be further explored in the following context.

Table 3: Studies regarding the average value of behaviour, physiological and performance parameters in cows and the effect of lameness on these variables

Parameter	Average	Increases (↑)	Decreases (↓)	Unaltered (→)
Lying time	10 - 12 h/d (Tucker et al., 2021)	(Beer et al., 2016; Frondelius, Lindeberg et al., 2022; Hut et al., 2021; Ito et al., 2010; King et al., 2017; Lorenzini, 2019; Schindhelm et al., 2017; Solano et al., 2016; Weigele et al., 2018; Westin et al., 2016)	(Bernhard et al., 2020; Pavlenko et al., 2011)	(Thompson et al., 2019; Yunta et al., 2012)
Number of lying bouts	9 - 11 bouts/d (Tucker et al., 2021)	(Frondelius, Lindeberg et al., 2022; King et al., 2017)	(Bernhard et al., 2020; Lorenzini, 2019; Schindhelm et al., 2017; Solano et al., 2016; Westin et al., 2016)	(Navarro et al., 2013; Thompson et al., 2019; Yunta et al., 2012)

Parameter	Average	Increases (↑)	Decreases (↓)	Unaltered (→)
Duration of lying bouts	60-99 min (Tucker et al., 2021)	(Beer et al., 2016; Bernhard et al., 2020; Hut et al., 2021; Ito et al., 2010; King et al., 2017; Lorenzini, 2019; Schindhelm et al., 2017; Solano et al., 2016; Weigele et al., 2018; Westin et al., 2016; Yunta et al., 2012)	/	(Thompson et al., 2019)
Feeding time	2.4-8.5 h/d (Beauchemin, 2018)	/	(Antanaitis, Juozaitienė, Urbonavičius et al., 2021; Beer et al., 2016; Bernhard et al., 2020; Frondelius, Lindeberg et al., 2022; Hut et al., 2021; Lorenzini, 2019; Schindhelm et al., 2017; Thorup et al., 2016; Weigele et al., 2018)	/
Feeding frequency	7-11 meals/d (Johnston & DeVries, 2018)	/	(Antanaitis, Juozaitienė, Urbonavičius et al., 2021; Beer et al., 2016; Frondelius, Lindeberg et al., 2022; Lorenzini, 2019; Schindhelm et al., 2017; Thorup et al., 2016)	/
Feeding pace	0.10-0.16 kg/min (Johnston & DeVries, 2018)	(Lorenzini, 2019; Norring et al., 2014; Proudfoot et al., 2010; Schindhelm et al., 2017; Thorup et al., 2016)	/	/

Parameter	Average	Increases (↑)	Decreases (↓)	Unaltered (→)
Feed intake	10.4-30.8 kg/d (Krizsan et al., 2014)	(Proudfoot et al., 2010)	(Häggman et al., 2012; Norring et al., 2014)	(Schindhelm et al., 2017; Thorup et al., 2016)
Drinking behaviour	66.5-100.7 L/d (Cardot et al., 2008) 0.67-0.73 min/h (Antanaitis, Juozaitienė, Urbonavičius et al., 2021) 147.96-157.95 n/h (Antanaitis, Juozaitienė, Urbonavičius et al., 2021)	(Pavlenko et al., 2011)	(Antanaitis, Juozaitienė, Urbonavičius et al., 2021)	(Walker et al., 2008)
Activity	Free stall: 1,120-4,918 steps/d (Shepley et al., 2020)	/	(Beer et al., 2016; Häggman et al., 2012; Hut et al., 2021; Magrin et al., 2022; Neirurerová et al., 2021; Weigele et al., 2018)	(Frondelius, Lindeberg et al., 2022; King et al., 2017)
Neck activity	309.8-421 units/d (Borchers et al., 2017)	/	(Van Hertem et al., 2014; Weigele et al., 2018)	/
Rumination time	2.5-10.5 h/d (Beauchemin, 2018) 25.3-42.2 min/2h (Pahl et al., 2014)	(Pavlenko et al., 2011)	(Antanaitis, Juozaitienė, Urbonavičius et al., 2021; Beer et al., 2016; Magrin et al., 2022)	(Thorup et al., 2016; Walker et al., 2008; Weigele et al., 2018)
Rumination frequency	357-605 boli/d (Pahl et al., 2014) 20,959-36,789 jaw movements/d (Pahl et al., 2014)	/	(Antanaitis, Juozaitienė, Urbonavičius et al., 2021; Beer et al., 2016)	(Walker et al., 2008; Weigele et al., 2018)
Body temperature	Reticular temperature: 38.9-39.7 °C (Schutz & Bewley, 2009) Rectal temperature: 38.5-39.2 °C (Schutz & Bewley, 2009)	(Tadich et al., 2013; Talvio, 2020)	/	(Adams et al., 2013)

Parameter	Average	Increases (↑)	Decreases (↓)	Unaltered (→)
Body weight and BCS	BCS: 2.5-3.5 (5 point scale) (Grubić et al., 2009) 583-726 kg (Johnston & DeVries, 2018)	/	(Alawneh et al., 2012; Magrin et al., 2022; Norring et al., 2014; Olechnowicz & Jaskowski, 2014; Singh et al., 2018)	/
Milk yield	23.9-44.3 kg/d (Glatz-Hoppe et al., 2020)	(Vlček et al., 2016)	(King et al., 2017; Magrin et al., 2022; Navarro et al., 2013; Pavlenko et al., 2011; Prasomsri, 2022; Urbonavicius et al., 2020; Van den Borne et al., 2022; Vlček et al., 2016)	(Proudfoot et al., 2010; Schindhelm et al., 2017; Thorup et al., 2016; Yunta et al., 2012)
Milkings	2-3/d (Piwczyński et al., 2020)	/	(King et al., 2017; Urbonavicius et al., 2020; Van den Borne et al., 2022)	/
Milk flow	1.65-3.42 kg/min (Piwczyński et al., 2020)	(Van Hertem et al., 2016)	(Juozaitienė et al., 2021; Urbonavicius et al., 2020; Wieland et al., 2022)	/
Conductivity	4.6-5.8 mS/cm (Juozaitienė et al., 2015)	(Juozaitienė et al., 2021; Malašauskienė et al., 2022; Paulauskas et al., 2023; Van Hertem et al., 2016)	(Malašauskienė et al., 2022)	/
Milk components	Milk urea: 150-250 mg/L Milk protein: 3.29-3.58% Milk fat: 3.28-4.56% Milk lactose: 4.67-4.99% (Glatz-Hoppe et al., 2020)	/	(Malašauskienė et al., 2022; Olechnowicz & Jaskowski, 2010; Slovák et al., 2021; Vlček et al., 2016)	(Pavlenko et al., 2011; Singh et al., 2018; Yunta et al., 2012)

Parameter	Average	Increases (↑)	Decreases (↓)	Unaltered (→)
Somatic cell count	< 100.000 cells/mL (Sumon et al., 2020)	(Gráff et al., 2016; Malašauskienė et al., 2022; Singh et al., 2018)	(Archer et al., 2011)	(Pavlenko et al., 2011)

2.4.1 Behaviour parameters

In terms of lying behaviour, most studies concur that lameness contributes to an increase in daily lying duration (Table 3). For example, in the study of Hut et al. (2021), an observed disparity of 26 minutes was noted between lame and non-lame cows, while King et al. (2017) reported a difference of 38 minutes. Considering that claw lesions are presumably more painful when supporting the cow's entire body weight, an increase in lying times may provide relief to the claws and diminish pain for the cow (Juarez et al., 2003). On the contrary, Bernhard et al. (2020) and Pavlenko et al. (2011) observed a decrease in lying times and prolonged standing duration per day in lame animals. Given that inadequate cow comfort resulting from less optimal housing conditions might lead to a reduction in lying times (Robles et al., 2021), it is challenging to ascertain whether the extended standing periods could be a consequence of these conditions and potentially have contributed to the onset of lameness in the first place. In reviewing the literature, it becomes evident that claw diseases are clearly associated with an extension of individual lying events, while there is still disagreement regarding the total number of lying bouts (Table 3). The studies reporting a reduced lying frequency justify this, for instance, by emphasising the greater load on feet during the process of rising and lying down, whereas in the investigations with an increase of lying bouts, no rationale is provided. Navarro et al. (2013) also highlighted the relevance of housing conditions; in pasture-based settings, cows with claw lesions exhibited a higher frequency of daily lying bouts, while indoor-housed lame cows showed fewer lying events compared to their healthy counterparts. Yunta et al. (2012) attributed the lack of effect in their study to the exclusion of severely lame cows, while Thompson et al. (2019) emphasised the importance of considering additional factors such as precipitation.

An unmistakable effect of lameness becomes apparent in relation to feeding behaviour, as lame animals demonstrate a notably quicker ingestion rate, shorter feeding durations and fewer visits to the feeding trough (Table 3). As the painful nature of claw diseases is evident through the symptom of lameness (Whay & Shearer, 2017), prolonged walking or standing can induce discomfort that cows seek to avoid. This avoidance can be manifested by reducing movements towards the feeding trough or minimizing prolonged standing, as seen for example in the study of Thorup et al. (2016) with a more than 40% reduction in feeding frequency. The result is an elevated feeding rate of the animals, aiming to consume as much feed as possible within a condensed timeframe. The examinations of the amount of consumed feed present a less straightforward picture (Table 3): findings include both, increased feed intake among lame animals directly after calving (Proudfoot et al., 2010) as well as decreased intake in cases of severe lameness (Häggman et al., 2012). Furthermore, some instances occurred where, in univariate analysis, no definitive correlation between lameness and feed intake could be determined (Schindhelm et al., 2017; Thorup et al., 2016). The studies on the alterations in drinking behaviour also display mixed findings: Antanaitis, Juozaitienė, Urbonavičius et al. (2021) reported a 42-minute reduction in drinking duration among lame cows compared to healthy ones, whereas Walker et al. (2008) found no noticeable impact and conversely, Pavlenko et al. (2011) observed an uptick in drinking events among animals afflicted with digital dermatitis.

In various scientific studies, activity levels exhibit a notable decline attributed to lameness, with findings indicating a reduction in step count, along with a decrease in walking speed, neck activity and stride length (Table 3). Other examinations have found no direct correlation between hoof diseases and overall activity levels, possibly due to the inherent variability in individual cow activity (Müller & Schrader, 2005) and its modulation by factors like lactation status or parity (Brzozowska et al., 2014).

Pavlenko et al. (2011) reported increased rumination times during standing in lame animals, whereas Antanaitis, Juozaitienė, Urbonavičius et al. (2021) observed a daily average reduction of 133 minutes in rumination time, and Beer et al. (2016) noted a distinct decrease in rumination events. Thorup et al. (2016) concluded in their study that claw problems might influence rumination considerably less than feeding behaviour. This could be due to the fact that rumination primarily occurs during lying (Schirmann et al., 2012), which is less detrimental to the claws, whereas feeding happens while standing, exposing the claws to potentially more harm.

2.4.2 Physiological parameters

Only a few studies investigated the impact of claw health problems on body temperature. Talvio (2020) observed an increase in body temperature in cows with sole ulcers, suggesting that these conditions not only induce local inflammation but also trigger a systemic reaction. Tadich et al. (2013) showed that an elevation in rectal temperature only occurred in severely lame animals, while Adams et al. (2013) detected no changes in reticular temperature measured with a bolus.

The consensus across studies regarding the effects of lameness on BCS and body weight indicates a consistent decline with worsening claw health. Alawneh et al. (2012) documented an average loss of 61 kg in body mass among lame animals, while Olechnowicz and Jaskowski (2014) observed lower BCS values in lame cows across all lactation stages compared to healthy ones.

2.4.3 Performance parameters

Despite the challenge of distinguishing between cause and effect, most studies have demonstrated a reduction in milk yield following a lameness event. Prasomsri (2022) observed a decrease in 305-day lactation performance of over 1200 kg when animals became lame during their first lactation, while King et al. (2017) noted a reduction of 1.6 kg per day in lame cows. According to Van den Borne et al. (2022), two-thirds of the recorded decrease in milk yield after lameness can be attributed to a reduced milking frequency, with lame animals experiencing 0.3 fewer milkings per day compared to healthy ones as reported by King et al. (2017). Vlček et al. (2016) discovered varying changes in milk yield based on parity: lame first-calving cows exhibited higher milk yields, whereas a decline in milk yield was noted in higher lactations after lameness occurrence. Some studies also failed to establish a clear correlation between lameness and milk yield, which, according to Schindhelm et al. (2017), can be credited to the difficulty in determining whether high milk yield in cows initially contributed to lameness or lameness subsequently led to a decline in milk yield. These two diverging effects may counteract each other and other factors like feeding behaviour could influence the interaction (Schindhelm et al., 2017).

Lameness generally exerts rather negative effects on milk flow while concurrently showing higher conductivity values in lame animals (Table 3). Juozaitienė et al. (2021) revealed a reduction of 1.77 kg in milk yield within the first minute among lame cows, accompanied by an elevation of 0.24 mS/cm in conductivity. Van Hertem et al. (2016) incorporated peak milk flow in his lameness detection model, yet identified elevated peak milk flow values in association with lameness. Malašauskienė et al. (2022) established the range of 4-6 mS/cm conductivity in healthy cows, whereas lame animals fell outside this range, registering values above 6 or below 4 mS/cm.

Malašauskienė et al. (2022), along with several other studies, observed an impact of lameness on milk composition. They recorded an average decrease of 2.1% in milk lactose and 0.04% in milk protein. However, no changes were noticeable in milk fat, while the somatic cell count in the milk was significantly higher in affected animals. Slovák et al. (2021) demonstrated, depending on lactation status, a reduction in milk protein of approximately 7-10% and in urea of 18-30% in lame cows, while Vlček et al. (2016) found a 44 kg decrease in protein in primiparous cows and a 60 kg reduction in multiparous cows due to lameness. Singh et al. (2018) provided evidence of an elevated probability of mastitis among lame cows attributed to higher somatic cell counts, while no statistically significant alterations in milk composition were discerned. Furthermore, Pavlenko et al. (2011) did not detect any disparities in protein, fat, and somatic cell count between lame and unaffected animals.

2.5 Effects on welfare and economy

2.5.1 Welfare

The negative consequences of lameness are not to be underestimated and animal welfare ranks among the most crucial factors when advocating for better detection and treatment of claw problems. So far, there is no unified definition of animal welfare, but Reimert et al. (2023) recently described it as a state where positive and negative influences balance over time. The health status of the animal is thus no longer considered a component of animal welfare itself but rather can influence animal welfare by interacting with the specific condition of the animal (Reimert et al., 2023). In this manner, lameness events can impact the welfare of dairy cows in various ways and, according to Whay and Shearer (2017), they can compromise all five freedom areas that can be used to assess welfare impairment, including hunger and thirst, discomfort, illness and pain, expression of normal behaviour, as well as fear and distress. The pronounced behavioural changes resulting from lameness significantly impact various aspects of a cow's life, potentially leading to undernourishment, a reduced lifespan and an altered social behaviour (Weigele et al., 2018). Kovács et al. (2015) focused their study on heart rate and its variations, demonstrating that lameness induces increased parasympathetic activity and consequently lowers heart rate, which could possibly be explained by the chronic stress affecting the animal. Passos et al. (2017) demonstrated that claw diseases, especially non-infectious ones, are associated with an increased pain response, which can, however, be reduced through appropriate treatment. Additionally, Sadiq et al. (2022) concluded from their research that a combination of therapeutic hoof care with blocking and painkillers results in higher pain reduction and healing rates than simple claw trimming. A survey conducted in Switzerland aligns with this research, drawing the conclusion that better education on pain recognition and the benefits of using analgesics is necessary, given that over 50% of farmers reported performing any painful interventions in the claw area without pain relief (Becker et al., 2013).

2.5.2 Economy

It is imperative to consider the adverse effects on the profitability of individual farms resulting from lameness events, as lameness following mastitis infections can be considered the second most cost-intensive production disease (Van Soest et al., 2019). The economic impact of lameness is caused by a range of factors, including diminished milk yield, prolonged calving intervals, elevated culling rates, and escalated treatment and labour expenses (Bruijnis et al., 2010). Research conducted by Puerto et al. (2021) indicated that the economic losses stemming from reduced overall milk production, ranging from 811 to 1290 kg per lame cow, coupled with heightened culling rates, constituted a substantial proportion of the total losses, which averaged between 599 US$ and 837 US$. Ibishi et al. (2022) drew the same conclusions, setting the proportion of reduced milk yield contributing to the overall loss at 45%, followed by culling at 31%, while discarded milk, treatment costs, and reduced weight comprised only approximately 8% of the annual costs of a lame cow. Furthermore, the investigation of Robcis et al. (2023) demonstrated that the expenses caused by a cow afflicted with digital dermatitis (391.80 € ± 10.0) surpassed the average costs associated with lameness (307.50 € ± 8.40). It was found that each additional week of lameness incurred a cost of approximately 12 € per cow. Conversely, according to Dolecheck et al. (2019), a case of digital dermatitis cost only 64 € ± 24 and was surpassed by the expenses associated with white line defects and sole ulcers. Moreover, claw problems at the beginning of lactation and in multiparous cows resulted in the highest costs (Dolecheck et al., 2019).

3. Lameness detection

3.1 Manual lameness detection

The early detection of lameness in cows is essential for effectively managing claw diseases on farm. Multiple manual locomotion scoring systems have been established to evaluate the locomotion of cows depending on gait, posture and other aspects, but no consensus has been reached regarding the precise number of scores or the specific features to be considered. Schlageter-Tello et al. (2014) listed 25 different manual locomotion scoring systems, featuring between 2 and 13 scoring levels.

The most well-known scoring system is the one by Sprecher et al. (1997), which employs a five-point scale. Mild lameness is identified by a curved back line during walking, while moderately lame cows exhibit this also while standing and take shortened steps (Sprecher et al., 1997). At stage 4, the cow prefers to reduce the load on certain limbs and only takes one step at a time, while severely lame cows, according to this classification, try to avoid any load on the affected limb (Sprecher et al., 1997). Thomsen and Baadsgaard (2006) observed a considerable variance of 0.36 to 0.80 in the prevalence-adjusted, bias-adjusted kappa while applying the locomotion score by Sprecher et al. (1997) and analysing intra- and inter-observer agreement. Notably, in their study the level of agreement varied significantly based on which of the five stages was set as the threshold for lameness, thus affecting when an observer classified a cow as lame.

Flower and Weary (2006) compared a visual analogue score, ranging from 0 to 100 and increasing with lameness attributes, with a numerical score consisting of nine levels that included the same attributes: asymmetry, back line, head movement, weight shifting, limb bending and stride length. It was found that the numerical score performed best in classifying lame and healthy cows. They concluded the nine-point score provided a better assessment of claw health (Flower & Weary, 2006).

Another often scientifically employed locomotion score is the one by Manson and Leaver (1988), which also contains nine levels and ranges from 1 to 5 with steps of 0.5. It includes features like adduction and abduction, unevenness, difficulty in turning and rising or affection of behaviour pattern and stage 3 was designated as the lameness threshold (Manson & Leaver, 1988). While Manson and Leaver (1988) reported an agreement of 89% among the observers, Channon et al. (2009) only found a 33.3% agreement in scores. This discrepancy could possibly be explained by the large number of different stages, as the observers agreed on lame/not lame to over 88% (Channon et al., 2009).

A critical point in the type of locomotion scores, that include multiple levels, is that they are especially applicable for scientific research but lack practical relevance (Channon et al., 2009). In the farmer's day-to-day operations, the primary concern is simply whether the animal is lame or not, signalling the need for treatment of claw diseases (Channon et al., 2009). The nuanced gradations of lameness, such as mild, moderate or severe, hold minimal significance for the farmer's daily work, as any degree of lameness warrants attention and treatment.

Scores with fewer levels have also gained popularity, such as the four-level score of DairyCo (2007), widely used in UK farms. Level 0 is considered as a healthy cow, while level 1 is characterised by imperfect mobility, where steps are uneven or shortened, but the affected foot is not identifiable. It is recommended that these animals could benefit from routine claw trimming and should be further monitored. At level 2, the affected foot becomes clearly identifiable, often accompanied by a curved back and should be treated as soon as possible. Severely lame animals are defined as those unable to keep up with the rest of the herd and besides immediate treatment, it is also recommended to keep them on straw bedding and seek professional help. Rutherford et al. (2009) utilised this locomotion score in their study and reported an inter-observer agreement of 67.2% and a weighted kappa range of 0.42 to 0.73.

Previous experiences with the unsatisfactory reliability of a five-point scoring system also compelled Grimm and Lorenzini to create a new three-level score (Lorenzini, Grimm et al., 2017), which should be suitable for both practice and research (Lorenzini, 2019). This approach centres on categorising animals as lame when exhibiting an irregular gait (Score 3), while those walking regularly and displaying traits such as a curved backline, head nodding, or shifting weight are flagged as suspected lame (Score 2). In the absence of these indicators, animals are classified as sound (Score 1). To prevent delays in treating mild lameness, according to Lorenzini (2019), it is suggested not to differentiate between mild and severe cases, given the inconsistent correlation between perceived pain and lameness. This locomotion score achieved a very good Kendall concordance coefficient in live assessment (0.89) and a good concordance over video scoring (0.70) (Lorenzini, Grimm et al., 2017).

A drawback of manual locomotion scoring is its susceptibility to high variability between different observers (Channon et al., 2009), owing to the inherently subjective nature of the method (Renn et al., 2014). Lorenzini (2019) was able to demonstrate that lameness typically manifests within an average of 14 days, making regular locomotion scoring of each animal at least every two weeks necessary in order to intervene early and prevent the worsening of the underlying disease. The rising number of cows per farm (Hofmann & Ippenberger, 2023) will pose additional challenges to conducting regular and systematic visual evaluations of all animals, indicating automated lameness detection systems as a promising alternative.

3.2 Automatic lameness detection

Automatic lameness detection systems offer greater objectivity, as the outcome is not influenced by the individual experience of the observer and the cows are not directly influenced by the presence of an observer in the barn. The automatic lameness detection systems can be categorised into direct and indirect detection tools.

3.2.1 Direct methods

Direct automatic lameness detection refers to technical setups capable of directly identifying lameness based on features such as gait, body posture, weight distribution or temperature. These systems can be further classified into kinetic, kinematic, and thermographic detection mechanisms.

3.2.1.1 Kinetic

In the kinetic approach, movement is analysed with the use of force plates, pressure-mapping systems or weighing platforms. Rajkondawar et al. (2002) were the first to introduce a one-dimensional dynamic force plate system, which consisted of two parallel force plates and was capable of identifying lame cows and their affected limbs based on vertical ground reaction forces. Thorup et al. (2014) advanced to three-dimensional force measurement and demonstrated that lame cows exhibit significantly slower gait and less left-right limb symmetry across all three dimensions compared to healthy cows. Pastell et al. (2008) were able to demonstrate that an electromechanical film, whose thickness varies based on the forces acting during the cow's steps, can also be a promising lameness detection tool. Volkmann et al. (2021) installed a tread surface with two different layers: the upper layer transmitted the sound of the hoof upon impact to a sensor, while the lower foam layer provided sound insulation. The sound signal was then utilised with a random forest algorithm to achieve a sensitivity of 81% and a specificity of 97% in identifying lame animals (Volkmann et al., 2021).

Unlike those force measurement systems, which can only measure the total forces exerted, pressure-sensitive systems gather information through a network of sensors, allowing for simultaneous capture and mapping of diverse pressure points. Using pressure-sensitive mats, Van Nuffel et al. (2013) observed that lame cows exhibit asymmetrical gait, reduced pressure on the affected foot, smaller steps as well as prolonged standing on the contralateral leg and suggested these metrics could aid in earlier lameness detection.

Weight-distributing platforms prioritise a static measurement approach, with each limb of the cow standing on a separate weighing unit, enabling the measurement of weight distribution between the limbs. Pastell et al. (2010) utilised a numerical rating to discern lame cows and compared these results with weighing plate measurements in cows afflicted with sole ulcers. A strong correlation, based on weight distribution asymmetry, allowed for the effective identification of affected animals, achieving an area under the curve (AUC) of 0.87 (Pastell et al., 2010). Nonetheless, mild lameness cases, such as sole haemorrhages and digital dermatitis, posed challenges for detection, potentially requiring extended periods of individual data collection to enhance accuracy (Pastell et al., 2010). The research of Chapinal and Tucker (2012) demonstrated that particularly the number of steps taken by the rear legs increases significantly in lame animals, making it a valuable indicator for lameness detection.

3.2.1.2 Kinematic

In kinematic applications, the focus is on the geometric aspects of specific movements, including the position of certain body parts and their displacement, velocity, and acceleration.

A subfield that has gained particular importance in recent times is image processing. Wu et al. (2020) utilised the YOLOv3 algorithm to detect leg positions, followed by deriving step sizes. This information was then used to calculate a relative step size vector, enabling the successful identification of lame animals through a neural network (Wu et al., 2020). Anagnostopoulos et al. (2023) assessed the accuracy of the commercially available Cattle Eye system, which employs a 2D camera positioned above the exit of the milking parlour to detect coordinates of specific reference points on the animal. These coordinates are then transformed into a mobility score ranging from 1 to 100 using a neural network (Anagnostopoulos et al., 2023). Results from the study revealed that the system achieved an inter-rater agreement of 80% and outperformed an experienced veterinarian in identifying painful claw diseases (Anagnostopoulos et al., 2023). Abdul Jabbar et al. (2017) also employed an overhead-installed camera, but this one was capable of recording videos in three dimensions to additionally detect changes in hip and spine height (Accuracy: 95.7%). Zhao et al. (2018) generated a movement curve based on leg positions, from which six features, precisely velocity, symmetry, tracking up, step length, tenderness and standing time, were extracted. Using a decision tree, lame animals could be classified into three grades with an accuracy of 90.18% (Zhao et al., 2018). Piette et al. (2020) emphasised the assessment of the cow's backline, deriving a back posture value that elevated with worsening lameness. By incorporating reference data from each cow's healthy state over a minimum period of 200 days and computing an individual threshold value per cow, they achieved an accuracy of 82% in lameness detection (Piette et al., 2020).

Sensors can also be directly attached to the cow to capture kinematic data. Zhang et al. (2023) opted for sensors equipped with both an accelerometer and a gyroscope on each limb of the cows, allowing for the measurement of angular velocity and acceleration across three dimensions. Employing time series analysis alongside gait reconstruction techniques, this method achieved a very high accuracy of 97.78% (Zhang et al., 2023). Ismail et al. (2024) equipped each cow with a smartwatch containing an accelerometer, gyroscope and magnetometer, secured to a randomly selected limb. Using a combination of a multi-sensor database and machine learning techniques, the animals were classified as lame or healthy with an accuracy of 77% (Ismail et al., 2024).

3.2.1.3 Thermographic

Another growing field is infrared thermography, which involves devices such as cameras deployed to detect temperature deviations in affected claw areas and create thermograms. Werema et al. (2021) compared visual 4-stage locomotion scoring with infrared cameras, noting that as the locomotion score increased by one stage, the average measured temperature rose by 0.994 °C, while achieving a sensitivity of 80.0% and a specificity of 92.4% in identifying lame animals. Most research conducted with handheld infrared cameras has centred on detecting digital dermatitis, attributing to this method the potential to identify these lesions based on the temperature increase caused by inflammation (Anagnostopoulos et al., 2021; Fabbri et al., 2020). Lin et al. (2018) investigated the application of handheld infrared laser thermometers, finding a correlation between temperature elevation and locomotion score escalation, thereby detecting a high-risk group requiring further observation. Research also indicated that capturing the heel region and utilising the maximum temperature as the decision criterion yielded the best results in categorising lame and non-lame cows (Harris-Bridge et al., 2018). Some studies have pointed out the need for improvement before these devices can be reliably used in daily lameness detection. The highlighted issues included too many animals being falsely classified as lame (Lin et al., 2018; Werema et al., 2021), labour intensity due to insufficient automation (Harris-Bridge et al., 2018; Werema et al., 2021) and high acquisition costs (Coe & Blackie, 2022). At least the latter could be mitigated, as suggested by Coe and Blackie (2022), by using less resolution cameras, which, in their trial, achieved only slightly lower accuracy compared to those specialised for research purposes.

3.2.2 Indirect

Within the indirect methods for lameness detection, the emphasis is placed on utilising the performance and behavioural data captured by animal-specific sensor systems to automatically detect lameness. Research has revealed that cows' behaviour frequently shifts prior to lameness becoming visually evident to farmers, potentially enabling earlier detection of lameness (Norring et al., 2014; Thorup et al., 2015). Costs can be saved in this area by simultaneously using behaviour-monitoring sensors for heat detection, lameness detection and the detection of other diseases (Grimm et al., 2019; Pfeiffer et al., 2020). Many different combinations of behaviour and performance predictors as well as various analytical techniques have been described in recent years. For instance, Taneja et al. (2020) applied fog networking to consolidate step counts, lying times, and get-ups into time-series data, enabling the categorisation of cows based on activity levels and subsequent classification as lame or healthy (accuracy: 87%). The clustered models achieved an 8% higher accuracy than a unified model, with lame animals detected on average three days earlier than the onset of visible symptoms (Taneja et al., 2020). Lavrova et al. (2023) utilised pedometer data of six German dairy farms for their lameness detection model and investigated various statistical approaches, attaining the highest accuracy of 81% by using a mixed linear regression model. This model incorporated several predictors, including activity level, duration of lying events, average daily milk yield, days in milk, parity, season and their interaction parameters, along with the individual cow as a random intercept (Lavrova et al., 2023). Beer et al. (2016) collected data from two 3D accelerometers and a neck collar sensor, discovering that the optimal logistic regression model, incorporating parameters such as walking speed, standing events and feeding duration time, achieved a sensitivity of 92.7% and a specificity of 91.7% in lameness detection. However, models containing solely the pedometer data already exhibited a commendable accuracy in lameness detection, with only a marginal 2.5% reduction in sensitivity (Beer et al., 2016). Magana et al. (2023) focused on the detection of digital dermatitis utilising an ear tag and machine learning models. They were able to identify affected animals with a probability of 79% and even ensure an accurate prediction two days before the onset of clinical symptoms, achieving an accuracy of 64% (Magana et al., 2023). The earlier detection of mild lameness was also evident in the study of Lemmens et al. (2023) through the integration of milking robot measurements and data from a neck or ear sensor, followed by successful modelling with random forest. They achieved an accuracy of 75% and highlighted that this approach is especially well-suited for practical deployment of automated lameness detection, given the growing abundance of behavioural and performance information on farms (Lemmens et al., 2023). Borghart et al. (2021) tested various model combinations and demonstrated that the accuracy of a lameness detection model using a behavioural sensor can be further improved by incorporating additional data such as milk parameters and body weight (accuracy: 85%).

Investigations by Grimm et al. (2019), which were performed on a Bavarian research farm by combining the data of a long-range pedometer and performance parameters, highlighted the intricate relationships and the necessity of incorporating various parameters for lameness detection. They showed that high milk yield only poses an increased risk of lameness when accompanied by reduced time spent at the feed trough or shorter lying durations below the average. Furthermore, an extended lying time per event was indicative of lameness only when overall feeding time decreased or when animals exhibited increased daytime feeding, emphasising the importance of considering the combination of these two behavioural parameters. The final ENET beta model comprised four regular predictors and five interaction parameters, achieving an accuracy of 94% in distinguishing lame from sound cows.

In the subsequent project, Lorenzini, Grimm, and Haidn (2021) built on this research and examined data from both the research farm and four additional commercial dairy farms. The top-performing model exhibited an AUC of 0.82 on the test dataset, incorporating eight fixed parameters, three interaction parameters, and five random effects. The predictors incorporated in the model belonged to the domains of feeding behaviour, lying behaviour, lactation status, and milk yield. The individual animal was considered as the random effect of the intercept, and it was revealed that the main challenge in lameness detection stems from the unique differences in the relationship between claw health, performance and behaviour among the cows and the application of the mixed model on previously unseen animals.

Efforts were made to address this issue by utilising neural networks, yet this approach only yielded slightly better results with an accuracy of 0.86 (Lorenzini, Grimm, Hertle et al., 2021). As an alternative solution, time series models were proposed, albeit requiring a different data structure than used in the two preceding projects (Lorenzini, Grimm, Hertle et al., 2021), a factor that was taken into account during the data collection for this study.

III. Study objectives

This study is a continuation of two preceding projects on indirect automatic lameness detection performed at the Institute for Agricultural Engineering and Animal Husbandry at the Bavarian State Research Centre for Agriculture (Lorenzini, 2019; Schindhelm, 2016). The trial was part of the demonstration project 5 “Animal-specific, interconnected sensor systems” within the experimental field DigiMilch. The study’s main aim was to examine which behaviour and performance parameters generated by different sensor systems from various manufacturers are best suited for automatic lameness detection by means of the previously developed models by Grimm and Lorenzini (Grimm et al., 2019; Lorenzini, 2019).

Partial objectives of the project were:

1. The recording of performance and behaviour data by use of different sensor systems
2. To gain reference data about lameness by recording videos covering the days before the claw trimming and documenting the visible findings as well as the pain test results during farm claw trimming
3. To create a score to explore the overgrowth of the central sole part as a reason for cows experiencing pain without evident defects or clinical findings
4. To carry out locomotion scoring retrospectively by using the video data in an attempt to detect changes of lameness or its onset
5. To summarise all data to create daily records
6. To integrate the data in different linear generalised mixed regression models to discover the possibilities of early detection by combining various sensor parameters
7. To further validate the three-point locomotion score by Grimm and Lorenzini

IV. Material and methods

1. General approach

Data gathering was performed on eight different project farms located in Bavaria, more precisely on three research farms and five commercial dairy farms. The chosen farms were all equipped with a milking robot and various sensor systems. Making use of a larger-scale trial than in the preceding studies, different sensors by various manufacturers could be included. Due to the higher amount of available data and the easier way of cow identification in comparison to milking parlours, it was decided to only consider herds with a milking robot for this project. In November 2020, suitable project farms were selected, the necessary camera equipment was installed and a preliminary test at the farm claw trimming was performed on RF1. The data collection for the study began in March 2021 and lasted until October 2022, containing sensor and lameness data from a total of 744 cows.

Reference data was acquired during the farm claw trimming and afterwards by locomotion scoring the cows using video footage. One to two cameras per farm were installed facing the milking robot exit and recording the cows leaving the milking robot during three weeks before the farm claw trimming date. Cow identification was possible by time synchronising the camera with the milking robot and, if available, the automatic gates. The video footage was reviewed after the trimming and the appearing cows were scored according to the three-step locomotion score by Lorenzini, Grimm et al. (2017). Each cow scored lame or unsound on the day preceding the claw trimming was then scored retrospectively for 21 days to detect the beginning and development of lameness. If the cow was sound on the day before claw trimming, it was only scored retrospectively every five days and, if the score remained unchanged, the days in between were interpolated.

On the date of the claw trimming, each cow entering the cattle crush was checked right away for pain reaction by exerting pressure on the claws in two different positions with claw pliers before the trimming started. Using this procedure cows without visible lesions, which nevertheless experienced pain, could be identified. A score for the growth in the sole centre was also established and then noted for the claws of every cow on the trimming date after the pain test and before the trimming. On the first three claw trimming dates, the findings documented by the claw trimmers were considered. Afterwards, due to missing claw health information in those documentations it was decided that the veterinarian should also record the findings during the following claw trimming dates.

Behaviour and performance data were collected on the project farms during the three weeks before the claw trimming by using the different sensor systems installed on the farms like boluses, pedometers or neck tags. The data were either transferred automatically to the DigiMilch database or exported manually by the examiner if no suitable interface existed or no contractual agreement with the sensor manufacturers could be reached during the period of data acquisition.

The collected data was used to develop daily records for each farm. Then by integrating the daily records into different regression models, the goal was to find out if these models containing behaviour and performance parameters recorded by sensor systems could detect the lame cows. Furthermore, the aim was to determine which of the used sensor parameters and models potentially provide the best results for automatic lameness detection.

2. Farms

Factors influencing the choice of farms for the project were:

- Inclusion of a high amount of different sensor technology
- Presence of a milking robot
- Possibility of taking part in the farm claw trimming on the farm
- General farmer compliance and willingness to take part in a project on digitalisation.

It was also important for the researchers to have a combination of both research and commercial dairy farms in the data set. The two research farms (RF1, RF2) and the teaching and research institute (RF3) were included due to prior usage as trial venues in previous projects and therefore familiarity with the study environment. Some of the commercial dairy farms were recruited by a survey which was created to find project farms for the whole experimental field. The survey, which included questions concerning general operating information of the farms and their equipment with sensors, was spread over social media, internet and the project partners, therefore interested farmers could complete the form. Others were suggested as suitable farms by some of the manufacturers taking part in the “DigiMilch” experimental field. A total of three research farms and five commercial farms could be included as project farms, and the total number of claw trimming dates per farm and the number of examined animals per date can be found in Table 4.

Table 4: Number of claw trimming dates (CT) and examined animals per CT (excluding dry cows) grouped by farm during the data collection period

	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
Examined animals per CT	57-60	43-45	57-62	62-65	52	29-36	115-123	129
Number of CT	5	3	4	2	1	5	2	1

2.1 Research Farm 1

The Research Farm 1 (RF1) was one out of two farms in this study belonging to the Bavarian State. The farm contained two dairy herds, one using a herringbone milking parlour, while the other one was milked with a milking robot. Only the milking robot herd was considered for this project and contained approximately 70 cows. A total of 102 different Simmental and 3 Brown-Swiss cows were examined over five claw trimming dates from March 2021 to October 2022. The farm was equipped with a DeLaval milking robot (VMS 3.0), the management system “DelPro” and five automatic selection gates. Additionally, weighing troughs developed by the Institute for Agricultural Engineering and Animal Husbandry, ventilators, curtains and climate sensors were installed. Track a Cow pedometers, Heatime SCR sensors and smaXtec boluses were attached to the cows. Information about diseases and treatment was stored in the GEA herd management program C21. Deep litter cubicles, concrete-based raised cubicles with rubber mattresses and waterbed cubicles separated by metal brackets or moveable bars, were installed in the lying area. The slatted floor was covered with rubber mats in all different areas and cleaned by a DeLaval scraper robot. For the drying-off period, the cows were regularly transferred to another stable with access to a pasture. Claw trimming took place three times a year and was carried out using two cattle crushes. In December 2021, the farm switched to a different claw trimmer and only one cattle crush was used on the following trimming dates. Overall, data from 105 different animals could be collected.

2.2 Research Farm 2

This Research Farm (RF2), also belonging to the Bavarian State, had one herringbone milking parlour and one milking robot herd. The latter was included in this project and consisted of approximately 50 cows. The total of 63 individual cows observed on this farm were milked by a Lely Astronaut A5 milking robot and the used sensor systems were collars with Nedap SmartTags (Premium (I) FERP). Besides the Lely management systems (T4C and later Horizon), HERDE plus (dsp-Agrosoft GmbH, Germany) was used as an additional herd management software. The walkway was mainly designed as solid concrete floor covered with rubber mats and cleaned by manure scrapers by Schauer (Schauer Agrotronic GmbH, Austria). Deep litter cubicles as well as concrete-based raised cubicles with rubber mattresses separated by metal brackets were installed in the lying area. Further technologies like ventilators and curtains were included to improve the indoor barn climate. The cows' claws were trimmed three times a year in one crush and the data were collected during three claw trimming dates from May 2021 to June 2022.

2.3 Research Farm 3

The Research Farm 3 (RF3) kept 150 cows in two herds, approximately 70 of them belonging to the milking robot herd. The automatic milking system used here was the Lely Astronaut A5 with the management system T4C/Horizon with Heatime SCR sensors (for the first claw trimming date only), Smaxtec boluses, Nedap pedometers and Nedap neck tags. The deep litter boxes were manually scattered with biogas digestate, a husk-clay-mix or chopped straw and separated by metal brackets. The floors in the walkway and the feeding area were solid and cleaned by manure scrapers by Prinzing (Peter Prinzing GmbH, Germany). The feeding places were layered with rubber mattresses and a metal partition was installed every two places. In summer the cows had access to a pasture and temperature was continuously monitored by climate sensors and controlled by ventilators, curtains and cow showers. Dates for claw trimming were planned three times a year and performed with one cattle crush. Data from a total of 97 different animals were recorded on four different dates between May 2021 and July 2022.

2.4 Commercial Dairy Farm 1

On commercial dairy farm 1 (CDF1) approximately 65 cows were milked by a Lely Astronaut A5 milking robot. The only employed sensor system was Heatime SCR and the management system used was T4C/Horizon. The floor in the feeding area was solid with a rubber base, while the other parts consisted of concrete floor whereas the transition area near the milking robot was slatted. There was a walkway with grooves in the lying area and deep litter boxes, which were littered automatically by a Hetwin robot (Hetwin Automation Systems GmbH, Austria). Furthermore, the farm utilised curtains and manure scrapers by Prinzing. The cows could also enter a farmyard which was partly equipped with solid floor and partly with grooved ground. Claw trimming took place once a year by using one cattle crush. Data were originally collected on two claw trimming dates in June 2021 and May 2022, but due to problems with the recorded video footage by the camera, only the second date could be taken into account, including 62 different cows.

2.5 Commercial Dairy Farm 2

The approximately 65 cows on commercial dairy farm 2 (CDF2) were milked by a milking robot from Lemmer Fullwood (Merlin 2) and carried pedometers of the same manufacturer. The used herd management system distributed by Lemmer-Fullwood was "Full-Expert". The walkway was made out of concrete and slatted and the cubicles were built as deep litter boxes. The farm was also equipped with a JozTech (Joz BV, The Netherlands) scraper robot, ventilators, curtains and a cow shower. The farmer regularly performed claw trimming on his own by trimming a group of 10 to 15 cows before the dry-off several times a year and used a professional claw trimmer for the first time during the data collection. The cows were trimmed in one crush in February 2022 and data of 52 cows could be collected.

2.6 Commercial Dairy Farm 3

Commercial dairy farm 3 (CDF 3) consisted of a herd of approximately 60 cows, which were milked by a DeLaval milking robot (VMS 300). The cows were fitted with collars with DeLaval neck tags and data was collected by the DelPro herd management system. A scraper robot by Lely cleaned the concrete slatted floor and the in-barn climate was controlled by a large ventilator. The concrete-based raised cubicles were separated by metal brackets. Claw trimming took place five times a year, but only half of the herd was trimmed on every trimming date. Claw health data was collected on five claw trimming dates on this farm from September 2021 to July 2022, but the video data regarding trimming dates three and four in February and May 2022 were lost as the result of a defective storage unit due to power failure caused by a malfunctioning fly screen. In summary, data from a total of 67 different cows could be collected.

2.7 Commercial Dairy Farm 4

The commercial dairy farm (CDF4) was an organic farm and included a herd with approximately 120 milking cows, which were milked by two Lemmer Fullwood milking robots. The installed sensor systems were Lemmer Fullwood pedometers and Smaxtec boluses. The ground in the barn was concrete slatted and cleaned manually by a Heitmann (KR Maschinen GmbH, Germany) scraper and the concrete-based raised cubicles were covered with rubber mattresses and separated by metal brackets. There was also the possibility for cows to enter a farmyard with concrete grooved flooring, which was cleaned by a manure scraper by Prinzing and equipped with cow showers. Young stock and dry off were kept in a separate stable with pasture access. Claw trimming was performed two times a year by using one cattle crush. During the two claw trimming dates in November 2021 and April 2022, data from 159 different cows were gathered.

2.8 Commercial Dairy Farm 5

Commercial dairy farm 5 (CDF5) was also an organic farm and contained two herds with approximately 65 cows each in two different stables, which were milked by two Lely A4 milking robots. T4C/Horizon was used as herd management system and the behaviour data were collected by SCR sensors attached to the cows' neck. Indoor barn climate was controlled by ventilators and sash windows. The cubicles were deep litter boxes with metal brackets and the solid concrete floor was cleaned by manure scrapers by Hartmann (Hartmann GmbH & Co. KG, Germany). Claw trimming was carried out two times a year in one cattle crush and for this study data were collected within one farm claw trimming during a two-day session in February 2022, including 129 cows.

3. Technology used in the study

3.1 Cameras

Figure 13: Mobotix D15 Dual Dome Camera

Owing to the long distances between the farms and the experiences from the previous project regarding observer presence impact, it was decided to install cameras instead of practicing on-site scoring. Mobotix cameras were installed on all project farms to record videos of the cows exiting the milking robot.

The Mobotix D15 Dual Dome camera (Mobotix AG, Langmeil, Germany) (Figure 13) includes two moveable lenses, each of which can cover a wide angle of up to 180° and can be rotated in different directions. Both colour (Figure 14) and monochrome cameras (Figure 15) were employed, the latter offering enhanced night vision qualities. A red light signalled the camera's recording mode, and the option was added for farmers or facility managers to install a switch for manual camera deactivation, providing them with control over its operation as needed. The utilisation of the NTP (Network Time Protocol) server allowed for automatic time synchronisation, yet at RF2, attempts for automatic setup failed, resulting in the need for regular manual adjustments. Thus, the timestamps logged by the milking robot during each cow's milking session, coupled with stall occupancy data where applicable, provided a reliable means to identify the cow's departure from the milking robot. Because the best evaluation was possible by watching the cows from the side while walking forward, the conditions on each farm needed to be inspected and factors such as ease of installment, shooting angle, preferred cow orientation, network connection, data storage and access options were discussed to find the most promising camera spot. The initial intention was to store the collected video data in terms of a circular buffer on a Zyxel NAS326 (Zyxel Communications Corp., Hsinchu, Taiwan), a Network Attached Storage system containing two 4TB hard discs. After encountering issues with overwriting old data with new information in the case of full storage, which led to recording interruptions, it was decided to switch to the previous generation Zyxel NAS 325. The cameras were installed on the farms on different dates between December 2020 and July 2021, all positioned to provide a clear view of the milking robot exit and to observe the cows in motion. Examples of the camera views are shown in Figure 14 and Figure 15.

Figure 14: Recording window of the Mobotix camera at RF1

Figure 15: Recording window of the Mobotix camera at RF2

3.2 Milking robots

Milking robots from three different manufacturers were employed on the project farms included in this study. Alongside the essential timestamps for video analysis during milking and milk yield for each milking session, various additional parameters were recorded depending on the type of milking robot.

Two research farms and one commercial dairy farm utilised Astronaut A5 milking robots by Lely and one other employed the Astronaut A4 version. The robots on the project farms documented an array of data points in addition to the basic milk quantity metrics, including milk flow, fat, protein and lactose content, conductivity, days in milk, milk colour, milk temperature and concentrate intake. All farms, except for CDF5, incorporated somatic cell count into their records, while CDF5 also documented the body weight of the animals. Throughout the study, all farms transitioned from the T4C Management Centre to the newer Horizon system, resulting in data being collected from both platforms.

RF1 implemented a DeLaval VMS V300 milking robot, whereas CDF3 had used the VMS V310 model. In addition to milk yield, these milking robots provided data on concentrate intake, days in milk, conductivity, blood content in the milk, milk flow, and the MDi. The data could be accessed through the management system DelPro associated with the robot.

CDF2 and CDF4 were equipped with M²erlin milking robots by Lemmer Fullwood. Beyond monitoring milk quantity, also concentrated feed intake, blood presence in the milk, conductivity, and, through the inline milk analyser, fat, protein and lactose levels could be tracked on these farms. The employed management system was Crystal.

3.3 Weighing troughs

36 weighing troughs are installed on RF1 for the collection of animal-specific feeding data and the following specifications regarding the weighing troughs are based on Fröhlich et al. (2005). The troughs consist of the feeding trough, a load cell, a lockable gate, an antenna and a process controller. The troughs' capacity is, on average, enough to hold one day's worth of feed (80-100 kg) for a maximum of two cows. When a cow enters the detection area of the antenna, the ear tag is detected by radio frequency identification. As the troughs are often used in feeding experiments, not all animals have access to all troughs at all times. Sometimes the herd is divided into feed groups and fed different feed rations. So according to the animal's ear tag number, the processor unlocks the gate, which can then be pushed down by the cow. The processing unit determines the weight of the trough before and after food intake as well as the starting and ending time to define the duration of the visit. The data can be stored in the processor for several days but is also saved by using an access database on another computer for longer term. Individual visit data or daily aggregated data can be exported from the program. These files include details such as the start and end timestamps for each cow, along with the calculated trough weight difference for each visit or daily summaries of total intake volumes per cow and trough.

A livestock scale, functioning similarly to the load cell in the weighing trough and employing identical software, is additionally incorporated into the milking robot on RF1 to regularly monitor the cows' individual weight fluctuations.

3.4 Pedometers

3.4.1 Track a cow (ENGS Dairy Solutions)

The "Track a cow" pedometers (Figure 16) by ENGS Dairy Solutions (Rosh Pina, Israel) and the associated application "EcoHerd" have already been used on RF1 during the preceding studies. At the onset of data acquisition of the present study in 2021, cows on RF1 without functional pedometers and those yet to be equipped were identified. Following this, the "EcoHerd" system was updated to ensure comprehensive and accurate data collection for the entire herd. This process was repeated in advance of every following claw trimming date.

The information regarding this sensor is based on ENGS (2023). The pedometers are so-called long-range pedometers (LRP), which can cover a range of up to 10 km through radio transmission. Every pedometer consists of a plastic casing containing a triaxial accelerometer, a position sensor and an RFID antenna. After being attached to the cow's front leg with a nylon strap and pins, the pedometer is capable of transforming the detected g-forces into three movement patterns: lying, standing, and walking. The device captures the animal's walking motion in terms of activity units, encompassing movements such as forward, backward, sideways or stationary leg movements. In addition to activity, parameters such as lying time and the number of lying bouts resulting from the alternation between lying and standing can also be extracted. The leg's position in relation to the ground is registered every eight seconds and aggregated datasets of two minutes length are created by the pedometer.

Data are transferred every 15 minutes to a receiver equipped with an antenna and subsequently relayed through a cable to a USB converter, which processes the data and forwards it to a computer. Data collected via "EcoHerd" undergoes daily backups, with storage facilitated through a Microsoft Access database, allowing for querying of both hourly values and total values per day.

The pedometers also serve to monitor the cows' feeding behaviour using an induction loop. This loop consists of a cable encircling the feeding table, through which an electrical signal is transmitted every 0.3 seconds by an activator, generating a magnetic field within the loop. When the cow enters the loop with the pedometer, the signal is detected, and the time stamp is considered as the beginning of the feed intake period. Any feeding visits occurring with interruptions of less than six minutes are considered as one single visit to the feeding trough. This gives the user information on the number of feeding table visits per day, the duration of each visit, and the total feeding intake duration.

In the previous project focused on automatic lameness detection, the induction loop on the cow side was initially positioned in a trench within the concrete floor, set at a distance from the feeding area. This arrangement ensured that the magnetic field was large enough for the cow to stand within it during feeding despite the large dimensions of the weighing troughs. However, since the end of data collection on the previous project, rubber mats were installed in the barn, and the corresponding trench for the cable was sealed during this process. At the beginning of the data collection in this study, the cable needed to be reinstalled in the same position to ensure precise and consistent recording of feeding behaviour.

3.4.2 CowControl (Nedap)

CowControl leg tags (Figure 17) are manufactured by Nedap Livestock Management (N.V. Nederlandsche Apparatenfabriek, Groenlo, the Netherlands). In this study, the Nedap pedometers were employed on RF3 in the version supplied by Lely. The pedometer details are derived from Nedap Livestock Management (2024). They typically consist of a yellow plastic housing, although the colour varies depending on the involved milking technology manufacturer, and they are attached to the front leg of the cow using a plastic belt with a ratchet function. The housing contains an accelerometer which can measure the acting g-forces in three dimensions. The leg tags can be deployed for animal identification, heat detection and monitoring of standing, lying and walking behaviour and the data is captured in intervals of 15 minutes. An antenna collects data through radio frequency in a range of 500 to 1000 meters depending on the housing system and passes them on to a processing unit. The processor analyses the data and transforms it into useful information for the farmer. Afterwards, it is transmitted to the CowControl software called Velos on the local computer and forwarded to the Nedap cloud for storage.

Figure 16: ENGS Pedometer

Figure 17: Lely pedometer (produced by Nedap)

3.4.3 Fullexpert DPP (Lemmer Fullwood)

The Lemmer Fullwood (Lemmer-Fullwood GmbH, Lohmar, Germany) Fullexpert differential precision pedometer (DPP) (Figure 18) and the DPP Plus (Figure 19), also recognised as “AfiTag Plus” and “AfiTag II” as they are manufactured by Afimilk (Afimilk Ltd., Kibbutz Afikim, Israel), can distinguish between activity and resting behaviour. The pedometers are described according to information by Lemmer-Fullwood (2024). They were deployed on CDF2 and CDF4, serve for the recognition of the cow in the milking robot and can detect standing, lying and moving based on a triaxial accelerometer. The pedometer can be attached to the cow's leg using either a webbing strap with a ring closure or a PVC band featuring a snap mechanism. Data transfer is managed during every milking or every 15 minutes depending on the pedometer version via radio frequency to an antenna inside a reader device, which collects the data and forwards it to the Crystal herd management system via Wi-Fi. Animal-specific data, including lying bouts, lying time, lying ratio, activity and an agitation index, can be exported through Crystal. The daily activity indicates the hourly average of steps over six recording intervals for each respective day. The agitation index is correlated with the activity; the higher it is, the more likely the cow is in heat. Notifications regarding heat detection and calving can be provided and a vitality profile can be visually integrated with milk yield and cow conductivity to assess the cow’s well-being.

Figure 18: Fullexpert DPP (AfiTag Plus)

Figure 19: Cow with Fullexpert DPP Plus (AfiTag II)

3.5 Neck tags

3.5.1 CowControl (Nedap)

The data transmission of the Nedap CowControl neck tags (Figure 20) operates in the same manner as the Nedap leg tags (3.4.2) and the information concerning these sensors is also based on Nedap Livestock Management (2024). The sensors are attached below the neck on a collar and contain a three-dimensional accelerometer, which is able to distinguish between different behaviours due to the direction of the movement. If a sensor is incorrectly attached, the user gets informed by receiving a notification. The premium (I)FERP neck tag variant was the one installed on RF2 (in the Nedap version) and RF3 (in the version supplied by Lely as Qwes ISO LD). They were used for ISO animal identification, heat detection and cow location tracking as well as for monitoring feeding, rumination and activity. For the location tracking, beacons need to be installed at 10 to 15 meters in the barn and periodically send signals to the neck tag. The tag receives the signals of several beacons and responds with an ultra-high frequency signal to an antenna, and a processor can calculate the cow's current location based on this information. A map of the barn with the position of all cows can be displayed and it can be searched for individual cows. The system is able to compare the gained data to standard values and earlier measurements of the specific cow or the whole group and uses all of this information to recognise significant changes. The data can also be retrieved through the milking robot of the distributing manufacturer instead of the Velos software and displayed in the form of graphs or lists.

Figure 20: Nedap CowControl Neck Tag

Figure 21: Lely Qwes ISO LD (produced by Nedap)

3.5.2 SCR HR-LDn (Allflex)

Two research farms (RF1, RF3) and two commercial dairy farms (CDF1, CDF5) operated with neck tags (Figure 22) by SCR (Allflex Livestock Intelligence, Dallas, USA). The description of this sensor is based on Allflex Livestock Intelligence Deutschland (2024). The transmitter used during data collection is called SCR HR-LDn, is fitted to the collar on the left side behind the ear and needs to have contact with the neck muscle. The optimal positioning of the neckband, and consequently the neck tag, is enabled by a weight beneath the cow's neck. The neck tags contain a triaxial accelerometer to detect the cow’s movements and a processing unit and forward the information via radio frequency over a distance of 200 to 500 meters to an antenna and further to the corresponding computer. On the two commercial dairy farms, the neck tags were supplied by Lely as QWES HR-LDn and the data retrieval and display were performed by the Lely milking robot. On the two research farms, the data was available through the Heatime Pro program, but on RF3 the SCR sensors were discontinued in the milking robot herd after the initial claw trimming session in the project. Rumination time in minutes, an activity index and the heat probability could be exported from Heatime or the milking robot. The sensors also help to monitor the behaviour of the whole herd and can generate an alarm to inform the farmer the cow might need calving assistance if rumination is already low for more than two hours during the expected calving period.

3.5.3 Activity meter system (DeLaval)

The neck-mounted activity tag (Figure 23) by DeLaval (DeLaval AB, Tumba, Sweden) is called “activity meter system” and is employed on CDF 3: The information about this sensor is drawn from DeLaval (2024). The neck tag uses a three-axis accelerometer to record the cow’s activity as an index and creates heat alerts. The activity meter is affixed to a collar on the cow’s right side, situated directly above a transponder, which is necessary for the identification of the cow in the milking robot. The neck tags forward the data via radio frequency to an antenna on a receiver four times per hour or each time the cow passes an RFID reader. The complete data from the last 24 hours is transmitted, ensuring that no data loss occurs even during intermittent periods of non-readouts. The data is then analysed with the assistance of a system controller to, for example, identify cows in oestrus and subsequently presented within the DelPro system. Cow activity data is retained for 180 days, enabling graphical representation and exportation in a list format. This list includes values like the daily average of activity, the relative activity, as well as the minimum and maximum levels of relative activity. The relative activity refers to the current activity level of the cow compared to its individual average, as the system also retains individual behavioural patterns. Additionally, the relative activity of the group can be compared to identify events such as heat stress that may affect the entire herd. In detecting an approaching calving, an increase in the percentage value for the likelihood of high activity can be an indicator.

Figure 22: SCR HR-LDn neck tag

Figure 23: Activity meter system (DeLaval)

3.6 Bolus (smaXtec)

The boluses (Figure 25) are developed by smaXtec (smaXtec animal care GmbH, Graz, Austria) and the specifications regarding these boluses are based on smaXtec (2024). The boluses are 105 mm x 35 mm in size and are placed in the reticulum of the cow by oral administration with an injector. On RF1, only some of the cows were equipped with boluses, initially utilising the first-generation smaXtec boluses, which were unable to record rumination, before transitioning to the smaXtec SX.2 boluses by the end of 2021. Both bolus generations were employed on RF3, while only the newer version, smaXtec SX.2, was used on CDF4.

In general, there are also two different types of boluses: the pH bolus and the classic bolus. The pH bolus measures the pH value in the reticulum in addition to the other recorded parameters. The accuracy of the pH measuring function is only guaranteed for 150 days and the manufacturer recommends equipping 6 to 10% of the herd with the pH boluses to monitor the cows' health and, if necessary, optimise the feeding management. The classic version, which was employed on the project farms, detects activity using an index from 1 to 100, rumination time, internal body temperature, drink cycles and creates a heat index. At the time of data collection in this project, the parameter for water intake quantity, which is now available, had not yet been integrated into the system. The rumination can be detected by the duration and number of reticuloruminal contractions, the internal body temperature can be measured with an accuracy of up to ±0.1°C and the drinking behaviour is displayed by a subsequent drop in body temperature upon water intake. The recorded body temperature in the reticulorumen usually shows a 0.5 to 1°C elevation compared to the rectal temperature and the normal temperature of each animal is calculated individually, facilitating rapid identification of any deviations. The bolus encompasses a 3D acceleration sensor, a temperature sensor, and optionally, the pH sensor.

Data is collected in 10-minute intervals and the boluses are able to store information for up to six days. Base stations (Figure 26) regularly retrieve the data and transmit it to a cloud via the Wi-Fi connection by their built-in SIM card. A climate sensor (Figure 24) installed in the stable measures temperature and relative humidity and calculates a corresponding THI (Temperature-Humidity-Index) curve. Rumination, body temperature and activity are continuously presented graphically in the smaXtec system and in case of deviations from the norm values, heat and calving alarms as well as notifications regarding variances in temperature, activity and rumination are generated. (smaXtec, 2024)

Figure 24: smaXtec climate station

Figure 25: smaXtec bolus

Figure 26: smaXtec base station

3.7 Weather station

A weather station was installed near RF1 in 2013, facilitating the monitoring of diverse outdoor climate parameters. These parameters encompass temperature readings at 2 and 20 cm elevations, soil temperature at a depth of 5 and 20 cm, relative humidity, wind velocity, precipitation levels and global radiation. Similar weather stations were also deployed on RF2 and RF3, recording the same climate parameters.

3.8 Additional data sources

Basic cow data essential for the study, such as identity, calving date, breed and lactation number, were sourced from the LKV Bayern (Landeskuratorium der Erzeugerringe für tierische Veredelung in Bayern e.V., Munich, Germany). This organisation conducts milk performance tests for each cow on the farms eleven times a year, which include protein, fat, lactose and urea content of the milk as well as somatic cell count and milk yield on the test day. Additionally, the total milk yield of the last lactation was also included in the dataset.

4. Data consolidation

Throughout the study, a variety of manually and automatically recorded data had to be documented, extracted from the recording system and collected in different ways.

4.1 Automatically collected parameters

Given the use of different sensor technologies from various manufacturers across the eight dairy farms, a unique array of parameters was collected on each farm. Table 5 and Table 6 provide an overview of the implemented sensor systems on the farms and the acquired variables for behaviour, physiology, performance, environment and animal characteristics.

Table 5: Installed sensor technology on the project farms

Sensors	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
Track a cow pedometer (ENGS)	X							
Fullexpert DP pedometer (Lemmer Fullwood)					X		X	
CowControl pedometer (Nedap/Lely)			X					
CowControl neck tag (Nedap/Lely)		X	X					
SCR HR-LDn neck tag (Allflex)	X		X	X				X
Bolus (Smaxtec)	X		X				X	
Neck tag (DeLaval)						X		
BCS Camera (DeLaval)	X							
Weighing troughs and scale	X							
Milking robot (DeLaval)	X					X		
Milking robot (Lely)		X	X	X				X
Milking robot (Lemmer Fullwood)					X		X	

Table 6: Automatically recorded parameters on the project farms

Parameters	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
Animal Characteristics								
Breed	X	X	X	X	X	X	X	X
Date of birth	X	X	X	X	X	X	X	X
Behaviour								
Activity	X	X	X	X	X	X	X	X
Lying behaviour	X		X		X		X	
Rumination	X	X	X	X			X	X
Feeding behaviour	X	X	X					
Drinking behaviour	X		X				X	
Physiology								
Body temperature	X		X				X	
Body weight	X							X
Body condition score	X							
Performance								
Lactation number	X	X	X	X	X	X	X	X
Days in milk	X	X	X	X	X	X	X	X

Parameters	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
Milk yield	X	X	X	X	X	X	X	X
Milkings	X	X	X	X	X	X	X	X
Maximum milking interval	X	X	X	X	X	X	X	X
Protein	X	X	X	X	X	X	X	X
Lactose	X	X	X	X	X	X	X	X
Fat	X	X	X	X	X	X	X	X
Urea	X	X	X	X	X	X	X	X
Somatic cell count	X	X	X	X	X	X	X	X
Conductivity	X	X	X	X	X	X	X	X
Milking flow	X	X	X	X		X		X
Blood	X				X	X	X	
Milk colour		X	X	X				X
Milk temperature		X	X	X				X
MDi	X					X		
Concentrated feed intake	X	X	X	X	X	X	X	X
Environment								
Temperature	X	X	X				X	
Humidity	X	X	X				X	
Soil temperature	X	X	X					
Precipitation	X	X	X					
Wind velocity	X	X	X					
Global radiation	X	X	X					

Efforts were directed towards incorporating as many automatically captured data points as possible into the SQL (Structured Query Language) database established within the experimental field DigiMilch via API interfaces, enabling subsequent retrieval of relevant parameters. However, this endeavour encountered limitations for certain systems and parameters utilised in the study. Challenges prompting an alternative approach included the absence of suitable interfaces, protracted or unsuccessful negotiations with manufacturers regarding data exchange agreements and limited access to raw data, which ultimately resulted in marginal benefits compared to other possible export methods. In addition to direct transmission via API interfaces, alternative methods such as semi-automated processes through a web client were employed, storing the corresponding data exports in a cloud from which they could be transferred to the database. Data from certain systems could only be manually exported and sometimes required additional file conversion steps. In instances where an export function was unavailable within the program, lists of parameters had to be manually copied at regular intervals, depending on availability, and then inserted into an Excel document.

4.2 Manually collected parameters

The manually collected data consisted of observations made during the claw trimming sessions, including visible clinical findings, the degree of the growth in the sole centre and the pain reaction, as well as locomotion scores carried out via video footage taken in the preceding three weeks.

4.2.1 Locomotion scoring

In this study, like in the two preceding projects on indirect automatic lameness detection, lameness assessment was conducted using locomotion scoring as the reference method. In the previous project, a three-point locomotion score (Figure 27) was developed, aiming for higher reliability and improved practical applicability (Lorenzini, 2019). This was driven by the understanding that, for these studies on indirect automatic lameness detection, similar to practical applications, identifying whether a cow is lame or not outweighed the importance of assessing the degree of lameness.

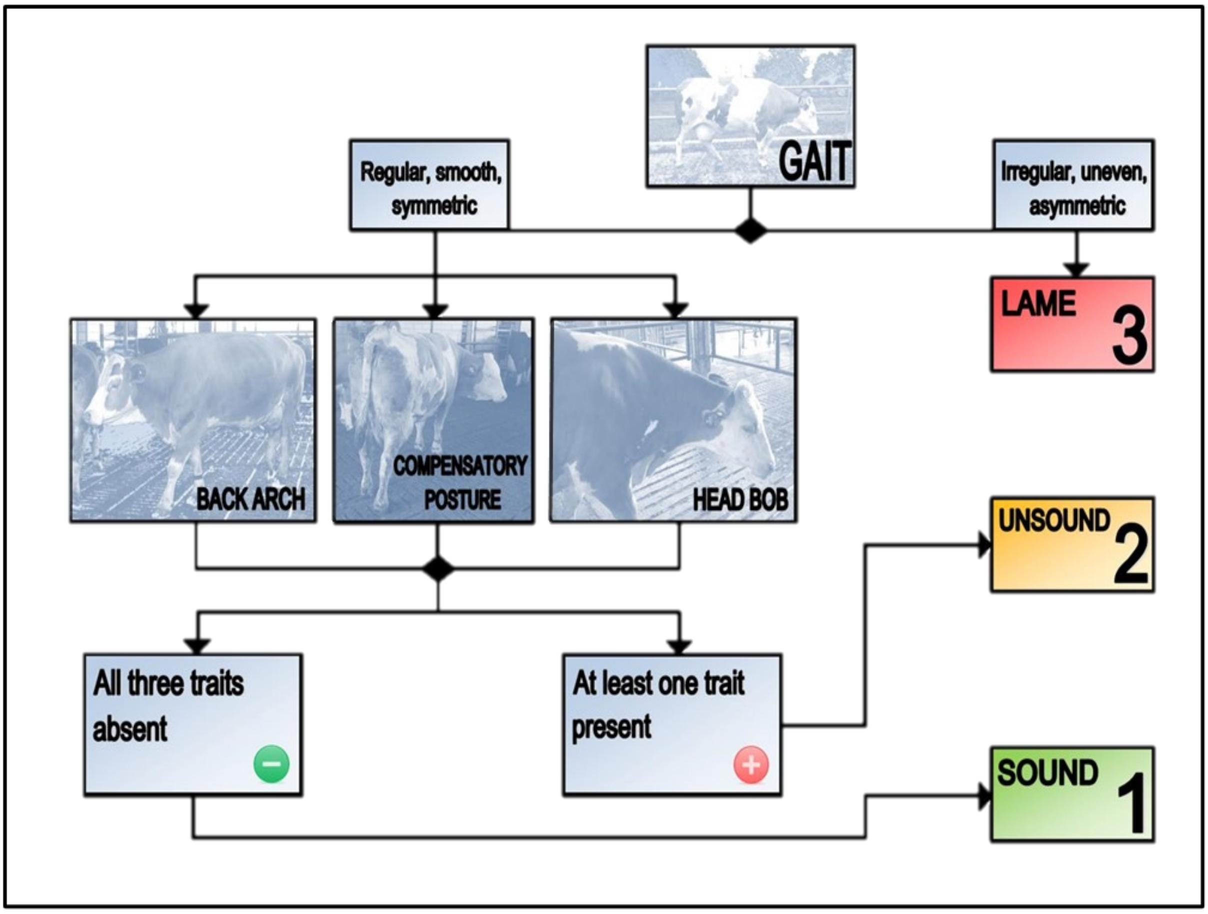


Figure 27: Three-point locomotion score according to Grimm and Lorenzini (Source: Lorenzini, Grimm et al. (2017))

Applying this locomotion score (LMS), the initial focus is on the gait of the cow, aiming to directly classify evidently lame cows exhibiting irregular, uneven and asymmetrical walking patterns as lame (LMS3) irrespective of the degree of lameness. If there are no abnormalities in the overall gait of the cow, three additional features are considered to investigate lameness suspicion (LMS2), if any of these characteristics occur. These include an arched backline, the stance of one or more limbs in relief or head bobbing. If the gait is regular, even and symmetrical and none of the other features are present, the cow can be classified as sound (LMS1).

To minimise the observer effect and due to the number of participating farms, it was decided to conduct locomotion scoring based on video recordings. Following the synchronisation of the camera with the milking robot, the timestamp provided during milking was utilised to accurately identify the cow exiting the robot. Daily locomotion scores were performed on all farms starting 21 days prior to claw trimming, aiming to capture the onset and progression of lameness. This 21-day timeframe was considered sufficient, as lameness develops over a period of nine days on average according to the results of Lorenzini (2019). During locomotion scoring of each cow, the procedure involved examining the day before the claw trimming session and then working backward up to 21 days prior to the trimming appointment. If a cow received a score of 1 on both days preceding the claw trimming, it was scored every five days, with the assumption of maintaining a consistent score of 1 for the days in between. Conversely, if a cow was scored 2 or 3, its gait was evaluated daily to monitor any changes.

Alongside the primary observer (Rater 1), locomotion scores for the cows were recorded by two additional raters for 4 of the 20 claw trimming dates. These raters had practiced locomotion scoring on at least 75 cows prior to the study, and their agreement with Rater 1 was evaluated before the actual locomotion scoring started.

4.2.2 Validation of the locomotion scoring system

Although the locomotion score has already been validated in the previous project (Lorenzini, 2019), additional validation was carried out in the present study. Both, inter-rater agreement, which measures the consistency between different observers, and intra-rater agreement, which assesses the consistency of the same observer across multiple scoring sessions, were calculated. Moreover, the locomotion score was validated using the results of the claw trimmings and pain tests. For this purpose, an additional lesion score (LS) was developed, including three different levels (Figure 28). Grade 1 was assigned to the animal if it exhibited no pain response in any of its claws and presented with either no lesions or only mild, generally non-painful findings such as chronic digital dermatitis (Stage M4), tylomas without digital dermatitis or minor sole haemorrhages on only one to three feet. Grade 2 was given if there was either a positive pain response combined with no or mild, generally non-painful findings, or a negative pain response coupled with evident clinical findings. Grade 3 was assigned in cases where a significant pain response occurred in any of the four feet along with evident clinical findings. This three-level lesion score was then compared to the locomotion score assessed one day prior to claw trimming.

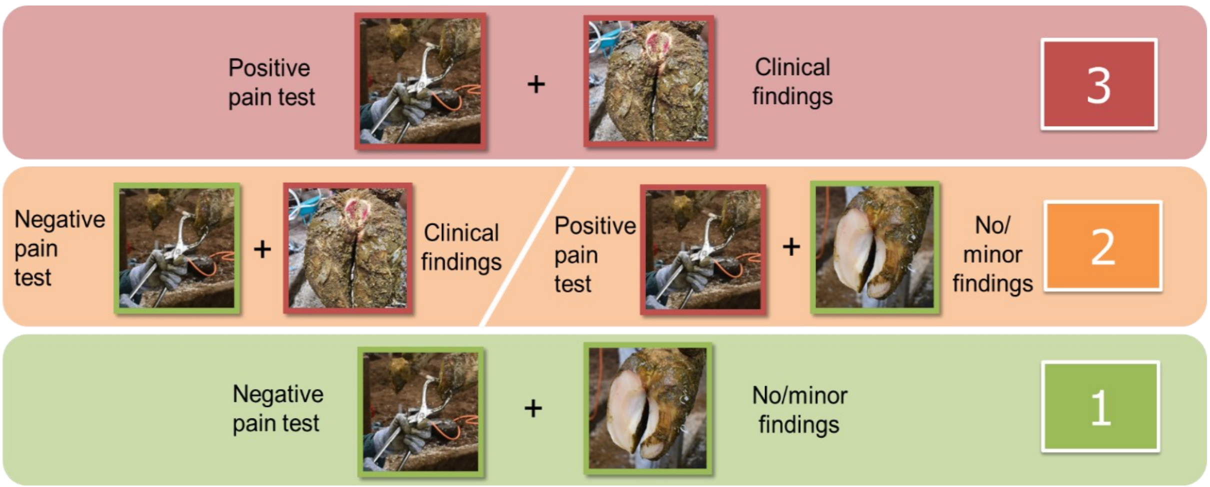


Figure 28: Three-level lesion score to validate the locomotion scoring system

4.2.3 Clinical findings

The documentation of visible clinical findings took place for all animals during the on-farm claw trimming sessions. Initially, for the first appointment on RF1, as well as the first appointments on RF2 and RF3, the recordings made by the claw trimmers were utilised. Due to incomplete documentation of less severe findings, the findings during the subsequent claw trimming dates were documented by the author of this study. The findings were noted based on the ICAR Claw Health Atlas (ICAR Working Group on Functional Traits (ICAR WGFT) and International Claw Health Experts, 2015) and the corresponding abbreviations and their descriptions are displayed in Table 7. The table was additionally supplemented with the abbreviations "OLU", signifying "otherwise located ulcers", to also describe ulcers not located in the typical area beneath the flexor tuberculum and CSH, meaning “central sole haemorrhage” as the preliminary stage of sole ulcers. In cases of digital dermatitis, the associated stage according to Table 2 was documented and for CSH and SHC, it was also noted whether there was an acute bleeding of the sole haemorrhage. HHE and WLD findings were noted only when they were clearly visible.

Table 7: Descriptions and abbreviations used for documentation of clinical findings, based on the ICAR Working Group on Functional Traits (ICAR WGFT) and International Claw Health Experts, 2015 (adapted from original with modifications)

Code	Name	Description
CC	Corkscrew claws	Any torsion of either the outer or inner claw. The dorsal edge of the wall deviates from a straight line
DD	Digital dermatitis	Infection of the digital and/or interdigital skin with erosion, mostly painful ulcerations and/or chronic hyperkeratosis/proliferation
DS	Double sole	Two or more layers of under-run sole horn
HHE	Heel-horn erosion	Erosion of the bulbs, in severe cases typically V-shaped, possibly extending to the corium
HF	Horn fissure	Crack in the claw wall
IH	Interdigital hyperplasia	Interdigital growth of fibrous tissue
IP	Interdigital phlegmon	Symmetric painful swelling of the foot commonly accompanied with odorous smell with sudden onset of lameness
SHD	Sole haemorrhage diffused form	Diffused light red to yellowish discolouration
SHC	Sole haemorrhage circumscribed form	Clear differentiation between discoloured and normally coloured horn
CSH	Central sole haemorrhage	Haemorrhage beneath the tuberculum flexorium, preliminary stage of sole ulcer without horn perforation
SU	Sole ulcer	Penetration through the sole horn exposing fresh or necrotic corium
BU	Bulb ulcer	Ulcer located at the bulb
TU	Toe ulcer	Ulcer located at the toe
OLU	Otherwise located ulcer	Ulcer located on other, unusual sites of the claw
TN	Toe necrosis	Necrosis of the tip of the toe with involvement of bone tissue
TS	Thin sole	Sole horn yields (feels spongy) when finger pressure is applied
WLF	White line fissure	Separation of the white line, which remains after balancing both soles
WLA	White line abscess	Necro-purulent inflammation of the corium

Besides the clinical findings, also the treatment of each claw carried out by the claw trimmer was documented by using the code as shown in Table 8.

Table 8: Code for therapeutic procedures by claw trimmers

Code	Name
B	Bandage
CB	Claw block
SAP	Salicylic Acid Paste
SAPO	Salicylic Acid Powder
CTC	Chlortetracycline spray
CZC	Copper and zinc chelate spray

4.2.4 Pain test

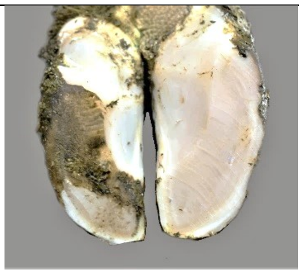
A pain test was performed on each claw before the trimming was carried out (Figure 29). The order in which the pain test was carried out depended on the preferred trimming sequence of each claw trimmer. The claw pliers were positioned at two different angles on each claw: once on the abaxial and axial claw wall and once at the claw tip. Pressure was then briefly applied to the claw and any potential pain response from the animal, such as claw withdrawal, was noted. If such a reaction occurred, the pain test was classified as positive; otherwise, it was recorded as negative. The pain test was conducted by the veterinarian; only during the first two claw trimming dates on RF1 the help of a colleague was needed since two claw trimming chutes were used at the same time.

Figure 29: Pain test performed using claw pliers

4.2.5 Growth in the sole centre (GSC)

The degree of growth in the sole centre was also assessed for all claws of each cow before the trimming to eventually rule it out as a possible cause of lameness or positive pain response in the absence of visible clinical findings. For this purpose, a three-level score was established as shown in Table 9, enabling the assignment of a specific degree of growth in the sole centre to each foot of a cow.

Table 9: Three-level score to grade the growth in the sole centre (GSC)

Score	GSC1	GSC2	GSC3
Description	Clear interdigital space with prominent, indentable groove	Clear interdigital space with no or slight, non-indentable groove	Completely closed or overgrown interdigital space
			

4.2.6 Corrected locomotion score (C_LMS)

In addition to the locomotion score, a corrected locomotion score was formed by taking the clinical findings and the pain test into account. If cows were identified with an LMS2, this score was upgraded to 3 for all days featuring the original LMS2, given that the animals showed either a positive pain test or visible and potentially painful findings during claw trimming. Subsequently, this C_LMS was integrated into the daily datasets as an alternative reference value alongside the standard LMS.

5. Data processing

After the data collection phase concluded at the end of 2022, the data processing phase commenced. In the first instance, data from various sources needed to be standardised into a unified CSV format and afterwards daily records of the different project farms could be generated by using the statistics tool RStudio. These farm-specific daily records included every parameter recorded within the individual farm, computed for each cow on a daily basis. The daily record of RF1 was completed within the DigiMilch SQL database, while the other ones were created directly in RStudio due to different file formats and export ways. Data was prepared by including the counts of each variable, which was recorded at regular time intervals, into the data frames and afterwards excluding the daily values with missing single recordings. Individual limits of allowed missing counts were determined for each parameter based on the total amount of counts registered by the sensors per day.

5.1 Daily records

The final daily datasets included data from the 21 days preceding the respective claw trimming appointment. The timestamps of data collection on each farm as well as the appointments excluded from the analysis due to data loss are represented as a timeline in Figure 30 and the specific claw trimming appointments used for further analysis can be found in the appendices in Table 32.

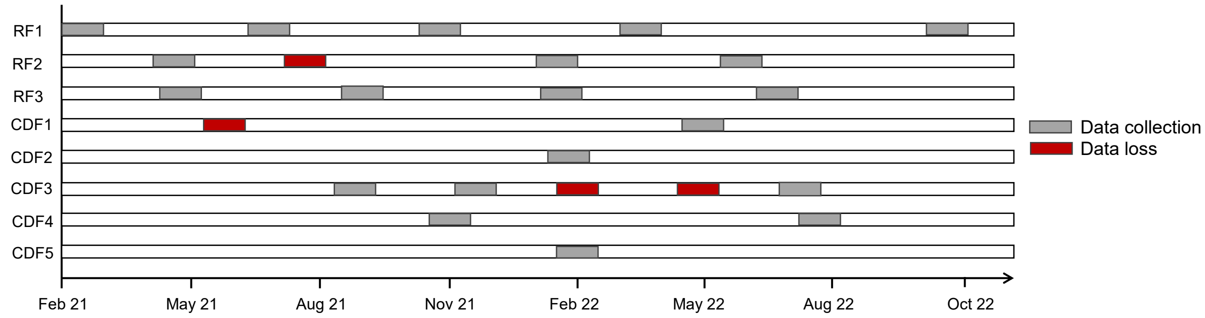


Figure 30: Timeline of all claw trimming dates, including discarded appointments due to data loss

Depending on the availability of technologies, the parameters collected on the farms varied, resulting in different variables included in the farm-specific datasets. Table 33 in the appendices provides a comprehensive list of all collected parameters, along with their respective data sources and the farms where each parameter was collected. In the following, the preprocessing of the data in order to build the final farm-specific daily data sets will be explained.

5.1.1 Daily time budget of behavioural parameters

As in the preceding automatic lameness project, in addition to the daily values spanning over the course of the entire day from 00:00 to 24:00, also the behaviour during daytime and the day/night ratio, meaning the behaviour during daytime compared to the day-long behaviour, were considered in the daily records. At first, the term "daytime" needed to be defined for each farm as, for example, different management routines could lead to varying circadian rhythms for the herds. Corresponding to the previous project, where activity exhibited the most variation (Lorenzini, 2019), and because it was the only behaviour parameter available on all farms in this study, activity was chosen as the determining parameter to define "daytime". The overall median for activity during all data collection periods was identified for each farm separately and at the same time the median activity values for each hour on the farm were computed. The start of daytime was established as the first hour in which the hourly median activity was higher than the total median activity and the end was set as the last hour in which this requirement was fulfilled. The calculated daytime periods per farm are displayed in Figure 31. No calculation of the daytime was performed for CDF2 and CDF3 as the sensor systems installed on these farms only generated daily values. Furthermore, for all sensor systems on the other farms, which only offered daily values, no daytime values and day/night ratios could be established.

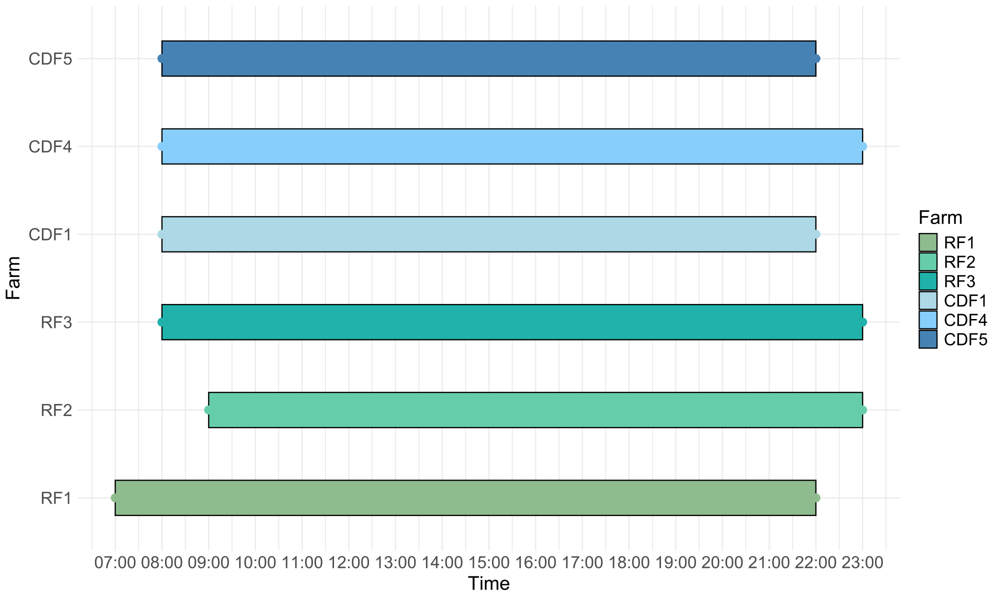


Figure 31: Daytime period on each project farm

5.1.2 Animal Characteristics

For the first identification of each cow, the animal's specific number on each farm as well as its unique ear tag number had to be documented. The date, as in the date of data collection, was included across all different data sources to create unique daily data sets without redundancy. The breed of each animal was also documented as labelled by the LKV and automatically exported to the DigiMilch database. The dataset included data from 699 Simmental cows, 10 Holstein Friesian cows, nine Brown-Swiss cows, two Gelbvieh cows, one Red Holstein Friesian cow and seven cows of other breeds. Additionally, the date of birth of each cow was noted according to LKV and HIT to gain information about the cow's age and the herd composition.

5.1.3 Reproductive status and lactation data

The reproductive status of each cow was only included in the final data sets to track missing milkings due to drying-off periods. As the reproductive status displayed by the milking robots was not always up to date, it was calculated manually. A cow was described as "lactating" if milk production was present on the current day. If the reported milk yield was NA (not available) in combination with a lactation number equal to zero, the animal was labelled as "heifer". With a lactation number larger than zero and no occurring milking, it was noted as "dry period". If a cow was first identified as being in the dry period but had less than 200 days of milk, its reproductive status was changed to "not milked". The days in milk were calculated by considering the day of the last calving as reported by the LKV as day 0 and then counting forward to the current date. The lactation data was acquired either through the LKV or through the milking robots.

5.1.4 LKV

A lot of milking data were collected through the LKV, including the cow's lactation number. If no lactation number was registered yet, the cow was considered to be a heifer and the lactation number was noted as 0. The total milk yield in last lactation recorded by the LKV referred to the total milk yield from the beginning to the end of the last lactation and could be collected for all farms except CDF1, because this farm only joined the LKV during the DigiMilch project. The results of the monthly milk performance tests, conducted by the LKV eleven times a year for each lactating cow, were also included in the daily records. The results of the milk performance test conducted on the last examination date were used as daily values for the days leading up to the next monthly examination. The incorporated parameters included daily milk yield, urea, protein, lactose and fat content and somatic cell count. Furthermore, the fat-protein ratio was calculated by utilising the protein and fat content documented by the LKV.

5.1.5 Milking robot

The number of milkings was determined according to the cow's visits to the milking robot and the maximum milking interval was calculated as the maximum duration between the end and start time stamp of two consecutive milkings on the same day. Since the milk yield of the cow is not produced during the milking process itself, but rather during the whole period from the end of the last milking to the start of the next milking, it was proportionally allocated to each respective day in case of inter-daily intervals between the milkings. To simplify calculations, the milk production rate was assumed to be constant and uniform. The total milk yield of the current lactation was created within the SQL DigiMilch Database for RF1. For the other farms, the total milk yield of the last lactation recorded by the milking robot was utilised. On RF2, RF3, CDF1 and CDF5, the milking robots also calculated the average daily milk yield in the last lactation.

The milk ingredients, including protein, fat and lactose, could be collected by the milking robots on all farms except RF1 and CDF3 and the corresponding fat-protein ratio was subsequently calculated. The somatic cell count could only be registered on RF2, RF3 and CDF1. Additionally, other changes in the milk composition were detected differently depending on the milking robot. The parameters regarding blood and colour were excluded from the dataset in the further analysis due to insufficient comparability and missing data points. The Lely milking robots also record the milk temperature and the DeLaval ones compute the Mastitis-Detection-Index (MDi), a combination of the parameters blood in milk, conductivity and milk interval. The milking flow, meaning the average speed and consistency of milk extraction during the milking process, and the maximum milking flow were acquired on all farms except CDF2 and CDF4. Conductivity was at first included as conductivity per quarter, but the median value of conductivity for all quarters was calculated later in the analysis to limit the number of parameters and simplify the analysis of the parameter conductivity. The conductivity was recorded once on all farms equipped with Lely milking robots within a company-owned unit and on all other farms within the unit mS/cm. Intake of concentrated feed and on RF2, RF3, CDF1 and CDF5 additionally the remains of concentrated feed at the end of the day were also included in the daily records.

5.1.6 Body condition score and body weight

On RF1, the body condition score was available through the milking robot, which collected the data of the BCS camera during every milking process. The body weight of each cow was also measured during the milking by a scale and transferred to a database. For both parameters, to create daily values, the median of all single assessments was formed. Moreover, the daily body weight could be exported on CDF5 through the daily lists generated by the milking robot.

5.1.7 Feeding

Information on the cows' feeding behaviour could be documented on RF1, RF2 and RF3, but data regarding the roughage intake were only accessible on RF1 through the weighing troughs. The weighing troughs not only measured the feed intake during every visit to the trough but also recorded the feeding duration. The feeding pace was calculated by dividing the feed intake by the corresponding feeding duration. The daily number of visits to the weighing trough was noted and the visits were summed up to create meals. A meal was characterised by a series of consecutive trough visits occurring within intervals of less than 6 minutes, provided that the cumulative recordings were greater than or equal to 6 minutes. The average feed intake and duration per weighing trough visit and meal were calculated by dividing the feed intake or feeding duration by the number of weighing trough visits or meals. The daytime values and day/night ratios were included in the daily record if possible.

The ENGS feeding data could only be collected on RF1 during the data collection before one claw trimming date due to issues that will be further explained in chapter V.1.2.1. ENGS also aggregates all feeding table visits with interruptions of less than 6 minutes into one meal and subsequently provides the total count of meals. Additionally, the feeding duration per day was supplied by the pedometers and the average feeding duration per meal as well as the daytime and day/night values could be calculated afterwards.

Only the total daily feeding duration was included for the Nedap neck tags, as it was not possible to directly access the raw data.

5.1.8 Rumination

SmaXtec provided users with the total daily rumination time. In contrast, the data output of the SCR sensors depended on the tool used to access the data. Within the Heatime system on RF1, rumination data could be exported in two-hour intervals, while the milking robots only provided the total daily rumination time. As a result, only the daytime values and the day/night ratio for RF1 could be established. Similarly, with Nedap, only the daily total rumination time was accessible.

5.1.9 Heat behaviour

SCR provided an activity-based index for heat probability via the milking robot. The higher the heat probability index, the more likely the cow was to exhibit heat on that particular day.

A similar variable was generated by the Lemmer-Fullwood pedometers called factor of restlessness, which was also based on the activity data and as this index increased, so did the probability of heat occurrence.

5.1.10 Lying

Lying data could be recorded on RF1, RF3, CDF2 and CDF4. As the lying data by ENGS included hourly values, the number of individual lying events and the average lying duration per bout could be included, but also the daytime and day/night values.

The Nedap and Lemmer-Fullwood pedometers recorded the total daily lying duration and the number of lying events.

5.1.11 Activity

The parameter of activity could be captured in various forms, either at the neck, at the leg or in the reticulum across all project farms. Hourly activity units could be found within the ENGS Ecoherd system on RF1, an activity index was recorded by smaXtec every 10 minutes and summed up for daily values and another activity index was created by SCR and provided every two hours.

Nedap counted the daily steps of the cows but also displayed the foot activity and the heat-associated neck activity every two hours. Daily sums and two-hourly medians as well as the daytime and day/night ratios were calculated for both types of activity loggers. Furthermore, the inactive neck time, meaning the time without any head or neck movement, was also recorded.

The Lemmer-Fullwood pedometers delivered the hourly average step count per day, while the DeLaval neck tags presented an average daily activity index, the relative activity as the current activity level of the cow compared to its individual average and the minimum and maximum relative activity of the cow on this day.

5.1.12 Body temperature

The body temperature could be collected on RF1, RF3 and CDF4 by using the smaXtec boluses. The 10-minute values created by the system were transformed into average, minimum and maximum values per day. The normal body temperature of the cow was detected by the bolus in the first training phase after bolus input and regularly updated. The body temperature still included the temperature drops caused by drinking events of the cow, while the body temperature without drink cycles was adjusted for drinking.

5.1.13 Climate

Temperature and humidity could be measured by the smaXtec climate stations on RF1, RF3 and CDF4, as the stations were installed in the barns together with the smaXtec bolus infrastructure. The Temperature-Humidity-Index (THI) was calculated manually, as the THI computed by smaXtec could not be exported via the interface. For this calculation, the used formula was created by Thom (1959) and modified by Zimbelman et al. (2009):

$$(0.8\, x\, Temperature) + [(rel.Humidity\, /\, 100)\, x\, (Temperature - 14.4)] + 46.4 \qquad (1)$$

Weather stations were implemented on the three research farms and recorded hourly values, which were transformed into a daily minimum, maximum and median. The collected parameters included temperature at 2 m height and 20 cm height from the ground, soil temperature at 5 cm depth and 20 cm depth, relative humidity, precipitation, wind velocity and global radiation. The THI was also calculated using the formula provided above and the temperature and humidity values detected by the weather station.

Season was added to consider a potential existing seasonal effect on lameness. For the manual calculation of the season in which the claw trimming occurred, the year was divided into quarters and assigned a value, as can be seen in Table 34 in the appendices.

5.1.14 Claw health

The data collected during the claw trimming events were initially recorded manually on printed lists and then entered into a Microsoft Excel 16 spreadsheet. The results of the locomotion scores were stored within the same spreadsheets and converted to CSV files with daily values. The values inserted into the daily dataset corresponded to the results of the locomotion scoring performed daily, whereas the results of the claw trimming session, including the pain test, growth in the sole centre and findings were collected only on the respective claw trimming date and retrospectively interpolated up to 21 days prior. The pain test and the growth in the sole centre were added to the dataset according to the documentation methods described in 4.2.4

and 4.2.5. The corrected locomotion score was documented according to the description in 4.2.6 and also added to the datasets.

5.2 Univariate Analysis

The data analysis was carried out with R Studio (Version 2022.07.2).

Descriptive statistics such as boxplots, histograms and Q-Q plots were used to check the distribution of all variables and to get a first overview of the parameters. Outliers were identified by calculating three times the interquartile range (3*IQR), as can be seen in Figure 32 and those exceeding the threshold were removed. The 3*IQR was used instead of the 1.5*IQR because the latter can be too strict for certain datasets, as observed in this study, leading to an excessive removal of data points that do not clearly qualify as outliers (Zhang et al., 2020).

The statistical key figures were computed for each farm and across the farms by creating summaries which included the mean, median, minimum, maximum, first and third quartile, standard deviation and the number of observations of each value.

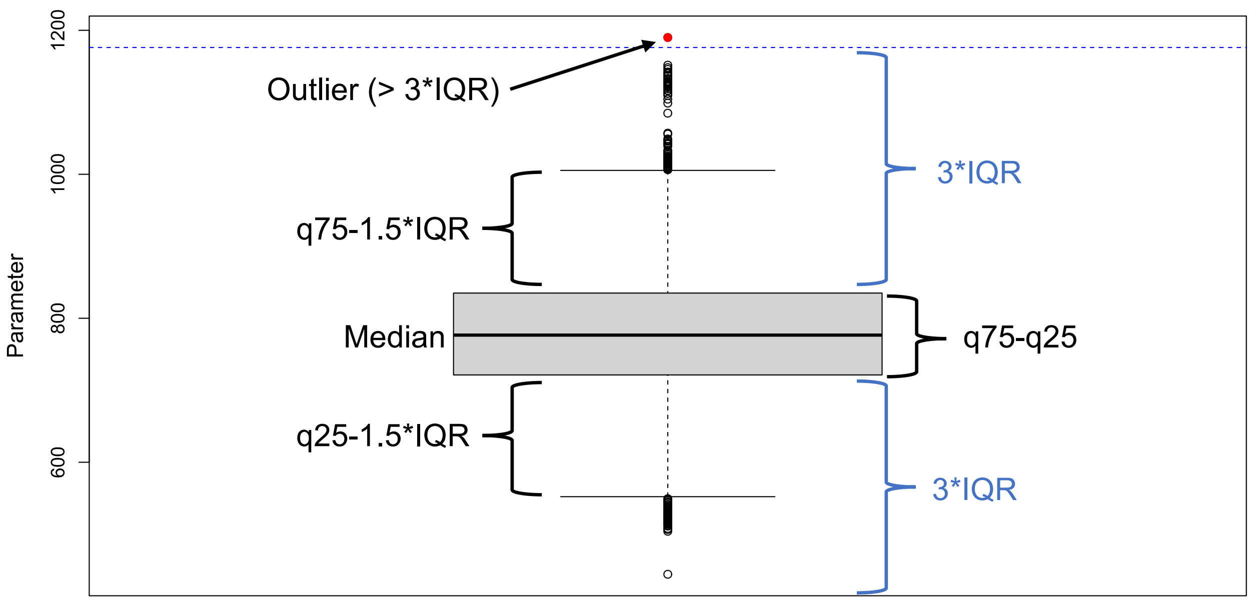


Figure 32: Example of the type of interquartile range (IQR) used in this study (IQR: interquartile range, q25: first quartile, q75: third quartile)

5.3 Bivariate analysis

Regarding the validation of the locomotion score, the intra- and inter-rater reliability as well as the agreement between LS and LMS were calculated. For the intra-rater reliability, the two rounds of locomotion scoring by the same observer (Rater 1) were compared to each other and the percentage of agreement (PA) as well as Cohen's Kappa (κ) according to the formula

$$\kappa = \frac{p0 - pe}{1 - pe} \tag{2}$$

were computed (Cohen, 1960). Thereby, p_0 represents the proportion of actual conformity while p_e displays the percentage of incidental concordance. The quadratic weighted Cohen's kappa (κ_{w}) was used to account for larger and smaller distances between scores and to weight them differently (Vanbelle, 2016). The inter-rater reliability was calculated by comparing one detection round of the same video footage of Rater 1 with the results of another rater (Rater 2).

Due to the non-normal distribution of the data, the non-parametric Kruskal-Wallis test (Van Hecke, 2010) was chosen to test for significant differences between the C_LMS and LMS groups for each variable. Afterwards, the Wilcoxon signed rank test was performed on the data as a post-hoc analysis to further investigate between which particular C_LMS or LMS pairings the differences were significant or not significant.

The correlation between LMS or C_LMS and the parameters was determined by Spearman's rank correlation coefficient, which is used instead of Pearson's correlation coefficient when data does not meet the assumptions of linear correlation or normal distribution (Rebekić et al., 2015). Additionally, the correlation between the different automatically recorded parameters was calculated, as it can be helpful to identify potential predictors for lameness and to assess the strength and direction of relationships between the different parameters. The Intraclass Correlation Coefficient (ICC) and its CI was measured for each parameter recorded by both, milking robot and LKV.

Binomial generalised logistic regression was carried out and provided the odds ratio, the lower and upper confidence interval and the p-value of each parameter implemented in the regression as the independent variable with the claw health status as the dependent variable. Based on the dependent variable, two different regression models were chosen, one with the locomotion score as reference and therefore LMS3 as lame and the other one focusing on the corrected locomotion score and consequently on C_LMS3 as the lame outcome.

The tests, correlation, and OR calculations were also performed at the farm level to identify farm-specific differences.

5.4 Multivariate analysis

For the development of regression models, the final farm-specific daily datasets were split or combined to form subsets according to the different parameter classes. The newly created datasets were checked for NA values and these were removed. The ETN (Ear Tag Number) was converted into a numeric identification number called FCN (Farm Cow Number) and afterwards centring and scaling were performed on the datasets. Centring adjusted the data by subtracting the mean, aligning values around zero to eliminate baseline differences and highlight key variations between samples (Van den Berg et al., 2006). Scaling transformed the data by dividing each variable by the standard deviation to equalise their variability and facilitate comparisons (Van den Berg et al., 2006).

For each parameter class, it was aimed to develop the best models for both C_LMS and LMS as references. Dummy variables were used, where 1 indicated a "lame" outcome, substituting for LMS3 or C_LMS3, and 0 indicated "not lame", representing LMS1 and LMS2 or C_LMS1 and C_LMS2. The outcome variables of the regression models were referred to as "*Claw health status$_n$*" for the non-corrected LMS and "*Claw health status$_c$*" for the C_LMS.

Following this, the respective dataset was split into a training set and a test set, with the former containing 80% and the latter containing 20% of the data. To ensure proper data partitioning, the FCN was randomly assigned to either the training set or the test set, ensuring it appeared in only one of the sets. Furthermore, the training data were subjected to SMOTE (Synthetic Minority Over-Sampling Technique) to achieve a balanced distribution between observations of lame and non-lame animals. SMOTE improves classifier performance on imbalanced datasets by generating synthetic examples for the minority class through interpolation between existing minority samples (Chawla et al., 2002).

Due to the results of the preceding automatic lameness detection project (Lorenzini, Grimm, & Haidn, 2021), generalised linear mixed regression models were used in the analysis. The lme4 package (Bates et al., 2015) in R was employed to analyse those generalised linear mixed models, which include both fixed and random effects. An example of the formula is displayed in the following:

$$a \sim b + c + d{:}e + (x \mid z) \tag{3}$$

In this context, according to Brown (2021), *a* represents the outcome variable, while *b* and *c* are fixed effects that have a direct influence on *a*. Additionally, interaction parameters such as *d: e* can be included to examine the combined effect on the outcome variable *a*. The parameters within the parentheses are known as random effects, with the grouping variable *z* positioned to the right of a vertical line, referred to as the pipe. This grouping variable defines a unique starting point as a random intercept based on *z*. When *x* is present, the model also incorporates the random slope, which captures individual variations in slope. Consequently, it is assumed that variable *x* exerts different effects on the outcome variable *a* depending on the value of *z*.

The regression models were created using a forward regression approach. This method involves sequentially adding new parameters as fixed effects, allowing for the evaluation of each parameter's contribution to the model's accuracy. A 10-fold cross-validation was employed in this case, involving splitting the data into 10 parts. The model is trained and tested 10 times, with each part serving as the test set once, and the performance results are averaged to provide a reliable estimate of the model.

To assess whether the parameters Farm and FCN should be included as random effects, the intraclass correlation coefficient (ICC) was calculated to assess how much of the total variance in the data could be explained by these variables as random effects.

Interaction terms were included in the models to illustrate how the effect of one independent variable on the dependent variable changes as another independent variable varies. To avoid manually testing every possible interaction term, an automated interaction analysis was conducted. This analysis assessed all interaction terms based on the model and the data, and only those with the most significant effects were afterwards re-evaluated in the regression model. To assess the goodness of fit of a model, the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the p-values of the parameters, the area under the curve (AUC), sensitivity and specificity were considered. Additionally, the Receiver Operating Characteristic (ROC) curve was calculated for all models. The ROC curve offers a detailed view of how well a diagnostic test performs by showing the balance between sensitivity and specificity across different decision thresholds (Kumar & Indrayan, 2011). The area under the ROC curve (AUC) quantifies a model's ability to differentiate between two classes (Kumar & Indrayan, 2011). An AUC of 1 would signify perfect distinction between lame and non-lame animals, while an AUC of 0.5 would indicate that the classification is no better than random chance.

Initially, the best regression models using only performance data were identified. In the second step, performance data and activity data, collected across all eight farms, were integrated into the models. Subsequently, various model versions were tested by adding one additional parameter from the parameter classes of constitution, feeding, rumination, lying, body temperature or climate to the activity and performance data in order to assess the extent of model improvement. These models could no longer be analysed across all farms, but only on those where the parameter classes were measured with sensors. Finally, two and ultimately three additional parameters were combined with the activity and performance data in the model.

V. Results

1. Limitations in data collection

1.1 Cameras

The video data of the first claw trimming date on CDF1 in June 2021 and the claw trimming date on RF2 in August 2021 could not be employed for analysis due to the mentioned malfunction of the circular buffer (Chapter IV.3.1), resulting in the storage of individual images rather than complete videos. At CDF3, an electric fly screen caused multiple power outages, which ultimately resulted in failure of the NAS, rendering the video footage from the two claw trimming sessions in February and May 2022 irrecoverable.

The video recordings should capture the 21-day period preceding each claw trimming date. However, for the first claw trimming session on RF3 in May 2021, the camera could only be activated 13 days prior to the trimming date. Furthermore, in some instances certain animals could not be scored due to dry periods, calving, illness or other factors. In such cases, the scoring period was restricted to the days when the animals were captured by the camera.

1.2 Sensor technology

1.2.1 ENGS

At the start of data collection in 2021, several attempts were made to reinstall the induction loop by ENGS on RF1 for reliable recording of feeding behaviour. Initially, attempts to attach the cable directly to the weighing trough frame proved unsuccessful, as the cows stood too far away to be detected within the magnetic field. Subsequently, efforts were made to lay the cable beneath the rubber mats, which was successful at the beginning, allowing for the collection of feeding data during claw trimming in November 2021. But due to the nubs on the underside of the rubber mats and the resulting friction from the movement of the cows on the mat, the cable was damaged and failed completely in January 2022. A third approach involved embedding the loop directly into the rubber mats and securing the cable with industrial adhesive. This solution proved inadequate due to moisture and ammonia present in the manure, causing the adhesive to lose its effectiveness over time. Consequently, recording feeding behaviour via the pedometers had to be discontinued in subsequent claw trimming sessions.

1.2.2 Weighing troughs

While reviewing the weighing trough data, consistent instances of implausible values, wherein the same cow was detected at multiple troughs simultaneously, were observed. This phenomenon occurred sporadically across different troughs, involving various cows, and lacked a clear explanation. Considering their minimal impact on the overall feeding duration when examining daily values, as those occurrences were mostly lasting less than a minute, it was decided to proceed with utilising the weighing trough data for the study.

2. Data cleaning

The first data sets were primarily cleaned by removing the values with faulty or insufficient counts, a variable that was created for all parameters that were recorded several times a day at regular intervals. The upper and lower limits for the number of counts per day were determined individually for each parameter depending on the frequency of measurements per day and can be found in Table 10.

Table 10: Upper and lower daily count limits depending on the sensor system

Sensor system	smaXtec	SCR	ENGS	Nedap
Upper daily count limit per cow	144	12	24	12
Lower daily count limit per cow	139	11	23	11

Afterwards, outliers exceeding three times the interquartile range were eliminated. The rows that included no value for the LMS at all and those scored on the claw trimming date were also excluded from the daily records.

The number of daily values and the number of cows in the first data sets and the final daily records after data cleaning, as well as the number of variables in the final data set, can be found in Table 11. A total of 27,690 daily values from 744 cows could be recorded on all farms and was reduced to 24,583 daily values and 730 cows after data cleaning.

Table 11: Daily values, number of cows and variables in the daily records

Farm	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
First data sets (daily values)	7,328	2,861	5,022	1,359	1,135	1,922	5,257	2,752
First data sets (number of cows)	108	64	97	62	54	70	160	129
Final data sets (daily values)	5,842	2,727	4,221	1,299	1,083	1,829	4,959	2,624
Final data sets (number of cows)	105	63	92	62	52	68	159	129
Number of variables	122	82	116	54	43	42	64	54

Even in the final daily datasets, there were some missing data points. Possible explanations for missing data include instances of sensor malfunctions, collection of clearly erroneous data, which had to be removed due to implausibility and that often not all animals on a farm were equipped with a particular sensor system. In Figure 33, the relative share of missing values for each system is displayed as a proportion of the total values recorded on the farms where the sensors were installed.

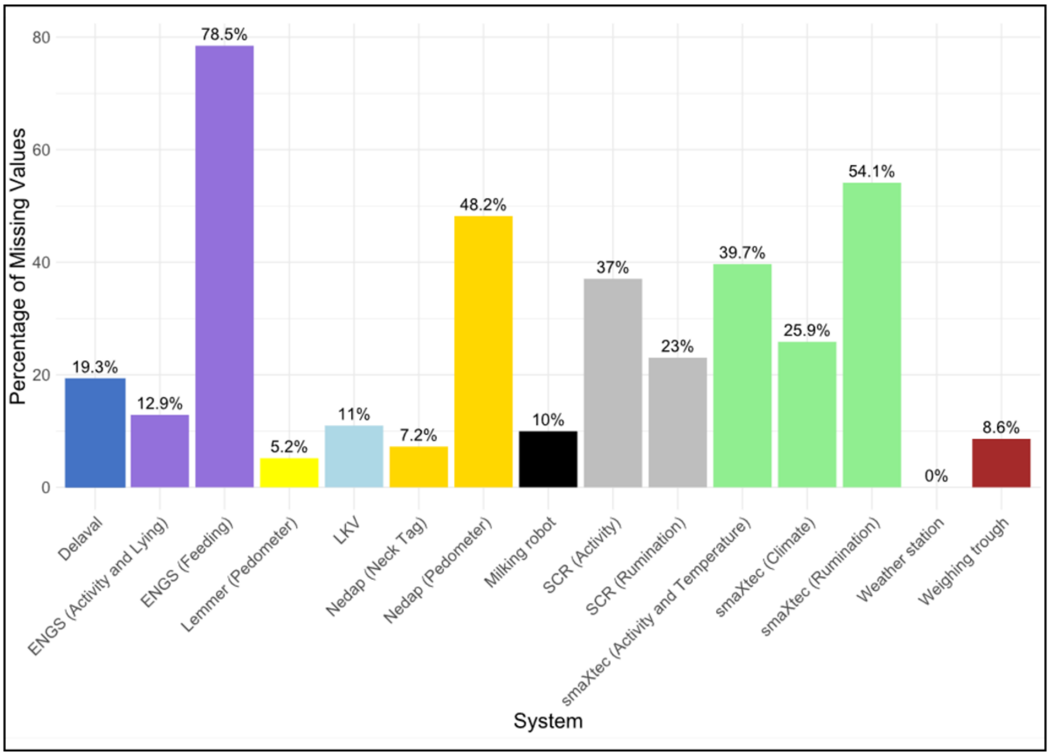


Figure 33: Relative proportion of missing values relative to total farm data

78.5% of ENGS (Feeding) values were missing on RF1. Due to the problems that occurred with the induction loop installation, only feeding data for the three-week period before one claw trimming date could be collected. The main reason for the 48.2% missing Nedap (pedometer) values and the missing smaXtec data points can be attributed to the fact that not all animals on RF3 were equipped with Nedap pedometers, and similarly, not all animals on RF1 were fitted with smaXtec boluses. Additionally, older generation boluses were occasionally used on RF1 and RF3, which did not capture rumination, resulting in further missing data points for this parameter. Furthermore, SCR sensors were only deployed on RF3 during the initial claw trimming period and were then discontinued. One main reason for missing values in the milking robot and LKV data was the dry period of the cows. As all the different sensor systems on each farm contained different missing values, the missing data points were kept in the daily farm records to avoid excessive data loss and only excluded for the combined data sets and the further analysis.

3. Univariate analysis

3.1 Claw Health

3.1.1 Locomotion score

The final daily records included 24,583 locomotion score (LMS) values. In 79% of the cases the cows showed a healthy gait (LMS1), while 15.2% displayed small deviations from the normal walking behaviour (LMS2) and 5.8% were clearly lame (LMS3). After correction to create the C_LMS (see Chapter IV.4.2.6), 4.6% were still considered unsound (C_LMS2) and 16.4% were categorised as lame (C_LMS3). 13,238 LMS were detected directly by watching video recordings (54%) while 11,345 LMS1 values (46%) were interpolated as explained in Chapter 3.1.1. The number of locomotion scores as well as the number of scored cows and assessments per farm and as a whole are displayed in Table 12.

Table 12: Number of locomotion scores (LMS), corrected locomotion scores (C_LMS), cows and assessments per farm and in total

	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5	Total
Total LMS	5,842	2,727	4,221	1,299	1,083	1,829	4,959	2,623	24,583
LMS1	4,498	2,153	3,373	1,041	857	1,332	3,993	2,184	19,431
LMS2	951	457	652	193	192	382	623	286	3,736
LMS3	393	117	196	65	34	115	343	153	1,416
C_LMS2	391	62	246	99	82	116	91	46	1,133
C_LMS3	953	512	602	159	144	381	875	393	4,019
Number of individual cows	105	63	92	62	52	68	159	129	730
Number of individual assessments	316	135	260	62	52	94	246	129	1,294

The percentages of the different locomotion scores recorded during the whole data collection period divided by farm can be seen in Figure 34. CDF4 had the largest proportion of cows scored as LMS3 (6.9%) while LMS2 was highest on CDF3 (20.9%). The lowest detection rate of LMS3 occurred on CDF2 (3.1%) and the smallest proportion of LMS2 was found on CDF5 (10.9%). If LMS2 and LMS3 are both considered, the highest prevalence of unsound and lame walking cows during the data collection period could be documented on CDF3 with 27.2%. The highest number of sound walking cows scored as LMS1 was recorded on CDF5 (83.3%) with 16.7% of the cows walking unsound or lame. After correction of the LMS2 due to the claw trimming findings or positive pain tests (C_LMS), the percentage of cows considered as lame increased over all farms (RF1: 16.3%, RF2: 18.8%, RF3: 14.3%, CDF1: 12.2%, CDF2: 13.3%, CDF3: 20.1%, CDF4: 17.6%, CDF5: 15.0%, Total: 16.4%).

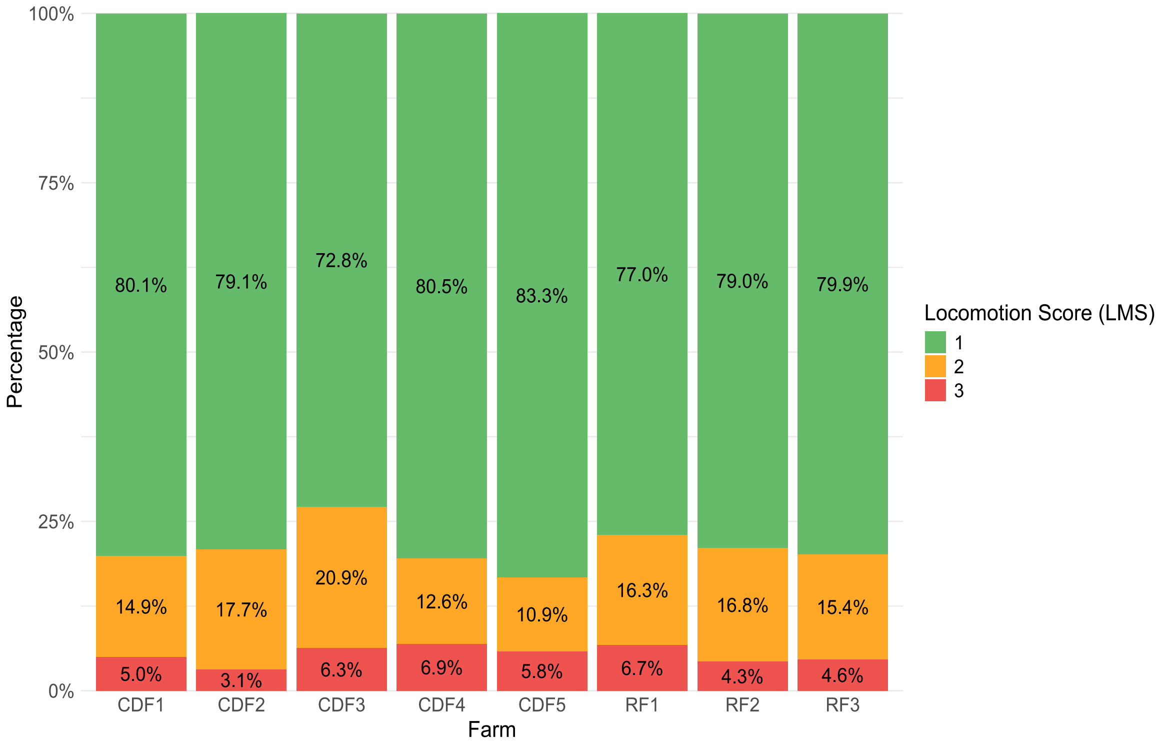


Figure 34: Relative proportion of the different locomotion scores recorded during the data collection period on each farm

To calculate the lameness prevalence on each farm, the locomotion scores detected on the day before the claw trimming were utilised. The overall lameness prevalence on the different farms, displayed by the LMS3 prevalence, is shown in Table 13 and the lameness prevalence for each claw trimming on the farms can be found in Table 35 in the appendices. The highest lameness prevalence was observed on CDF3 with 10.0%, followed by RF1 with 9.5%, whereas on CDF2 only 1.9% of the animals were clearly lame.

Table 13: Total count and relative proportion of locomotion scores (LMS) on the different farms

	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5	Total
LMS1	199	97	160	46	39	57	173	94	865
LMS2	59	26	45	13	12	24	48	28	255
LMS3	27	8	19	3	1	9	17	7	91
LMS1 (%)	69.8	74.0	71.4	74.2	75.0	63.3	72.7	72.9	71.4
LMS2 (%)	20.7	19.9	20.1	21.0	23.1	26.7	20.2	21.7	21.1
LMS3 (%)	9.5	6.1	8.5	4.8	1.9	10.0	7.1	5.4	7.5

Using the LMS, the average number of days required for lameness to develop was calculated. Only cases in which a cow received an LMS3 at least once and an LMS1 within the preceding 20 days were considered, i.e. when the cow went from sound to lame in the three weeks preceding claw trimming. This was the case for n = 68 records from 64 different cows. The days to lameness development were defined as the interval between the last day the cow received an LMS1 score and the earliest day the cow received an LMS3 score. The shortest interval for lameness development was one day, the longest was 13 days. The time for lameness development from the last time the cow walked sound to the first time being scored as lame across all observations was on average four and in median three days (Figure 35) with a standard deviation of 2.97. A table reporting the median and standard deviation of lameness development for each project farm separately can be found in Table 36 in the appendices.

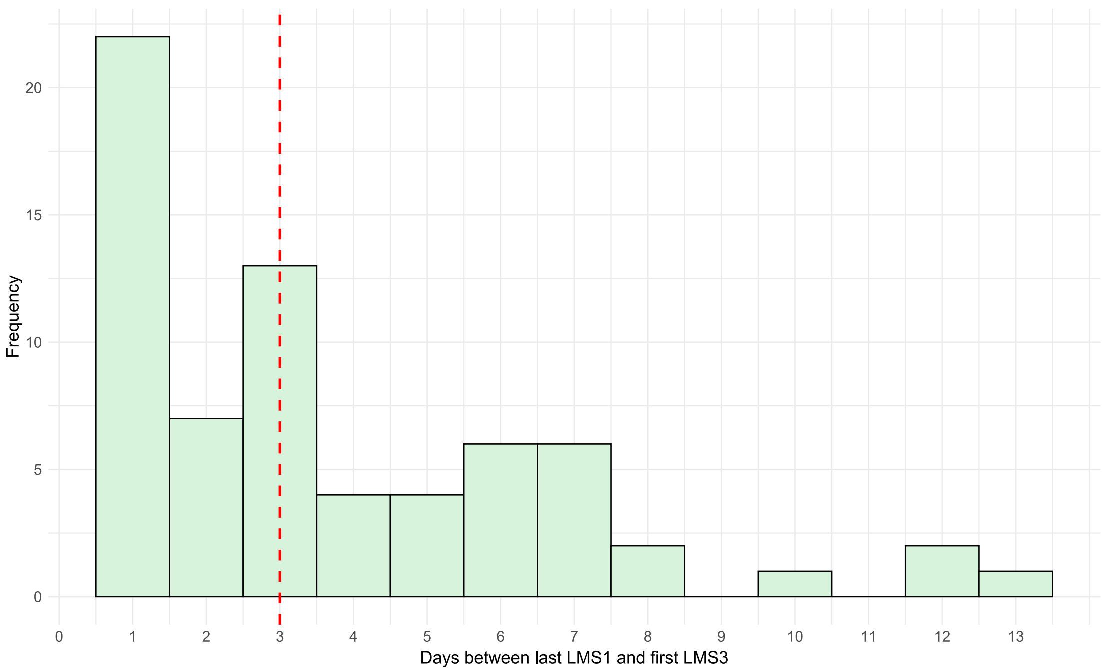


Figure 35: Histogram of the duration of lameness development from locomotion score (LMS) 1 to LMS3 in days (Median: 3 days)

3.1.2 Pain test

During the data collection period, 4,804 pain tests (PT) could be recorded on the project farms, as this parameter, unlike the LMS, was measured only on the claw trimming date. The results included 276 positive and 4,528 negative pain tests. The counts of negative and positive pain reactions on the different farms are shown in Table 14 and the relative proportions of positive and negative pain tests are displayed in Figure 36. The relative proportion of positive pain test results was 5.7% in total and highest on RF2 (12.4%), while the lowest percentage was observed on CDF1 (2.4%). A more comprehensive listing of the positive and negative pain test results for each claw trimming date is provided in Table 37 in the appendices.

Table 14: Counts of negative and positive pain test (PT) results on the project farms

	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5	Total
Positive pain test	66	65	59	6	6	18	36	20	276
Negative pain test	1,038	459	837	242	202	342	912	496	4,528
Total count of pain tests	1,104	524	896	248	208	360	948	516	4,804

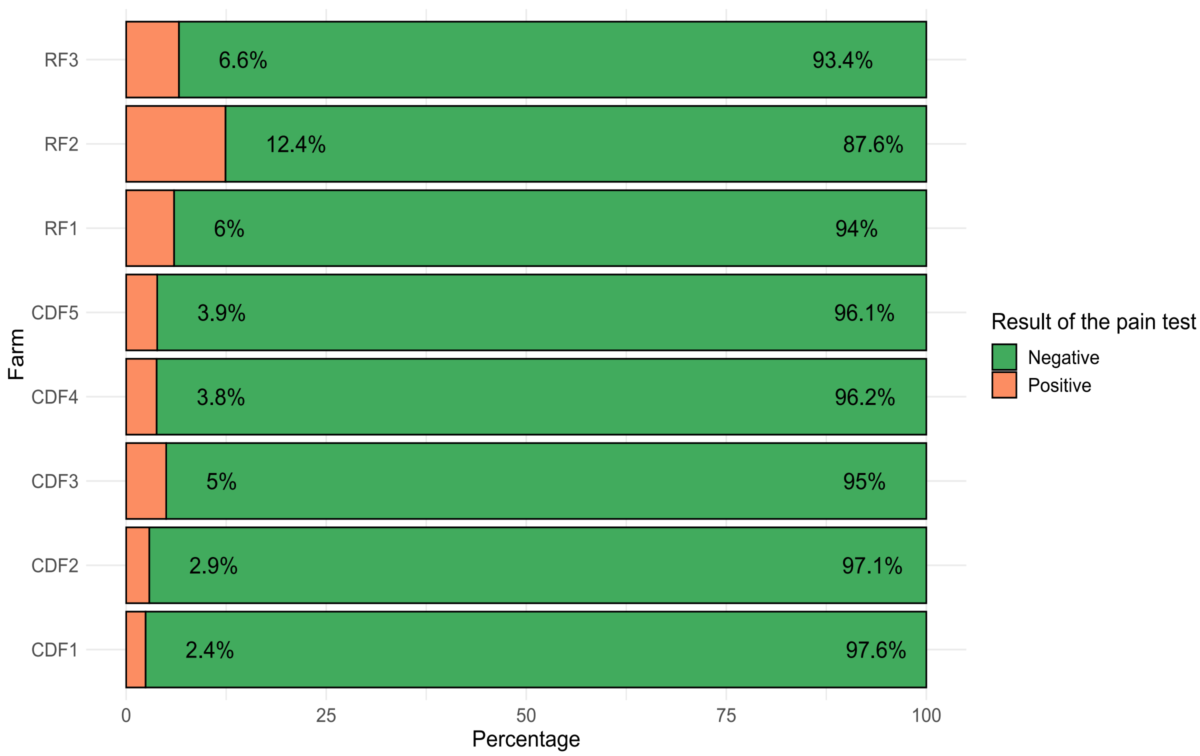


Figure 36: Relative proportion of negative and positive pain test results on the different farms

As the pain response was assessed separately for each of the cow's four feet, a difference in the occurrence of a positive pain reaction could be observed depending on the foot. When considering the results of the pain test across all farms, a positive reaction was most frequently elicited in the left hind foot at 7.7%, followed by the left front and right hind feet at 5.5% each, while the right front foot showed a pain reaction in only 4.3% of cases (Figure 37). Combining the positive reactions from both hind and front feet, the hind feet displayed a positivity rate of 13.2%, contrasting with the lower rate of 9.8% observed in the front feet.

For the final datasets, the pain test data from the four feet of each cow were consolidated into a single value. A pain reaction was recorded as positive if any one of the feet showed a reaction and as negative if all four feet showed no reaction. This method reduced the number of pain test results in the dataset to 1201 values, including 226 (18.8%) positive and 975 (81.2%) negative pain responses (Table 15).

Table 15: Count of aggregated positive and negative pain test results on the project farms

	RF1	RF2	RF3	CDF 1	CDF 2	CDF 3	CDF 4	CDF 5	Total	Total rel. (%)
Positive pain test	53	47	51	5	6	17	32	15	226	18.8%
Negative pain test	223	84	173	57	46	73	205	114	975	81.2%
Total count of pain tests	276	131	224	62	52	90	237	129	1,201	100%

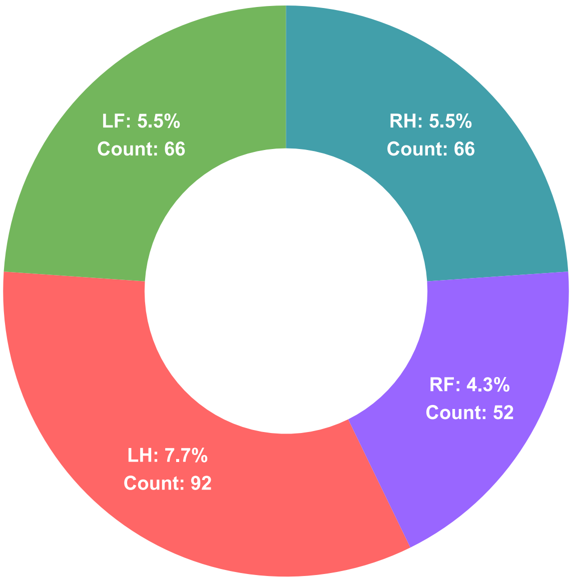


Figure 37: Percentage of positive pain reactions divided by the individual foot

3.1.3 Growth in the sole centre

The growth in the sole centre (GSC) was also assessed for each foot and a score from 1 to 3 was assigned. In total, 4,804 results for GSC were documented, including 24 times the result GSC1, 1,664 times the result GSC2 and 3,116 times the result GSC3 (Table 16). The relative proportion of the different GSC results divided by farm is shown in Figure 38, indicating a clear predominant presence of GSC3 on CDF1, CDF2 and CDF5, while on the other farms, a more balanced ratio was observed between GSC2 and GSC3. GSC1 was observed only in very small proportions on RF1, RF2, RF3 and CDF3 and could not be recorded at all on the other farms. The count and percentage of the GSC on the different claw trimming dates are displayed in Table 38 in the appendices.

Table 16: Counts of the score for the growth in the sole centre (GSC) on the project farms

	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5	Total	Total rel. (%)
GSC1	8	1	9	0	0	6	0	0	24	0.5
GSC2	477	199	444	21	5	152	322	44	1,664	34.6
GSC3	619	324	443	227	203	202	626	472	3,116	64.9
Total	1,104	524	896	248	208	360	948	516	4,804	100.0
Total rel. (%)	23.0	10.9	18.7	5.2	4.3	7.5	19.7	10.7	100.0	

Similarly to the pain test procedure, the four values of each cow were summarised into a total GSC per cow per day, employing the median of these four individual values. The counts of the aggregated GSC values are displayed in Table 17 and consist of 1,201 total values.

Table 17:Count of aggregated values of the growth in the sole centre (GSC)

GSC	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3	Total
Count	2	1	3	3	246	59	204	91	592	1,201
Rel. counts (%)	0.2	0.1	0.2	0.2	20.5	4.9	17.0	7.6	49.3	100.0

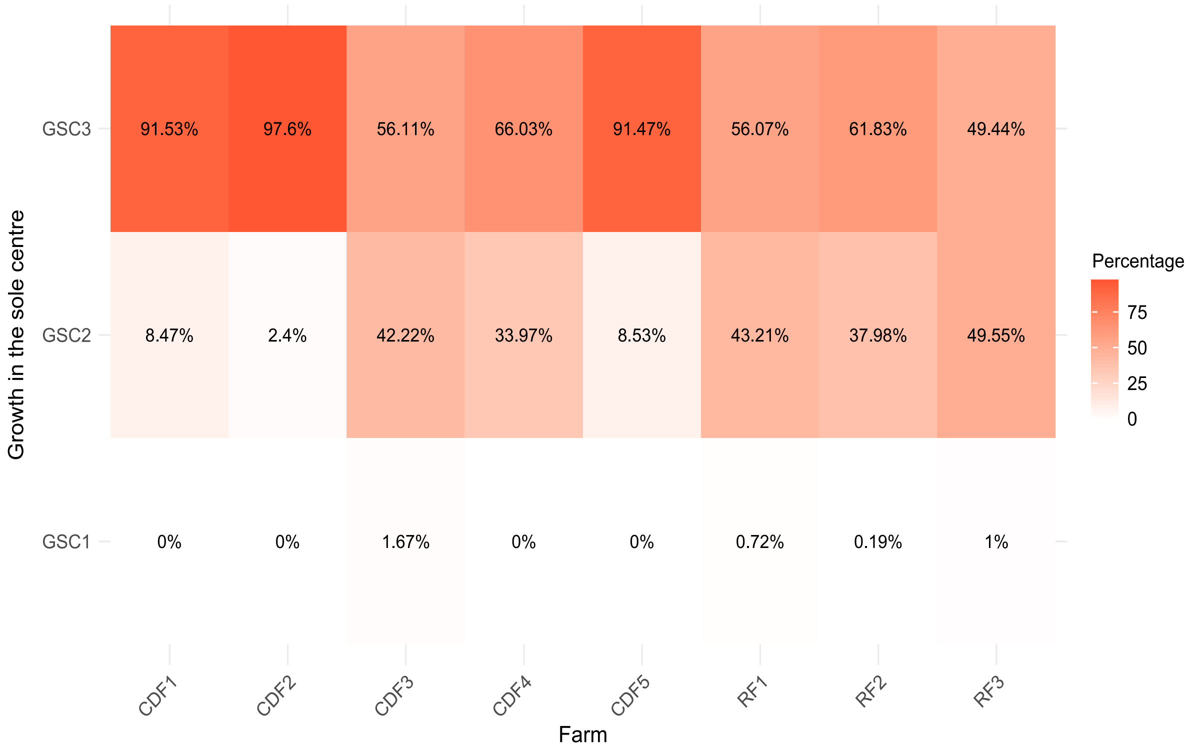


Figure 38: Relative proportion of the scores of the growth in the sole centre assessed on each farm

The distribution of different GSC score results is further broken down in Figure 39 according to the occurrence on the individual foot. The proportion of GSC3 is slightly higher in the hind feet compared to the front feet, whereas a higher proportion of GSC2 is observed in the front feet instead.

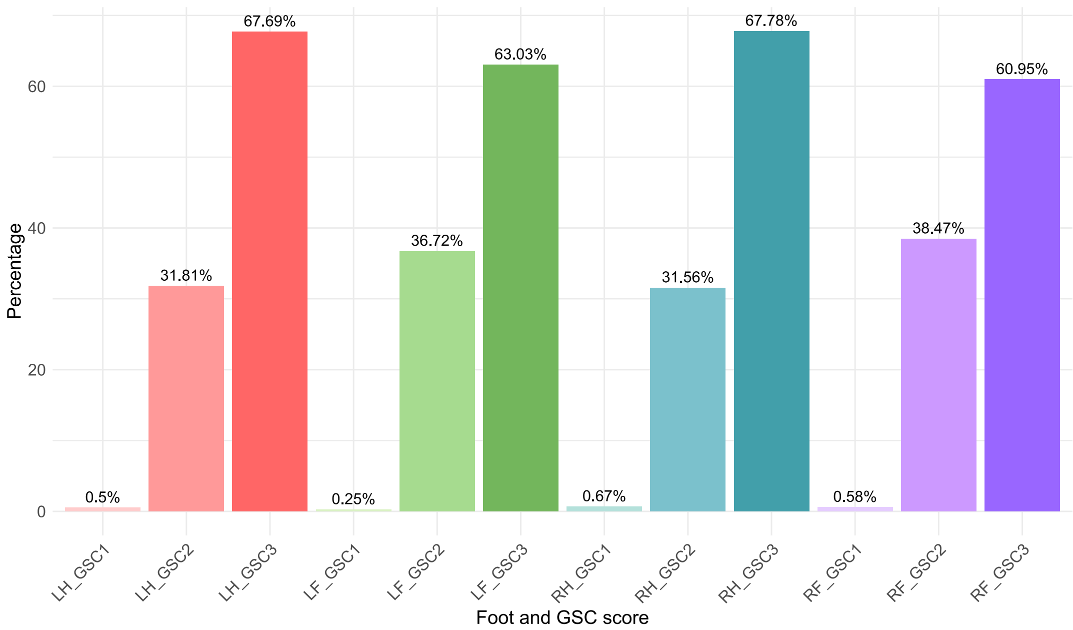
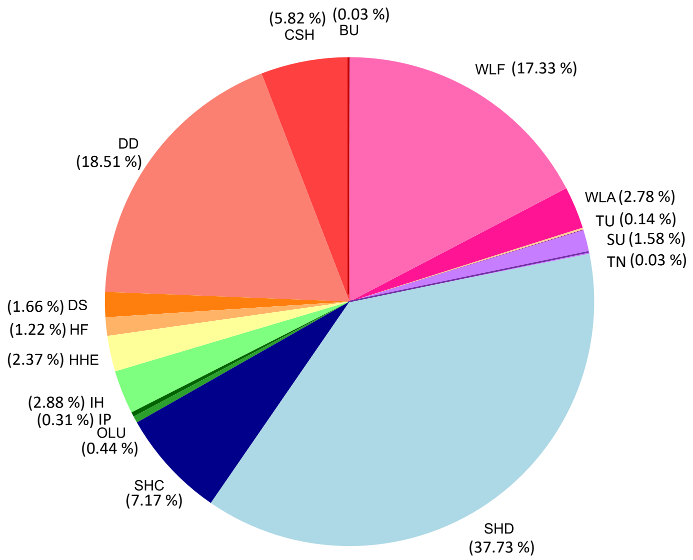


Figure 39: Relative proportion of the scores of the growth in the sole centre (GSC) divided by feet (LH = left hind, LF = left front, RH = right hind, RF = right front)

3.1.4 Findings and Treatments

In total, 2,955 findings and 991 treatments could be recorded during the study and the relative shares of the different claw diseases over all farms are depicted in Figure 40. The different digital dermatitis stages were combined into one total value for this analysis. SHD constituted the largest share at 37.73%, followed by DD with 18.51% and WLF with 17.33%. The prevalence of each diagnosis divided by farms is displayed in Table 18 and the single counts of findings and treatments in total and on each farm are enlisted in Table 39 to Table 47 in the appendices. SHD also constituted the largest proportion of findings on the different farms, except for CDF2 and CDF5, where WLF findings predominated. Moreover, CDF1 showed a complete absence of DD cases, whereas the incidence of DDM2 cases on RF2, at 15.95%, significantly exceeded that observed in other facilities. The highest number of chronic dermatitis cases were observed at CDF3 (16.31%), while RF1 exhibited the most SHC findings (12.31%). Sole ulcers were seen predominantly on CDF4 at 2.77%, aligning with the highest incidence of CSH (8.65%) on this farm. The highest share of WLA was documented on CDF1 (8.48%), while the greatest occurrence of IH was noted on RF3 (3.96%) and most DS were observed on CDF2 (4%).



Code	Findings	Percentage
SHD	Sole haemorrhage diffused form	37.73 %
DD	Digital dermatitis	18.51 %
WLF	White line fissure	17.33 %
SHC	Sole haemorrhage circumscribed form	7.17 %
CSH	Central sole haemorrhage	5.82 %
IH	Interdigital hyperplasia	2.88 %
WLA	White line abscess	2.78 %
HHE	Heel-horn erosion	2.37 %
DS	Double sole	1.66 %
SU	Sole ulcer	1.58 %
HF	Horn fissure	1.22 %
OLU	Otherwise located ulcer	0.44 %
IP	Interdigital phlegmon	0.31 %
TU	Toe ulcer	0.14 %
BU	Bulb ulcer	0.03 %
TN	Toe necrosis	0.03 %

Figure 40: Pie chart and table of the relative share of each diagnosis documented during the claw trimmings

Table 18: Prevalence of the different findings on each project farm (abbreviations explained in Table 7)

Findings	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
TU	0.15	0.00	0.00	0.61	0.00	0.00	0.00	0.68
OLU	0.60	1.43	0.00	0.00	0.00	0.60	0.16	0.34
IP	0.74	0.29	0.00	0.00	1.33	0.00	0.00	0.68
SU	1.49	1.71	0.66	0.00	1.33	1.51	2.77	1.70
DDM1	5.66	2.85	12.97	0.00	2.67	3.93	0.00	0.68
DDM2	4.47	15.95	12.97	0.00	9.33	6.65	7.99	9.18
DDM3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DDM4	9.54	3.13	1.10	0.00	6.67	16.31	2.45	1.02
DDM4.1	0.45	0.28	0.00	0.00	0.00	2.42	0.65	0.00
HHE	1.48	2.85	0.44	1.21	1.33	2.72	0.16	11.90
CSH	5.37	3.42	4.84	8.48	4.00	3.32	8.65	7.14
SHD	30.40	42.17	43.96	50.30	16.00	36.25	43.88	26.87
SHC	12.67	3.70	3.74	1.21	16.00	0.00	11.42	4.42
WLF	17.29	15.67	12.09	26.06	24.00	19.64	12.89	27.55
WLA	1.49	1.71	0.88	8.48	8.00	1.21	4.73	3.06
HF	1.94	1.71	0.87	0.00	4.00	0.60	1.14	0.35
IH	3.73	2.00	3.95	0.62	1.34	3.33	1.97	3.41
DS	2.38	0.85	1.53	3.03	4.00	1.51	1.14	1.02
TN	0.00	0.28	0.00	0.00	0.00	0.00	0.00	0.00
BU	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total rel. (%)	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

The distribution of relative proportions of cases across different limbs was also analysed for the findings, as can be seen in Figure 41. The majority of findings, comprising over 70%, were found in the hind feet, whereas the smallest proportion, at 13.0%, was observed in the right front limb.

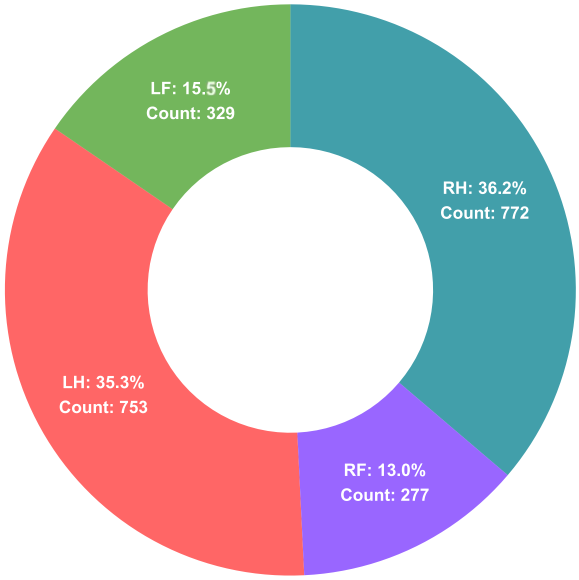


Figure 41: Relative distribution of findings by foot

3.2 Statistical summaries

Statistical summaries were calculated for all numeric parameters across all farms and for each farm individually. The corresponding tables can be found in Table 48 to Table 56 in the appendices. The parameters *Robot_blood, Robot_blood_percent, Colour_lv, Colour_rv, Colour_lh* and *Colour_rh* were removed from the datasets for further analysis due to the lack of comparability and the small number of values per parameter.

4. Bivariate analysis

4.1 Pain test and findings

Among the 226 aggregated positive pain samples, 53 showed no findings at all, while 173 presented with clinical findings (Table 19). Of the 975 negative pain test results, 229 did not display any visible findings, whereas the remaining 746 demonstrated visible claw diseases. Consequently, 23.5% of the animals displayed visible signs of pain despite the absence of findings and only 18.8% of the animals with visible findings also showed a pain reaction. The distribution of positive pain reactions with simultaneous absence of clinical findings across different farms is shown in Table 19.

The different shares of positive and negative pain tests by claw disease can be found in Table 57 in the appendices.

Table 19: Pain test (PT) results grouped by the occurrence or absence of visible findings

	Positive PT	Negative PT	Total
Visible findings	173	746	919
No visible findings	53	229	282
Total	226	975	1,201

Table 20: Positive pain tests without clinical findings divided by farm

	RF1	RF2	RF3	CDF3	CDF4	CDF5
Positive pain tests with no findings	15	19	10	2	5	2

4.2 Pain test and growth in the sole centre

The score for the growth in the sole centre was recorded to explore the potential relationship between positive pain tests in the absence of visible clinical findings and an excessive growth in the sole centre. For this purpose, the median and the average of the GSC for all recordings with a positive PT were compared to the median and average of the GSC for all recordings with a negative PT. The values for the negative PT group (median: 3, average: 2.7) appeared to be higher than the ones noted for the positive PT group (median: 2.5, average: 2.5). In cases with a positive PT and no findings, the median was 2.3, while the average was 2.4.

4.3 Validation of the locomotion scoring system

A calculation of the intra-rater and inter-rater reliability as well as a comparative analysis between a three-level lesion score (LS) (Figure 28) and the locomotion score (Figure 27) was carried out to validate the locomotion scoring system.

As described by Hertle et al. (2022), videos of 355 cows were watched and locomotion scores were assigned to each cow by the observer (Rater 1) twice with a six-month interruption. The calculated percentage of agreement of the intra-rater reliability was 93.2% and the κ_w was 0.89. The same procedure was performed to determine the inter-rater reliability, gaining the values PA = 82.1% and κ_w = 0.72. As described by Yang and Laven (2019), point estimates may not be sufficient because the true kappa value always falls in a specific range and can vary through the influence of diverse factors. A more advanced approach utilises the 95% confidence interval, which signifies that the calculated interval limits enclose the actual value with a probability of 95%. For the intra-rater reliability, the 95% confidence interval (CI) was 0.84-0.94 and therefore, according to the introduced levels by Landis and Koch (1977), the strength of agreement was almost perfect. The result for the CI of the inter-rater reliability (0.64-0.81) implies a substantial to almost perfect accordance between the two raters. In this study, besides Rater 1, two additional raters (Rater 3 and Rater 4) were involved in the locomotion scoring and scored the corresponding cows to 4 out of 20 claw trimming dates. Prior to the scoring process, the inter-rater reliability between these additional raters and Rater 1 was also calculated. The results of all inter-rater agreement analyses are presented in Table 21.

Table 21: Inter-rater reliability results, including the percentage of agreement (PA) and quadratic weighted kappa (κ_w) of Rater 1 compared to three other raters

Raters	Rater 1 and Rater 2	Rater 1 and Rater 3	Rater1 and Rater 4
N	355	105	75
PA	82.1%	85.2%	80.1%
κ_w	0.72	0.85	0.82

In an initial analysis, two subsets of data were used to compare locomotion scores with lesion scores (Hertle et al., 2022). The first subset comprised 110 cows, and the second subset included 115 cows. The gained results were a κ_w of 0.51 (CI: 0.34-0.68) and a PA of 66.4% for the first dataset, while the second dataset yielded a κ_w = 0.72 (CI: 0.58-0.86) and a PA = 80.0%.

After the completion of locomotion scoring, lesion scores were calculated for the entire dataset, utilising 1,201 assessments from 727 different cows. The calculated percentage of agreement on this data was 65.7% and the κ_w was 0.44 (CI: 0.40-0.50), displaying a moderate agreement between locomotion and lesion score. The correlation and divergence of locomotion and lesion scores can be observed in Figure 42. Most of the deviating values show a difference of 1, with the majority having an LMS of 1 and an LS of 2. Significantly fewer observations show a difference of 2, with the combination LS3-LMS1 occurring more frequently than LMS3-LS1. The values of PA, κ_w and CI on each farm can be found in Table 58 in the appendices.

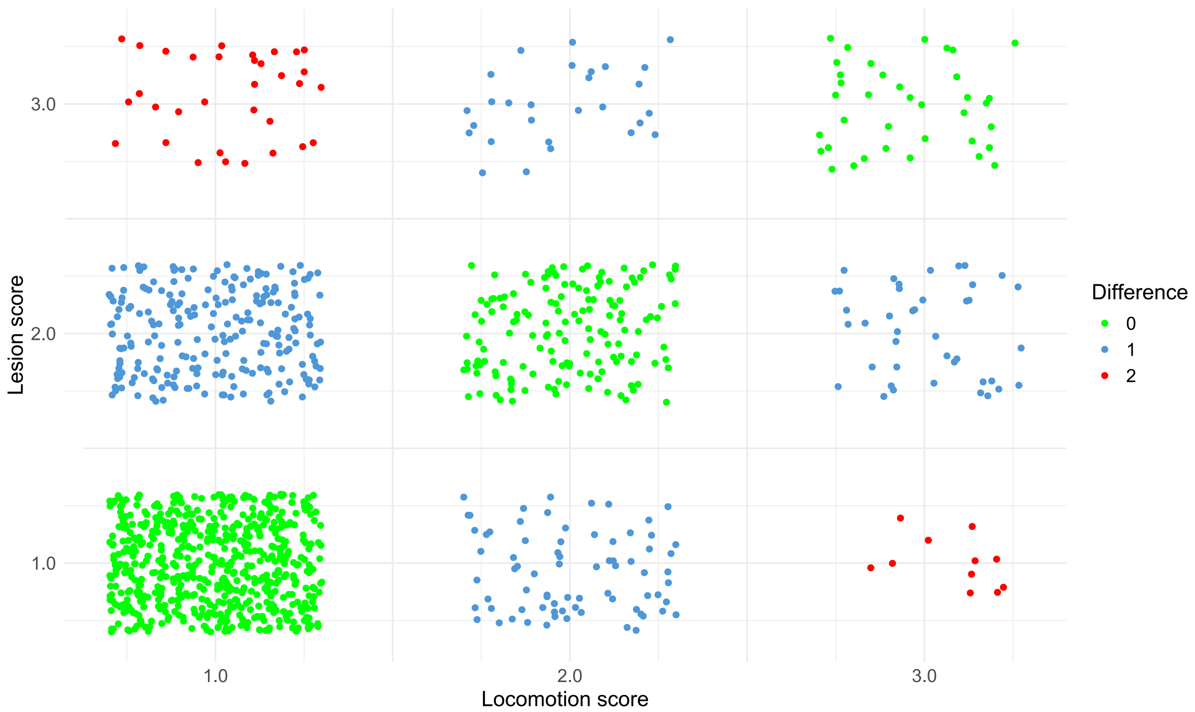


Figure 42: Jitter plot showing the differences between locomotion and lesion scores

4.4 Relationships between claw health parameters and the locomotion score

The growth in the sole centre and the pain test results were compared to the plain locomotion score instead of the corrected locomotion due to the influence of the pain test on the C_LMS itself. The statistical summaries for GSC or PT and each LMS group are shown in Table 22 and the percentages of the different PT and GSC results for each LMS group are displayed in Figure 43. The Spearman's rank correlation coefficient for GSC and the LMS was negative (ρ = -0.06). Statistically significant differences between all LMS groups were found according to the Kruskal-Wallis and the Wilcoxon signed rank test. The differences in PT between LMS groups were also consistently statistically significant across both tests, although PT demonstrated a positive correlation with LMS (ρ = 0.19) (Figure 43). The odds ratio for GSC was 0.496 (CI: 0.441-0.559) and indicated a protective effect, while for PT it was 5.775 (CI: 5.167-6.456), indicating it strongly increases the risk of an animal being classified as lame, both with $p < 0.001$.

Table 22: Statistical summaries of growth in the sole centre (GSC) and pain test (PT) for each locomotion score (LMS) group

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	PT	0	0	0	0.1	0	1	0.4	19,316
2	PT	0	0	0	0.2	0	1	0.4	3,678
3	PT	0	0	1	0.5	1	1	0.5	1,379
1	GSC	0	2.5	3	2.7	3	3	0.4	19,316
2	GSC	1	2.5	2.8	2.6	3	3	0.4	3,699
3	GSC	1.2	2	2.5	2.5	3	3	0.4	1,379

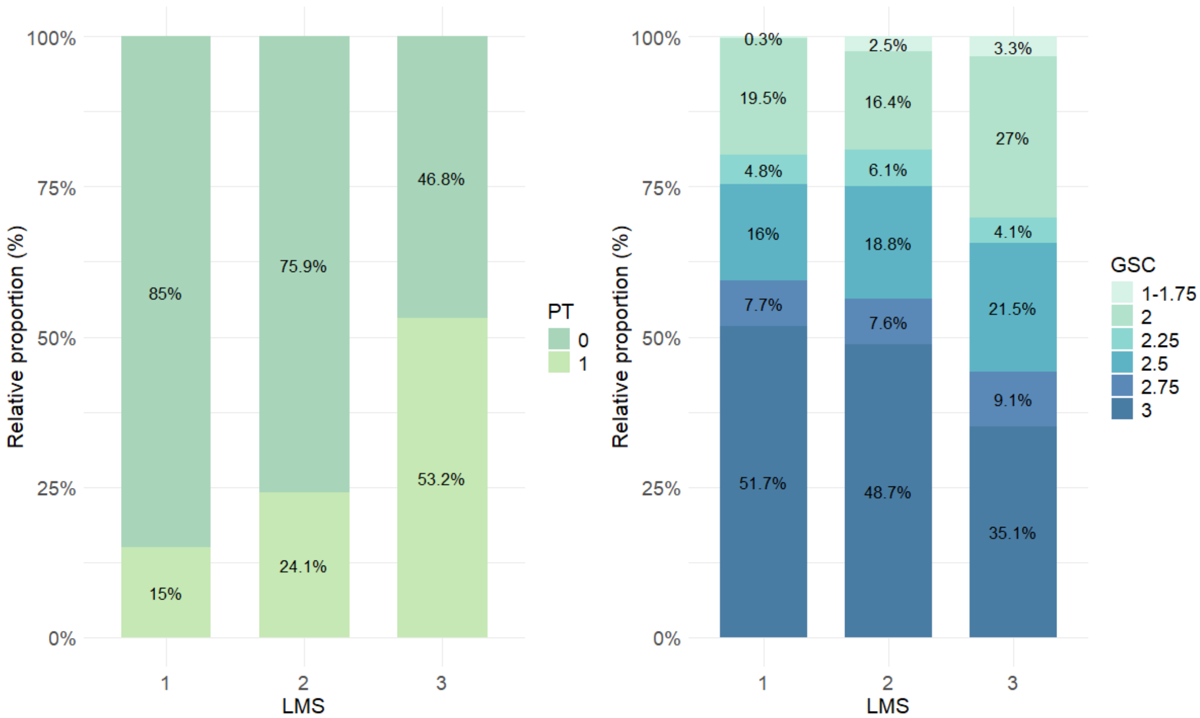


Figure 43: Relative proportion of pain test (PT) and growth in the sole centre (GSC) grouped by locomotion score (LMS)

4.5 Differences in variables across corrected locomotion score groups

For the analysis of the other automatically recorded parameters, it was decided to prioritise the comparison to the C_LMS, as this one also took the PT and the documented findings into account, and the results compared to the original LMS were only noted in cases of significant discrepancies. Statistical summaries were calculated for each variable combination and C_LMS across all farms and can be found in Table 59 in the appendices (Statistical summaries with LMS: Table 60). As the parameters of the data sets did not follow a normal distribution, the corresponding tests for non-normally distributed variables were conducted. The Spearman's rank correlation was tested between the ordinal variable C_LMS and each of the numeric parameters and can be found in Table 23.

Table 23: Spearman correlation between corrected locomotion score (C_LMS) and each variable across all farms (parameters explained in Table 33)

Variable	Positive/ no correlation	Variable	Negative correlation
WT_feed_intake_per_visit	0.35	WT_trough_visits	-0.31
WT_feeding_pace	0.27	WT_trough_visits_day	-0.31
WT_feeding_duration_per_visit	0.24	Delaval_act_avg	-0.25
Nedap_inactive	0.19	Lemmer_act	-0.25
WT_feed_intake_per_meal	0.18	Lemmer_factor_of_restlessness	-0.23
ENGS_lying_day_night	0.17	ENGS_act_day	-0.23
Smaxtec_temp_normal_median	0.17	SCR_act_day	-0.21
Smaxtec_temp_without_drink_cycles_median	0.16	ENGS_act	-0.20
Smaxtec_temp_max	0.15	SCR_act	-0.20
Smaxtec_temp_without_drink_cycles_max	0.15	Nedap_act_foot_median_day	-0.19
Smaxtec_temp_median	0.14	Nedap_get_ups	-0.18
SCR_rum_day_night	0.13	Nedap_act_foot_sum_day	-0.18
Lemmer_lying	0.13	Nedap_act	-0.17
Lactation_number	0.11	WT_feeding_duration	-0.16
LKV_milk_yield_in_last_lactation	0.11	WT_feeding_duration_day	-0.16
Body_weight	0.11	Nedap_act_foot_median	-0.15
ENGS_lying_duration_per_bout	0.11	Nedap_act_foot_sum_day_night	-0.15
Lemmer_get_ups	0.09	WT_number_of_meals	-0.14
Smaxtec_temp_without_drink_cycles_min	0.09	WT_number_of_meals_day	-0.14
Robot_milk_yield_in_last_lactation	0.07	ENGS_lying_bouts	-0.14
MDi	0.07	Delaval_act_rel_min	-0.14
WT_feed_intake	0.07	Delaval_act_rel	-0.13
ENGS_lying_day	0.07	Nedap_rum	-0.12
Maximum_milking_interval	0.06	ENGS_lying_bouts_day	-0.12
Milking_temperature	0.05	Nedap_act_foot_median_day_night	-0.12
ENGS_lying_bouts_day_night	0.05	ENGS_act_day_night	-0.11
LKV_daily_milk_yield	0.04	Nedap_act_collar_median_day	-0.11
Concentrated_feed_remains	0.04	Nedap_act_collar_sum_day	-0.11
WS_rel_hum_med	0.04	Nedap_act_collar_sum_day_night	-0.11
WS_rel_hum_min	0.04	SCR_act_day_night	-0.09
Robot_daily_milk_yield	0.03	Nedap_act_collar_median	-0.09
Robot_conduct_lely	0.03	Nedap_act_collar_sum	-0.09
Smaxtec_climate_hum_median	0.03	Nedap_act_collar_median_day_night	-0.09
Robot_milk_yield_in_current_lactation	0.02	Delaval_act_rel_max	-0.08
Robot_daily_milk_yield_in_last_lactation	0.02	Smaxtec_temp_min	-0.08
Max_milking_flow	0.02	Milkings	-0.07
Robot_fat	0.02	Nedap_feeding	-0.06

Variable	Positive/ no correlation	Variable	Negative correlation
Robot_fat_protein_ratio	0.02	WS_thi_med	-0.06
ENGS_feeding	0.02	WS_thi_min	-0.06
ENGS_feeding_day	0.02	WS_thi_max	-0.06
ENGS_feeding_duration_per_meal	0.02	WS_temp_2m_med	-0.06
Smaxtec_rum	0.02	WS_temp_2m_min	-0.06
Smaxtec_climate_hum_min	0.02	WS_temp_2m_max	-0.06
Smaxtec_climate_hum_max	0.02	WS_temp_20cm_med	-0.06
WS_global_rad_min	0.02	WS_temp_20cm_max	-0.06
Season	0.02	WS_soil_temp_5cm_med	-0.06
WS_wind_velocity_min	0.01	WS_soil_temp_5cm_min	-0.06
WS_rain_med	0.01	Breed	-0.05
WS_rain_max	0.01	LKV_protein	-0.05
LKV_urea	0	Milking_flow	-0.05
Robot_conduct	0	WS_temp_20cm_min	-0.05
Concentrated_feed_intake	0	WS_soil_temp_5cm_max	-0.05
ENGS_feeding_day_night	0	WS_soil_temp_20cm_med	-0.05
SCR_rum_day	0	WS_soil_temp_20cm_min	-0.05
ENGS_lying	0	WS_soil_temp_20cm_max	-0.05
Smaxtec_climate_temp_min	0	WS_global_rad_med	-0.05
Smaxtec_thi_min	0	WS_global_rad_max	-0.05
WS_rel_hum_max	0	LKV_fat	-0.04
WS_wind_velocity_med	0	Robot_BCS	-0.04
		WT_feeding_duration_per_meal	-0.04
		ENGS_number_of_meals_day_night	-0.04
		SCR_heat_probability	-0.04
		Smaxtec_act_day	-0.04
		Smaxtec_act_day_night	-0.04
		LKV_lactose	-0.03
		Robot_somatic_cell_count	-0.03
		WT_number_of_meals_day_night	-0.03
		SCR_rum	-0.03
		SCR_heat_probability_day	-0.03
		Nedap_lying	-0.03
		Smaxtec_act	-0.03
		Smaxtec_climate_temp_max	-0.03
		Smaxtec_thi_max	-0.03
		Days_in_milk	-0.02
		ENGS_number_of_meals_day	-0.02
		LKV_somatic_cell_count	-0.01
		LKV_fat_protein_ratio	-0.01
		Robot_effect_of_scc	-0.01
		Robot_protein	-0.01
		Robot_lactose	-0.01
		WT_feeding_duration_day_night	-0.01
		WT_trough_visits_day_night	-0.01
		ENGS_number_of_meals	-0.01
		Smaxtec_climate_temp_median	-0.01
		Smaxtec_thi_median	-0.01
		WS_wind_velocity_max	-0.01
		WS_rain_min	-0.01

Statistically significant differences for each parameter across all three C_LMS groups and all farms were tested by applying the Kruskal-Wallis test and the results are displayed in Table 61 in the appendices. Most parameters demonstrated statistically significant differences between the corrected locomotion score groups, with $p < 0.05$ and the majority even reaching $p < 0.01$. Non-statistically significant parameter differences occurred in the group of milking parameters, for example *LKV_urea* ($p = 0.17$) and *Concentrated_feed_intake* ($p = 0.39$), in the group of climate parameters, for instance, *WS_wind_velocity_max* ($p = 0.12$), in rumination with *Smaxtec_rum* ($p = 0.07$), in heat behaviour with *SCR_heat_probability_day* ($p = 0.09$) and in terms of feeding behaviour, where particularly the ENGS parameters like *ENGS_number_of_meals* (p = 0.32) and the day-night ratios like *WT_feeding_ duration_day_night* (p = 0.22) were not statistically significant. In contrast to the LMS groups, the differences in *ENGS_lying* (p = 0.30) and *Nedap_lying* (p = 0.13) were also not significant between the C_LMS groups.

To further specify the statistically significant differences between C_LMS groups, a post-hoc analysis using the Wilcoxon signed-rank test was conducted. This analysis examined the significance of differences between C_LMS1 vs. C_LMS2, C_LMS1 vs. C_LMS3, and C_LMS2 vs. C_LMS3 (Table 62 in the appendices). For the LMS, the same analysis was conducted, and the results can be found in Table 63 in the appendices. The counts of all variables with and without a statistically significant difference (p > 0.05) between the C_LMS groups grouped by parameter classes are displayed in Table 24.

Table 24: Count of variables with and without statistically significant differences between the corrected locomotion score (C_LMS) groups (p > 0.05) for each parameter class (sig. = statistically significant differences, n.s. = no statistically significant differences)

Variable	C_LMS1 vs. C_LMS2		C_LMS1 vs. C_LMS3		C_LMS2 vs. C_LMS3	
	sig.	n.s.	sig.	n.s.	sig.	n.s.
Animal characteristics	1	0	1	0	0	1
Milking parameters	19	9	20	8	12	16
Constitution	2	0	2	0	2	0
Feeding behaviour	11	14	14	11	13	12
Rumination	2	3	3	2	2	3
Heat behaviour	1	2	1	2	0	3
Lying behaviour	6	5	9	2	2	9
Activity	22	5	26	1	11	16
Body temperature	7	0	7	0	6	1
Climate	11	26	27	10	28	9

Furthermore, the odds ratio, measuring the association between an exposure variable and an outcome, was calculated for all these parameters, once based on the outcome lame as C_LMS = 3 and once with LMS = 3, and can be found in the appendices (Table 64).

4.5.1 Animal characteristics

The percentage distribution of each C_LMS group by breed is illustrated in Figure 44, with Holstein cows exhibiting the highest percentage within the C_LMS3 category (33.0%), followed by Simmental (16.7%) cows. However, this cannot be considered a breed-specific lameness comparison, as the majority of the cows in this study were Simmental cows, with other breeds represented only sporadically. No statistically significant differences could be demonstrated between C_LMS2 and C_LMS3 and the OR was 0.828.

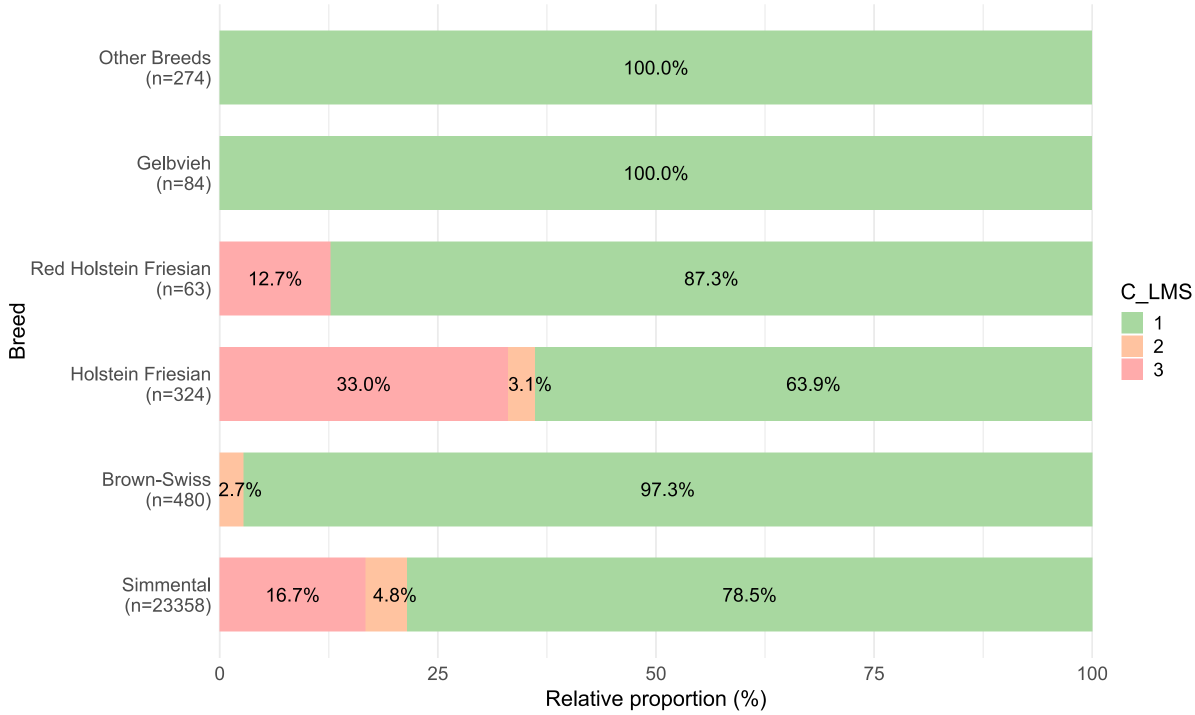


Figure 44. Relative proportion of the corrected locomotion score (C_LMS) by breed and the number of n assessments recorded per breed

4.5.2 Milking parameters

The milking data could be gathered from both the milking robot and LKV Bayern. The boxplots in Figure 45 represent the daily milk yield recorded by LKV and the milking robots for each corrected locomotion score group across all farms. In both evaluations, no significant differences could be observed between C_LMS2 and C_LMS3 ($p = 1.00$) and for *Robot_daily_milk_yield* the differences between C_LMS1 and C_LMS2 were also not significant. A positive correlation could be documented (*LKV_daily_milk_yield* ($\rho = 0.04$), *Robot_daily_milk_yield* ($\rho = 0.03$) and the odds ratios presented a slight positive association for C_LMS. In contrast, when compared with the LMS, LMS2 animals displayed the highest daily milk yields and no statistically significant differences could be observed between LMS1 and LMS3 cows. Considering the LMS, the Robot_daily_milk_yield revealed an OR below 1, whereas for LKV_daily_milk_yield, the odds ratio results did not suggest a statistically significant association.

The daily milk yield during the last lactation displayed significant differences between the C_LMS groups except for C_LMS1/C_LMS2 and showed a correlation of $\rho = 0.02$ and an OR greater than 1. Even though the median of the total milk yield in the last lactation was highest among the C_LMS2 cows as shown in Figure 46, the Wilcoxon signed-rank test did not reveal any significant differences between the C_LMS2 and C_LMS3 groups. In contrast, the differences compared to the C_LMS1 group were significant, both for LKV and milking robots. A positive correlation was reported (*LKV_milk_yield_in_last_lactation* ($\rho = 0.11$), *Robot_milk_yield_in_last_lactation* ($\rho = 0.07$) and an odds ratio of 1 was determined for both parameters, implying no difference in odds ratio between the groups. Regarding the total milk yield throughout the current lactation, C_LMS2 animals tended to have a significantly higher milk yield compared to C_LMS1 cows, but the OR appeared to be not statistically significant.

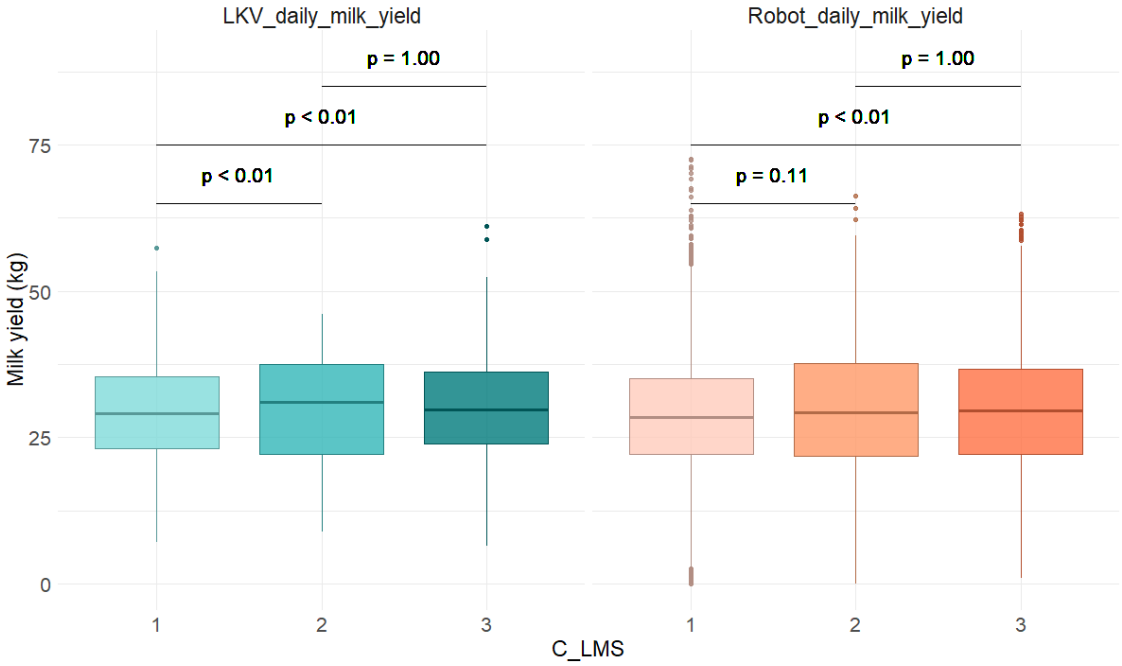


Figure 45: Boxplots of the daily milk yield in each corrected locomotion score (C_LMS) group measured by the LKV and the milking robot

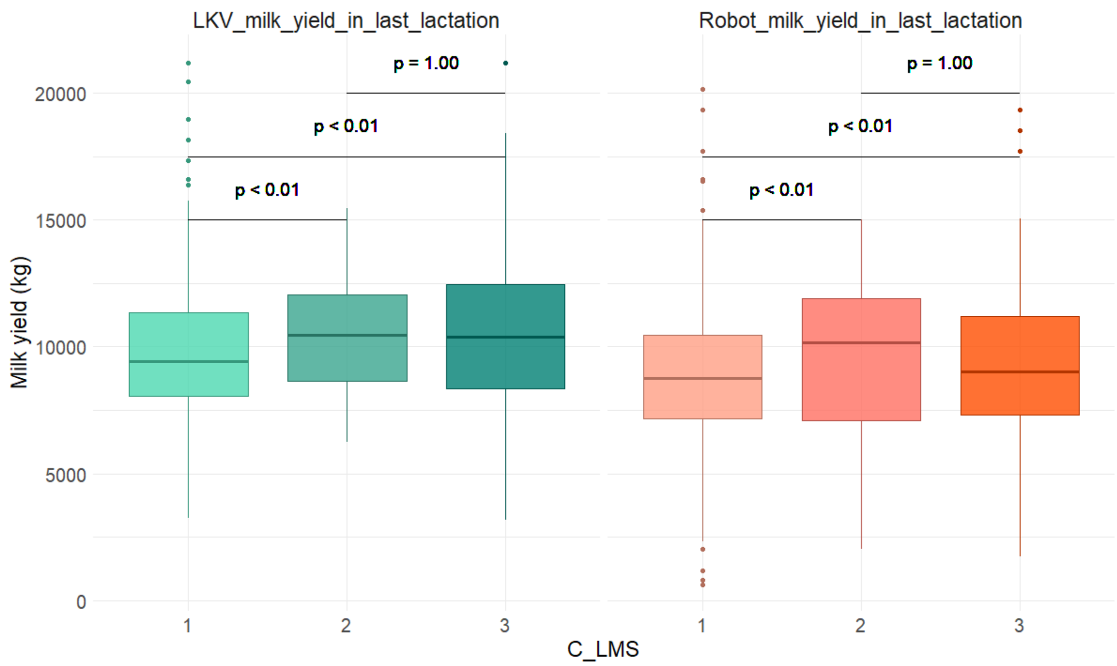


Figure 46: Boxplots of the total milk yield in last lactation in each corrected locomotion score (C_LMS) group measured by the LKV and the milking robot

Upon analysis of milk constituents captured by both the LKV and milking robots, there was an increase in milk protein content from C_LMS1 to the C_LMS2 group before the protein content decreased again in C_LMS3 cows. The Spearman's rank correlation coefficient was negative (*LKV_protein* (ρ = -0.05), *Robot_protein* (ρ = -0.01)), while the OR for *LKV protein* was 0.565

and for *Robot_protein* was 0.630, which also implied a negative association. Regarding lactose content in milk, there were fewer marked differences observed. *LKV_lactose* exhibited a slight decline in concentration with increasing C_LMS (ρ = -0.03), notably within the C_LMS2 group. *Robot_lactose* demonstrated a more modest negative trend (ρ = -0.01), significant only between C_LMS1/C_LMS3 and C_LMS2/C_LMS3. The OR was below 1 for both variables, also suggesting a lower probability of lameness with rising lactose. There were contrasting trends in fat content with increasing C_LMS, where *LKV_fat* notably decreased among C_LMS2 and C_LMS3 cows, while *Robot_fat* showed a slight positive correlation (ρ = 0.02). The odds ratio was 0.9 for *LKV_fat*, while *Robot_fat* yielded no statistically significant differences regarding C_LMS3 and an OR greater than 1 concerning LMS3. Accordingly, *Robot_fat_protein_ratio* demonstrated a positive correlation (ρ = 0.02) with significant differences between the groups C_LMS1 and C_LMS3, while *LKV_fat_protein_ratio* displayed a negative correlation (ρ = -0.01) with significant differences between the groups C_LMS1 and C_LMS2 and between C_LMS2 and C_LMS3. *LKV_urea* exhibited no significant association or correlation in any tests. The somatic cell count recorded by LKV and milking_robots as well as *Robot_effect_scc* presented a negative correlation, but no statistically significant odd ratios.

The milking parameters registered by both milking robots and LKV were compared to evaluate the degree of alignment between the monthly data provided by the LKV and the data collected by the milking robot during each milking session in order to assess whether the monthly recordings might be sufficient. For this analysis, the Intraclass Correlation Coefficient (ICC) and its confidence interval were calculated (Table 25). The ICC was selected as it effectively combines both correlation and agreement into a single metric (Koo & Li, 2016), providing an ideal measure for evaluating the consistency between two measurements obtained from different sources. According to Koo and Li (2016), the 95% CI of the ICC between LKV and the milking robot can be designated as excellent for the milk yield in last lactation, good for the daily milk yield and poor for the other milk parameters.

Table 25: Intraclass Correlation Coefficient (ICC) between milk parameters recorded by LKV and the milking robots (parameters explained in Table 33)

Variables	Intraclass Correlation Coefficient (ICC)
LKV_milk_yield_in_last_lactation / Robot_milk_yield_in_last_lactation	0.90 (CI: 0.89-0.90)
LKV_daily_milk_yield / Robot_daily_milk_yield	0.86 (CI: 0.86-0.87)
LKV_protein / Robot_protein	0.47 (CI: 0.46-0.48)
LKV_fat / Robot_fat	0.34 (CI: 0.32-0.35)
LKV_lactose / Robot_lactose	0.31 (CI: 0.30-0.32)
LKV_somatic_cell_count / Robot_somatic_cell_count	0.21 (CI: 0.19-0.23)

Other milk parameters grouped by the C_LMS are graphically represented in Figure 47 as violin plots. The median lactation number increased with higher C_LMS, rising from 2 at LMS1 to 3 at both LMS2 and LMS3. The parameter exhibited both a positive correlation (ρ = 0.11) and an OR exceeding 1, thereby suggesting an increased risk of being classified as lame with increasing parity. Regarding days in milk, the differences were statistically significant. The median initially increased from C_LMS1 to C_LMS2, before declining again at C_LMS3. Overall, only a slight negative correlation and a protective effect of the days in milk were observed. The maximum milking interval increased with higher C_LMS (ρ = 0.06), but no statistically significant differences could be reported for C_LMS2/C_LMS3. The number of milkings per day presented the same median in all C_LMS groups and showed no differences between C_LMS2 and C_LMS3, but when examining the OR (0.792) and the correlation (ρ = -0.07), a reduction with increasing C_LMS could be observed.

In order to better assess the differences in conductivity in relation to LMS, a median value *Robot_conduct* was formed from the individual values per udder quarter. The conductivity values generated by the Lely milking robots were recorded separately as the parameter *Robot_conduct_lely* due to the different format. No significant differences between LMS1 and LMS3 were detected for *Robot_conduct* and the correlation was zero, indicating the absence of a linear relationship. *Robot_conduct_lely* and *Max_milking_flow* were only significant between C_LMS1 and C_LMS3 and exhibited a positive correlation. The milking temperature did not achieve any significant odds ratio results but presented statistically significant differences shown by the Wilcoxon signed-rank test and a ρ = 0.05. Additionally, the *MDi* exhibited a positive correlation with the C_LMS according to Spearman's rank correlation as well as an OR of 1.339.

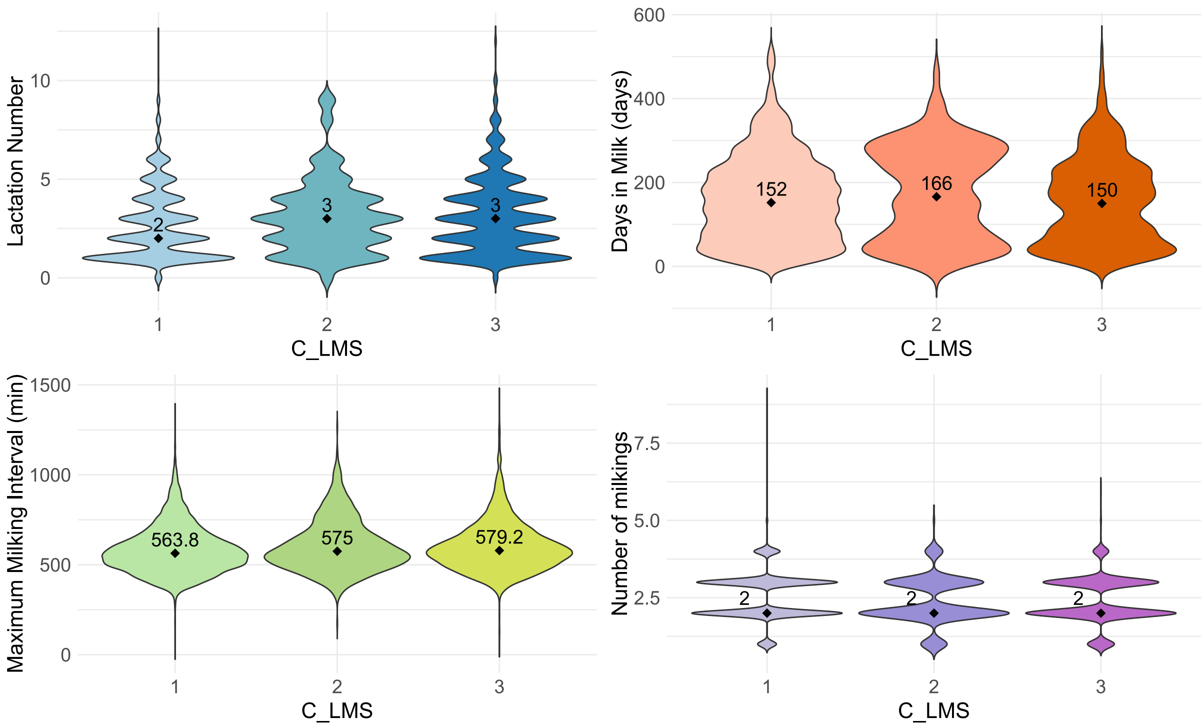


Figure 47: Lactation number, days in milk, maximum milking interval and milkings and their medians grouped by corrected locomotion score (C_LMS)

4.5.3 Constitution

The parameters *Body_weight* and *Robot_BCS* exhibited opposite trends with increasing C_LMS: as *Body_weight* increased (ρ = 0.11), *Robot_BCS* decreased (ρ = -0.04). The odds ratio only demonstrated a slight positive association in *Body_weight* (1.001), while the OR of *Robot_BCS* (0.602) was clearly below 1. In Figure 48, an increase in body weight, especially in the C_LMS2 group, is visualised. In contrast, the decline of *Robot_BCS* can be particularly seen in the C_LMS3 cows.

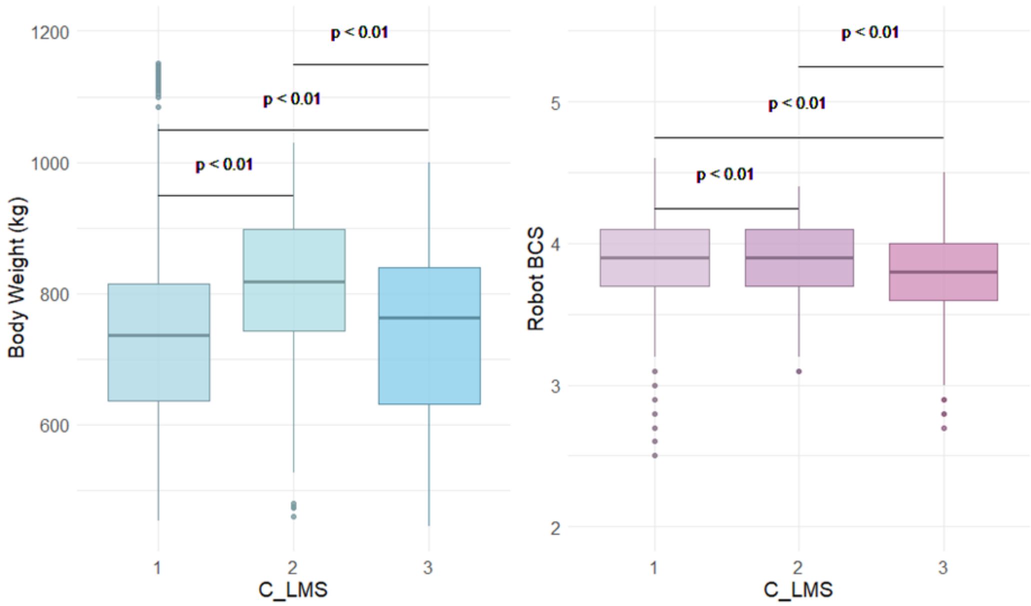


Figure 48: Body weight and body condition score (BCS) in each corrected locomotion score (C_LMS) group

4.5.4 Feeding

4.5.4.1 Feeding duration

The feeding duration was assessed by weighing troughs and the ENGS pedometers on RF1 and by Nedap collars on RF2 and RF3. As displayed in Figure 49, the weighing troughs reported a significant decrease in feeding duration in the C_LMS3 group ($\rho = -0.16$, OR = 0.991).

The feeding duration measured by ENGS pedometers showed no difference between C_LMS1 and C_LMS3, but increased in the C_LMS2 group with an overall slight positive correlation ($\rho = 0.02$). The OR on the other hand was below 1 (0.996). The daytime proportions of feeding duration showed the same trend for ENGS and WT as the overall feeding duration, while the day-night ratios did not yield any significant OR results.

Nedap_feeding showed no significant differences between C_LMS1 and C_LMS3, but there was a significant decline in C_LMS2 cows ($\rho = -0.06$), even if the OR results also confirmed no significant differences. In contrast, a comparison with the LMS revealed a gradual decrease in the *Nedap_feeding* parameter as the LMS increased. The median feeding duration recorded by Nedap was significantly higher in all C_LMS groups compared to the ones noted by the other two sensor systems.

4.5.4.2 Feed intake and feeding pace recorded by the weighing troughs

The parameter *WT_feed_intake* demonstrated a positive relationship ($\rho = 0.07$, OR = 1.005) and statistically significant differences across all C_LMS groups. The variable *WT_feeding_pace* showed a high positive correlation with C_LMS ($\rho = 0.27$), statistically significant differences between all C_LMS groups and an OR greater than 1, thereby suggesting an increased risk of being classified as lame with increasing feeding pace.

4.5.4.3 Feeding frequency parameters by ENGS and weighing troughs

The parameters *WT_feed_intake_per_visit* ($\rho = 0.35$), *WT_feeding_duration_per_visit* ($\rho = 0.24$) and *WT_feed_intake_per_meal* ($\rho = 0.18$) displayed high positive correlations with increasing C_LMS and increased the risk of being classified as lame according to the OR. Conversely, *WT_feeding_duration_per_meal* displayed significant disparities only between C_LMS1 and C_LMS3, revealing a discernible negative correlation (ρ = -0.04) and association (OR: 0.990). *ENGS_feeding_duration_per_meal* showed a positive correlation but a negative association according to its OR. The number of weighing trough visits (ρ = -0.31) and meals at the weighing troughs (ρ = -0.14) as well as their daytime proportions decreased significantly and demonstrated a negative association according to the OR. *WT_number_of_meals_day_night* only reported significant differences between C_LMS1 and C_LMS3, demonstrated a negative correlation and showed no differences in OR. The parameters *ENGS_number_of_meals, ENGS_number_of_meals_day, ENGS_number_of_meals_day_night* and *WT_trough_visits _day_night* did not display statistically significant differences in the Wilcoxon signed-rank test and the OR analysis.

4.5.4.4 Concentrated feed intake

Concentrated_feed_remains was only significant between C_LMS1 and C_LMS3 but showed a positive correlation and association. The parameter *Concentrated_feed_ intake* was not statistically significant in the Wilcoxon signed-rank test or the OR analysis.

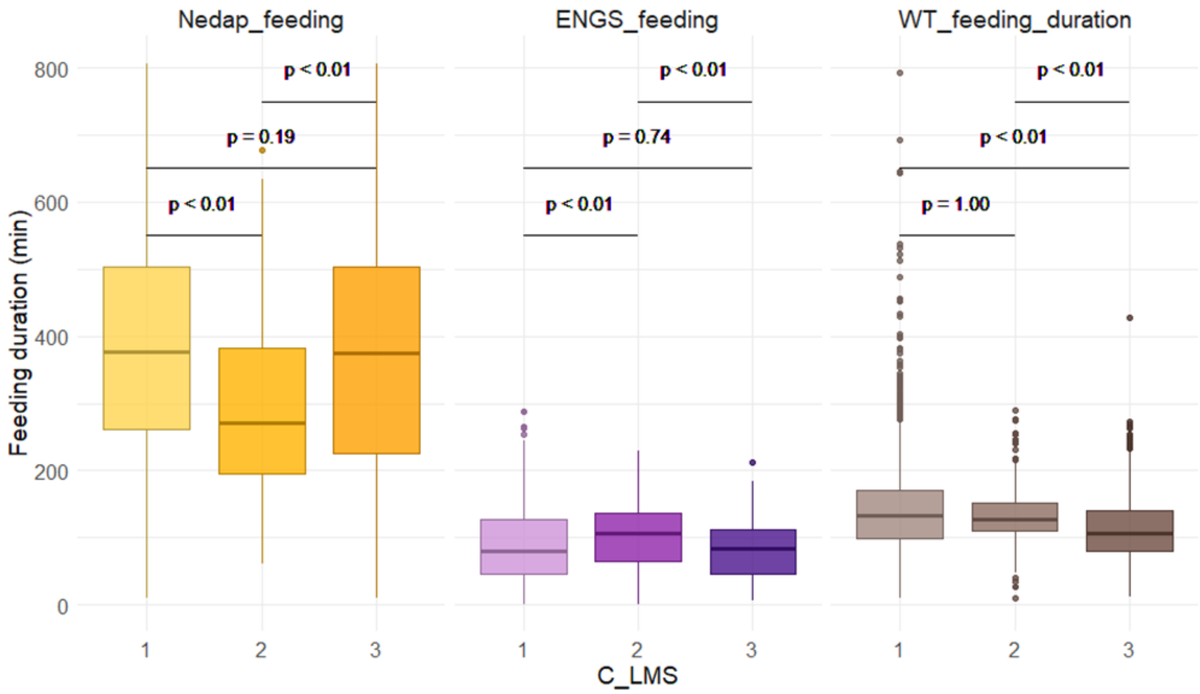


Figure 49: Feeding duration recorded by weighing troughs, ENGS and Nedap sensor systems and grouped by corrected locomotion score (C_LMS)

4.5.5 Rumination

Regarding rumination, the three sensors displayed differing changes in parameter results according to the C_LMS groups. *Smaxtec_rum* did not exhibit any statistically significant differences in rumination among the three C_LMS groups, *Nedap_rum* significantly declined in CLMS3 cows (ρ = -0.12) and *SCR_rum* showed only a slight reduction at higher C_LMS levels (ρ = -0.03) (Figure 50). Similarly, the OR was not significant for *Smaxtec_rum* but showed negative associations for *SCR_rum* and *Nedap_rum*. The rumination values recorded on the farms with Nedap collars appeared to be generally lower than those gained by the other two systems. *SCR_rum_day* showed no correlation or significant OR results and

SCR_rum_day_night was only statistically significant when considering C_LMS1 in comparison with another C_LMS showing a positive correlation and high positive association (ρ = 0.13, OR = 42.912).

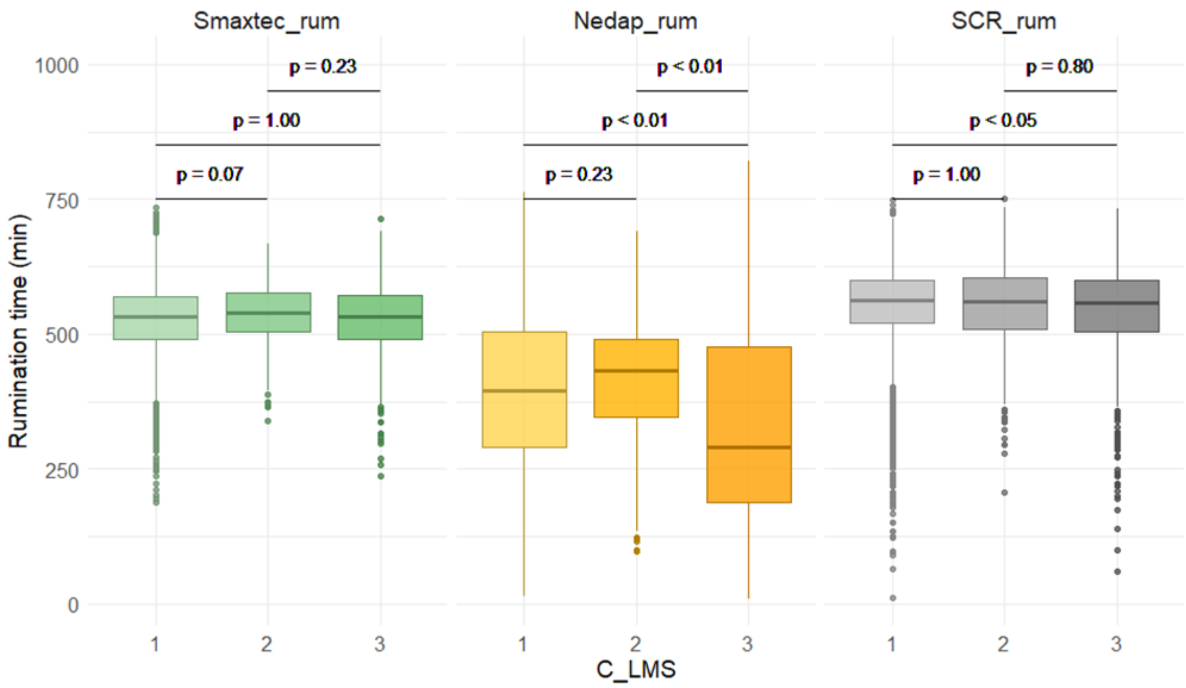


Figure 50: Rumination time recorded by smaXtec, Nedap and SCR sensor systems and grouped by the corrected locomotion score (C_LMS)

4.5.6 Heat probability

The *SCR_heat_probability* and its daily value did not result in any statistically significant differences between the C_LMS groups, while the *Lemmer_factor_of_restlessness* significantly decreased with higher locomotion scores (ρ = -0.23) and displayed an odds ratio below 1.

4.5.7 Lying

4.5.7.1 Lying duration

The lying duration measured by Lemmer-Fullwood showed a clearly positive correlation (ρ = 0.13) and slight positive association (OR: 1.002) with the C_LMS, increasing from C_LMS1 to C_LMS3 cows (Figure 51). In contrast, for Nedap and ENGS sensors, no statistically significant differences could be reported between any of the C_LMS groups. *ENGS_lying* also appeared to have no correlation at all and an OR of 1, while *Nedap_lying* showed a slight negative correlation (ρ = -0.03). *ENGS_lying_day, ENGS_lying_day_night* and *ENGS_lying_duration_per_bout* all showed clear positive correlations and odds ratios greater than 1, but *ENGS_lying_day* was not significant between C_LM1 and C_LMS3 and the other two parameters did not show clear differences between the C_LMS2 and C_LMS3 group.

4.5.7.2 Lying events

The lying events data and their relationship to claw health status captured by Lemmer-Fullwood were opposed to the ENGS and Nedap sensor data, as the former showed an increase with higher C_LMS (ρ = 0.09), especially in the C_LMS2 group (Figure 52), whereas the latter two systems exhibited a negative correlation (ENGS: ρ = -0.14, Nedap: ρ = -0.18).

As can be seen in Figure 52, the average lying bouts measured by ENGS sensors decreased continuously with rising C_LMS, while the get-ups measured by Nedap sensors declined from C_LMS1 to C_LMS2 and then also stayed on this lower level in the C_LMS3 group. The daily proportion of lying events measured by ENGS sensors exhibited a similar trend as the normal value, while the day-night ratio showed significance only between C_LMS1 and C_LMS3 and indicated a positive correlation and association.

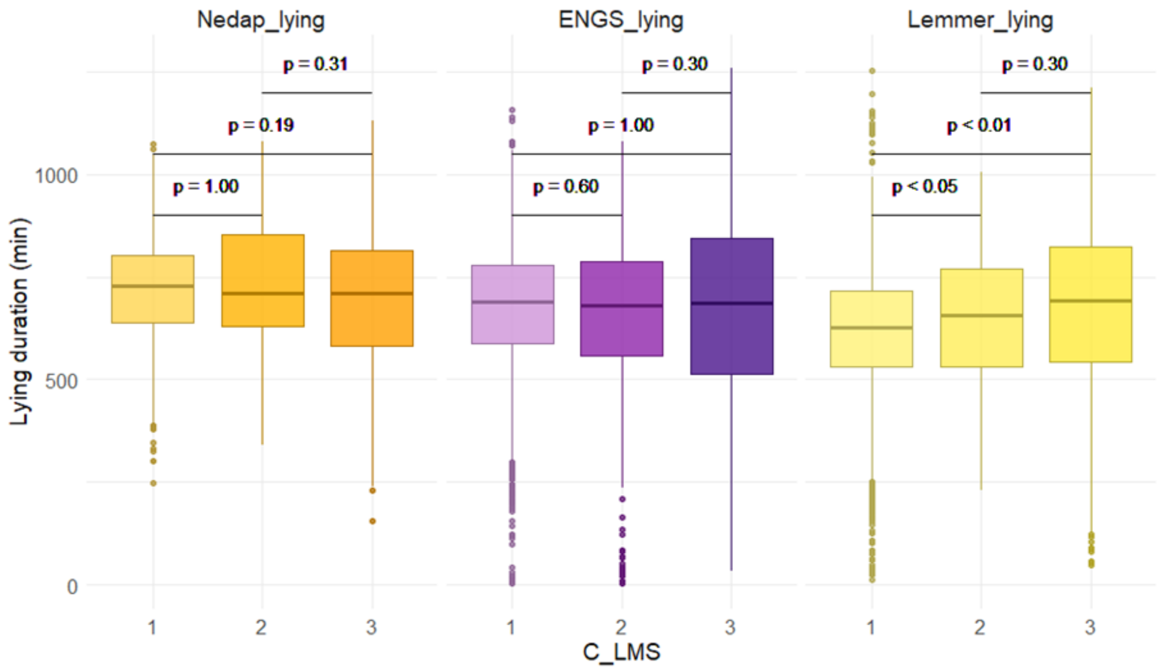


Figure 51: Lying duration recorded by Nedap, ENGS and Lemmer-Fullwood pedometers and grouped by the corrected locomotion score (C_LMS)

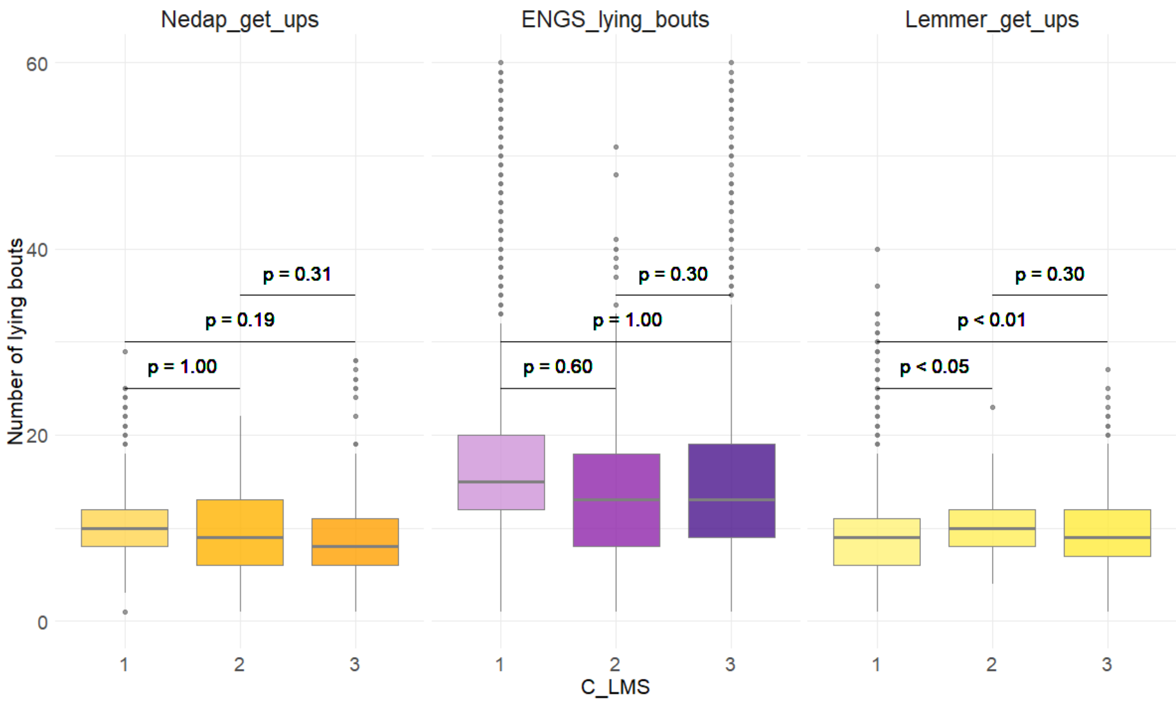


Figure 52: Lying bouts/get-ups measured by Nedap, ENGS and Lemmer-Fullwood pedometers and grouped by the corrected locomotion score (C_LMS)

4.5.8 Activity

Seven different sensor systems, including three pedometers, three collars and one bolus, detected the cows' activity and all of them noted an activity decrease with rising C_LMS (*ENGS_act* (ρ = -0.20), *Lemmer_act* (ρ = -0.25), *Nedap_act* (ρ = -0.17), *Nedap_act_collar_median* (ρ = -0.09), *SCR_act* (ρ = -0.20), *Delaval_act_avg* (ρ = -0.26), *Smaxtec_act* (ρ = -0.03)) (Figure 53 and Figure 54). All other measured or calculated activity parameters except for Nedap_inactivity also showed a negative correlation with increasing C_LMS, although the differences between C_LMS2 and C_LMS3 were not statistically significant in many activity variables such as *Lemmer_act, DeLaval_act_avg, SCR_act_day_night*, all activity parameters by ENGS and most of the Nedap activity parameters. *Smaxtec_act* noted a higher activity level for the C_LMS2 group before falling in the C_LMS3 cows. The relative activity variables detected by DeLaval showed no significant differences between C_LMS1 and C_LMS2. Most of the OR results denoted a negative association between C_LMS3 and activity, except for *Smaxtec_act_day_night, SCR_act_day_night* and *DeLaval_act_rel_max* with not statistically significant differences and *ENGS_act, Nedap_act* and *Nedap_act_foot_sum_day* with an OR of 1. The assessed inactivity as the variable *Nedap_inactivity* rose accordingly with higher locomotion scores (ρ = 0.19) and thus had a positive association with C_LMS.

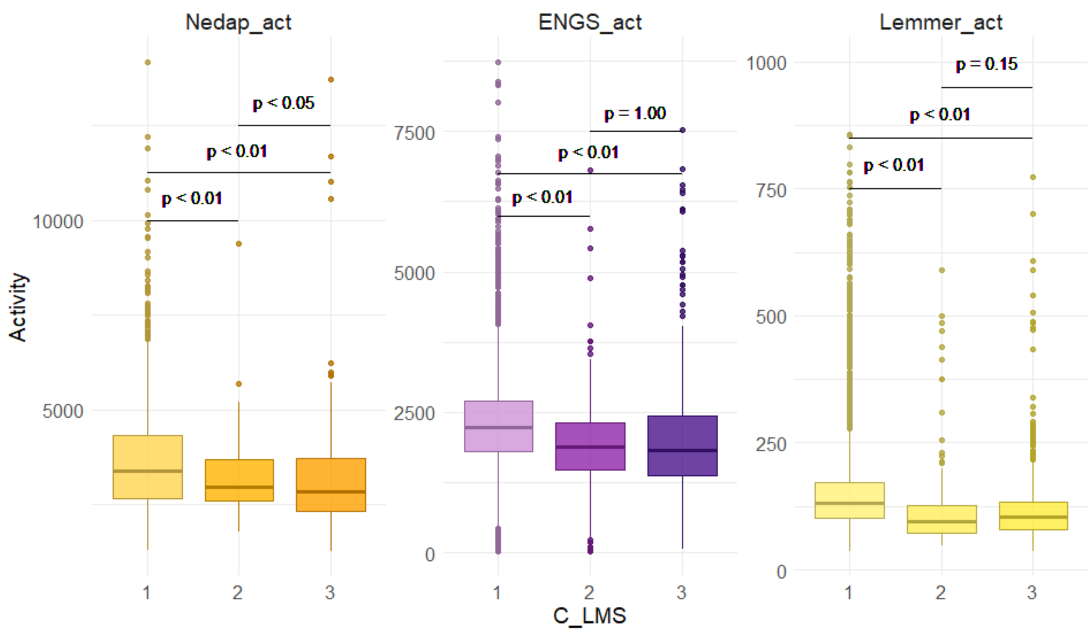


Figure 53: Activity measured by pedometers from Nedap, ENGS and Lemmer-Fullwood and grouped by the corrected locomotion score (C_LMS)

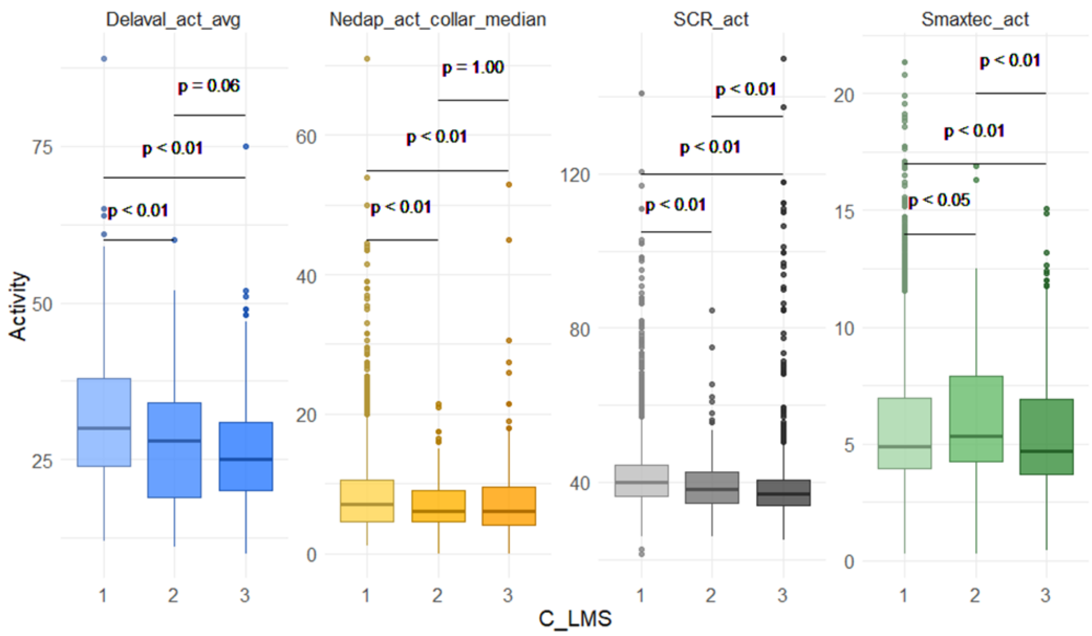


Figure 54: Activity measured by collars from DeLaval, Nedap and SCR and by boluses from smaXtec grouped by the corrected locomotion score (C_LMS)

4.5.9 Body temperature

The parameter *Smaxtec_normal_temp_median* rose with increasing C_LMS values (ρ = 0.17). The highest temperatures occurred in the C_LMS2 group, as displayed in Figure 55. Most of the other variables regarding the body temperature and the body temperature without the drink cycles measured by smaXtec also showed a positive correlation with the C_LMS, except for *Smaxtec_temp_min* (ρ = -0.08), which also resulted in an OR below 1 in contrast to the positive associations displayed by the calculated OR of the other parameters. *Smaxtec_temp_med* was the only parameter not demonstrating statistically significant differences in all groups, more precisely between C_LMS2 and C_LMS3.

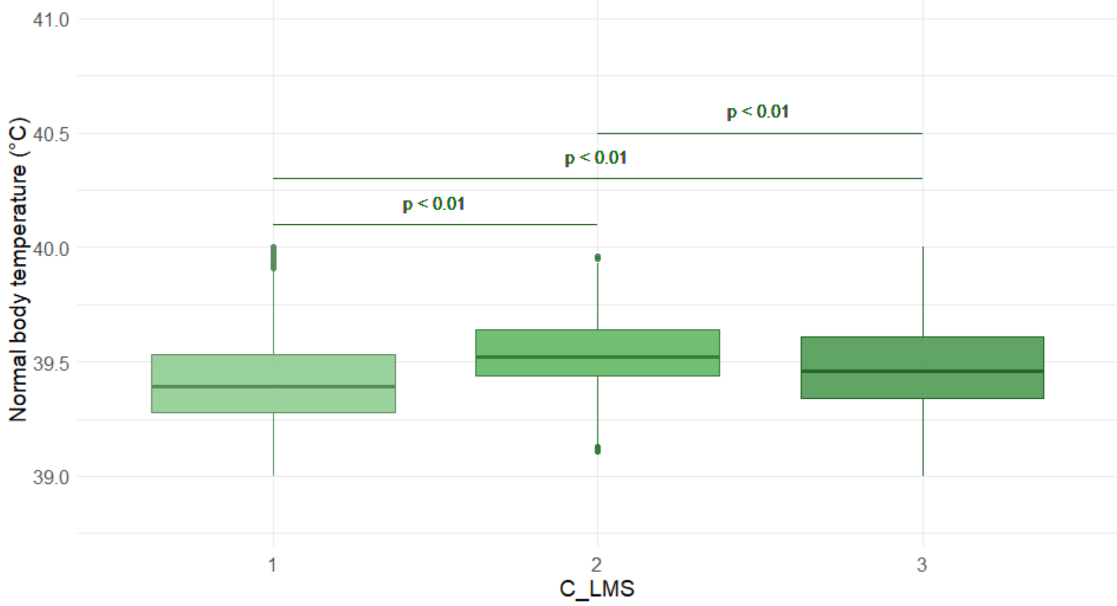


Figure 55: Normal body temperature recorded by smaXtec boluses and grouped by the corrected locomotion score (C_LMS)

In Figure 56, the decrease in temperature due to drinking cycles in the different C_LMS groups was compared by analysing the difference between *Smaxtec_temp_without_drink_cycles_median* and *Smaxtec_temp_median*. A significant distinction was notably evident between all C_LMS groups, as the temperature difference increased in C_LMS2 cows and decreased again in the C_LMS3 group to the lowest level.

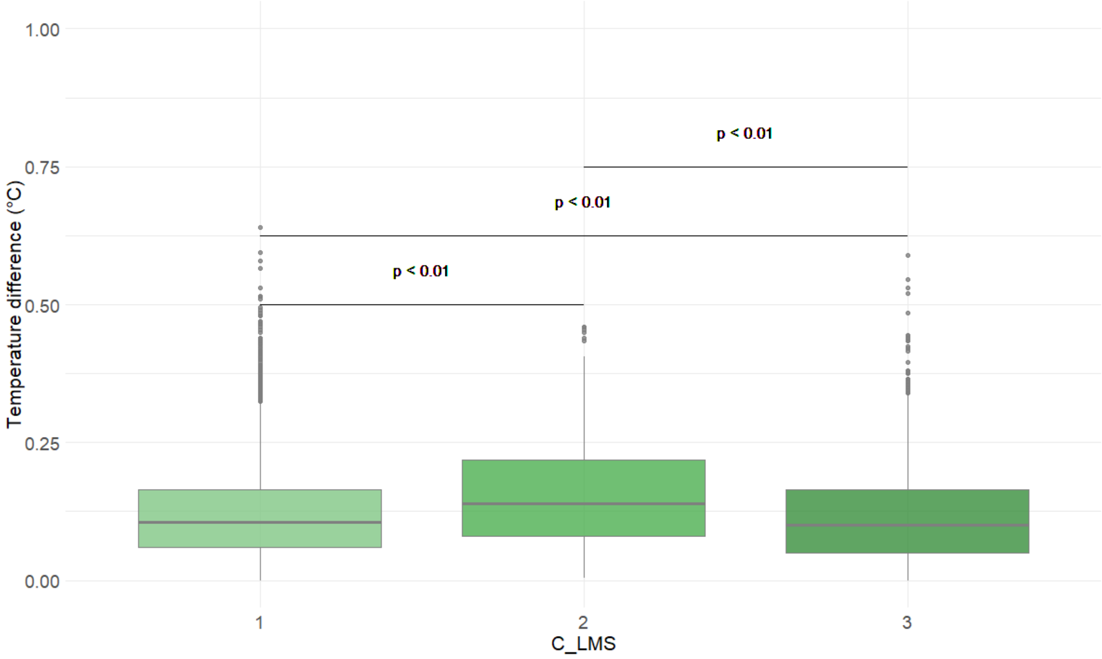


Figure 56: Calculated body temperature difference (*Smaxtec_temp_without_drink_cycles_median* - *Smaxtec_temp_median*) grouped by corrected locomotion score (C_LMS) to quantify the temperature drop induced by drinking

4.5.10 Climate

According to data by smaXtec, C_LMS2 cows were observed at higher temperatures and THI, whereas C_LMS3 cows were noted at lower temperatures and THI. At the weather stations, statistically significant decreases were noted in the C_LMS3 group, whereas all temperature parameters and the THI recorded by the weather stations did not demonstrate a statistically significant difference between C_LMS1 and C_LMS2. They also showed a negative correlation and a protective effect according to the OR results. The temperature and THI values measured by smaXtec displayed the same negative trend except for the minimum values, which showed no correlation at all. The humidity data recorded by smaXtec and the weather stations indicated an increase with increasing C_LMS and resulted in odds ratios greater than 1, except for the maximum humidity, which appeared to be not significant in the OR analysis. The remaining parameters from the weather stations also exhibited either non-significant differences, marginal correlations or no significant associations in the OR analysis. The manually created parameter *Season* displayed a positive correlation ($\rho = 0.02$) with the C_LMS3, as can be seen in Figure 57, as the distribution of LMS3 detections was higher in winter (19.0%) and autumn (17.5%) than in spring (16.6%) or summer (14.2%). Statistically significant differences could be observed between C_LMS1 and C_LMS3.

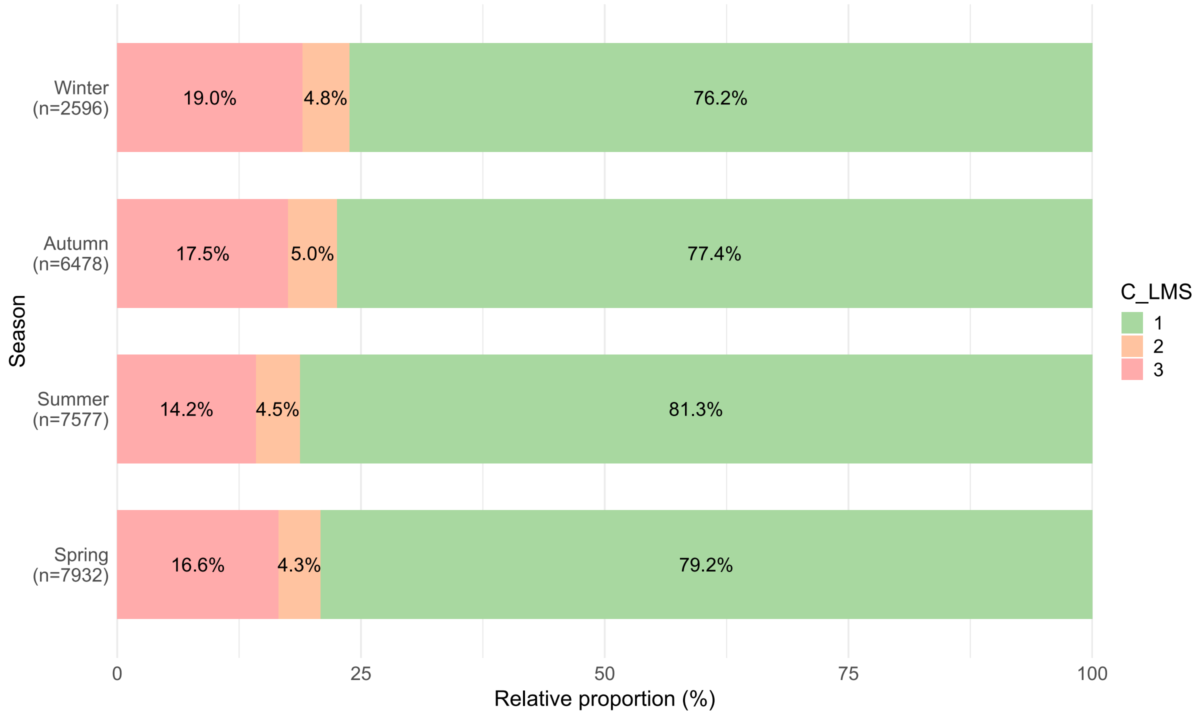


Figure 57: Relative proportion of the corrected locomotion score (C_LMS) by season and the number of n assessments recorded per season

4.6 Farm-level comparison: Differences in variables between corrected locomotion score groups

The differences in variables between the project farms were also investigated. Table 26 presents the results of the Kruskal-Wallis test, indicating whether there are significant differences between the C_LMS groups. Due to the large number of parameters, this table was restricted to those parameters collected on more than one farm and for which the calculated significance varied between the individual farms. In the same manner, the Spearman's rank correlations are presented in Table 65 and the odds ratios are displayed in Table 66 in the appendices.

Table 26: Reduced results of the differences between the C_LMS groups divided by farm, displaying only the parameters varying between the different farms (/ = not recoded on that farm) (parameters explained in Table 33)

Parameter	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
Body_weight	<0.01	/	/	/	/	/	/	>0.05
Concentrated_feed_ intake	<0.01	<0.01	<0.01	<0.05	<0.01	>0.05	<0.01	<0.01
Days_in_milk	<0.01	>0.05	<0.05	<0.01	<0.01	<0.01	<0.01	<0.01
GSC	>0.05	<0.01	<0.01	<0.01	<0.01	<0.05	>0.05	<0.01
Lactation_number	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	>0.05	<0.05
Lemmer_get_ups	/	/	/	/	>0.05	/	<0.01	/
LKV_fat	<0.01	<0.01	>0.05	>0.05	>0.05	<0.01	<0.01	>0.05
LKV_fat_protein_ ratio	<0.01	<0.01	>0.05	<0.01	<0.05	<0.01	<0.01	<0.01
LKV_lactose	<0.01	<0.01	>0.05	<0.05	>0.05	<0.01	>0.05	<0.01

Parameter	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
LKV_somatic_cell_count	>0.05	<0.01	<0.01	<0.01	>0.05	<0.01	<0.01	<0.05
LKV_urea	<0.01	<0.01	<0.01	>0.05	<0.05	<0.01	<0.01	<0.01
Maximum_milking_interval	>0.05	<0.01	>0.05	<0.01	<0.01	<0.05	<0.01	<0.01
MDi	<0.01	/	/	/	/	>0.05	/	/
Milkings	>0.05	<0.01	>0.05	<0.01	<0.01	<0.01	<0.01	<0.01
Robot_conduct	<0.01	/	/	/	<0.01	<0.01	>0.05	/
Robot_daily_milk_yield	<0.01	<0.01	<0.01	<0.01	<0.01	>0.05	<0.01	<0.05
Robot_effect_scc	/	<0.01	<0.01	>0.05	/	/	/	/
Robot_fat	/	<0.01	<0.01	<0.01	<0.01	/	<0.01	>0.05
Robot_lactose	/	<0.01	>0.05	<0.01	>0.05	/	>0.05	<0.01
Robot_milk_yield_in_last_lactation	/	<0.01	<0.01	>0.05	<0.01	<0.01	<0.01	<0.01
Robot_protein	/	<0.05	<0.01	<0.01	>0.05	/	<0.01	>0.05
Robot_somatic_cell_count	/	<0.01	<0.01	>0.05	/	/	/	/
SCR_act_day_night	<0.01	/	>0.05	<0.01	/	/	/	<0.01
SCR_heat_probability	/	/	>0.05	<0.05	/	/	/	>0.05
Smaxtec_act_day_night	<0.01	/	<0.01	/	/	/	>0.05	/
Smaxtec_climate_hum_min	>0.05	/	>0.05	/	/	/	<0.01	/
Smaxtec_climate_hum_median	<0.01	/	>0.05	/	/	/	<0.01	/
Smaxtec_climate_hum_max	<0.01	/	>0.05	/	/	/	<0.01	/
Smaxtec_climate_temp_min	<0.01	/	<0.01	/	/	/	>0.05	/
Smaxtec_thi_min	<0.01	/	<0.01	/	/	/	>0.05	/
WS_global_rad_max	<0.01	<0.01	>0.05	/	/	/	/	/
WS_rain_max	>0.05	<0.05	<0.05	/	/	/	/	/
WS_rel_hum_max	<0.05	>0.05	<0.05	/	/	/	/	/
WS_wind_velocity_max	<0.01	>0.05	<0.01	/	/	/	/	/
WS_wind_velocity_min	>0.05	<0.05	<0.01	/	/	/	/	/

4.7 Correlations between automatically recorded parameters

Spearman's rank correlation coefficient was computed for all combinations of the automatically recorded data, resulting in a correlation matrix. Due to its extensive size, only parameters with correlations above 0.4 were considered. The corresponding table was further streamlined for clarity by initially eliminating parameter combinations that were derived from one another, like WS_thi_median from WS_temperature_median. Furthermore, all rows corresponding to the same parameter, whether from the same sensor or different sensors, were excluded. The corresponding correlation table can be found in the appendices (Table 67). Parameter pairs demonstrating a distinct and strong direct influence on each other, such as days in milk and milk yield, might be included in the table, along with parameter pairs where the relationship is less evident.

Furthermore, particular emphasis was placed on parameters categorised under distinct general parameter categories that nonetheless exhibit a strong correlation and the highest correlation coefficient observed for these relationships was documented in Table 27.

Table 27: Highest correlation results between different categories of automatically recorded parameters

Parameter 1	Parameter 2	Correlation
Milking temperature	Climate	0.67
Days in milk	Milk contents	0.57
Feeding behaviour	Activity	0.56
Feeding behaviour	Climate	0.54
Activity	Climate	0.50
Milking temperature	Body temperature	0.49
Lactation number	Feeding behaviour	0.48
Milk contents	Milk yield	0.47
Body weight	Feeding behaviour	0.46
Milking temperature	Rumination	0.42
Body temperature	Climate	0.42
Milk contents	Concentrated feed intake	0.41
Milk yield	Feeding behaviour	0.41
Body weight	Activity	0.41
Lying behaviour	Body temperature	0.41

5. Multivariate analysis

5.1 Generalised linear mixed models

The unadjusted ICC, calculated without incorporating any fixed effects, was 0.006 for Farm and 0.581 for FCN. Subsequently, the parameters that could be measured across all farms were included in the model as fixed effects, and the adjusted ICC was calculated. The adjusted ICC resulted in 0.006 for Farm and 0.639 for FCN. Based on these results, only the variable FCN was considered as a random effect in the subsequent models.

5.1.1 Performance data

The first model was centred on performance data, which could be collected on all eight project farms. The performance data included the breed, lactation number, lactation status, results of the milk performance test, milk yield recorded by LKV and the milking robot and all additional milk-related parameters recorded by the milking robot. The *LKV_daily_milk_yield* was included as a random slope in the models.

The best-performing model with C_LMS as the dependent variable contained the following predictors:

$$Claw\ health\ status_c \sim LKV\_lactose + Milkings + Days\_in\_milk \\ + Lactation\_number : LKV\_protein + (LKV\_daily\_milk\_yield \mid FCN)$$

Model 1: Best performing model with performance data from all farms and the corrected LMS as outcome variable

The mean area under the curve (AUC) was 0.98 on the training data with a 95%-confidence interval (CI) of 0.981 to 0.984, the specificity (SP) was 0.91 (CI: 0.90, 0.91) and the sensitivity (SN) was 0.96 (CI: 0.96, 0.97). On the test data, the model yielded an AUC of 0.59 (CI: 0.56, 0.62), an SP of 0.75 (CI: 0.73, 0.77) and an SN of 0.47 (CI:0.42, 0.51). Further reduction of parameters could not reduce overfitting indicated by the difference in results between training and test data sets. The model for non-corrected LMS3 as the outcome variable was structured very similarly, including only the lactation number as an additional parameter and *LKV_protein* instead of *LKV_lactose*:

$$\begin{aligned} Claw\ health\ status_n \sim\ & LKV\_protein + Milkings + Days\_in\_milk \\ & + Lactation\_number{:}LKV\_protein + Lactation\_number \\ & + (LKV\_daily\_milk\_yield \mid FCN) \end{aligned}$$

Model 2: Best performing model with performance data from all farms and non-corrected LMS as outcome variable

In this analysis, the achieved results were also significantly higher in the training dataset 0.98 (CI: 0.98, 0.99) compared to the test dataset 0.60 (CI: 0.56, 0.64), with a sensitivity of 0.99 (CI: 0.98, 1.00) in the training set and 0.42 (CI: 0.35, 0.49) in the test set, and a specificity of 0.92 (CI: 0.92, 0.93) in the training set and 0.78 (CI: 0.77, 0.80) in the test set (Figure 58).

The other performance parameters, which could not be uniformly recorded across all farms, were analysed afterwards using partial datasets with data from one or more farms, but all of these regression models performed worse than Model 1 and Model 2.

5.1.2 Activity data

In the following step, the models were expanded to include the average daily activity in addition to the performance parameters, as this was the only behavioural variable available on all eight farms. If the activity was recorded by multiple sensors on a farm, the parameter with the fewest missing values was selected. The C_LMS3 model included four fixed effects, of which one was an interaction parameter, and two random effects and did not show any noticeable improvement compared to Model 1:

$$\begin{aligned} Claw\ health\ status_c \sim\ & Maximum\_milking\_interval + Days\_in\_milk + Activity \\ & + Lactation\_number{:}Activity + (LKV\_daily\_milk\_yield \mid FCN) \end{aligned}$$

Model 3: Expansion of Model 1 with added activity parameters

The AUC for the training dataset was 0.99 (CI: 0.98, 0.99), with an SP of 0.91 (CI: 0.91, 0.92) and an SN of 0.97 (CI: 0.97, 0.97). For the test dataset, the AUC was 0.60 (CI: 0.57, 0.63) with a specificity of 0.64 (CI: 0.62, 0.66) and a sensitivity of 0.56 (CI: 0.52, 0.61).

In contrast, the best LMS3 model included *Days_in_milk* as an additional random slope and added the predictor *LKV_protein*:

$$\begin{aligned} Claw\ health\ status_n \sim\ & LKV\_protein + Maximum\_milking\_interval + Activity \\ & + Activity{:}Lactation\_number + (Days\_in\_milk \\ & + LKV\_daily\_milk\_yield \mid FCN) \end{aligned}$$

Model 4: Expansion of Model 2 with added activity parameters

It performed better than Model 2 with an AUC of 0.70 (CI: 0.65, 0.74) on the test data, with a SN of 0.85 (CI: 0.77, 0.90) and a SP of 0.53 (CI: 0.51, 0.55) (Training: AUC (0.99), SP (0.96), SN (0.99).

5.1.3 Performance, activity and one additional parameter class

During further analysis, an additional class of parameters was incorporated in the regression models alongside the performance parameters. The models were then analysed both with and without activity as an additional parameter. Since all models with activity showed better results, the predictor activity was retained in the model. Depending on the type of parameter, the models were tested on the data of the corresponding farm, where the respective parameters could be collected. The performance of the best models is shown in Table 28 for C_LMS as the dependent variable and in Table 29 for the non-corrected LMS as the dependent variable. For the feeding parameter class, an additional model was evaluated using data from RF1, as this farm provided a substantially larger dataset on feeding behaviour compared to the other farms.

Table 28: Best-performing regression models with C_LMS as the dependent variable, including performance, activity and one additional parameter class. The model formulas can be found in the appendices (AUC = Area under the curve, SN = Sensitivity, SP = Specificity)

Variables	Best model	Training			Test			Farms
		AUC	SN	SP	AUC	SN	SP	
Body weight and BCS	Model 7	0.98 (CI: 0.98, 0.99)	0.94 (CI: 0.91, 0.96)	0.91 (CI: 0.90, 0.93)	0.75 (CI: 0.68, 0.83)	0.78 (CI: 0.64, 0.88)	0.69 (CI: 0.64, 0.74)	RF1
Lying	Model 8	0.99 (CI: 0.99, 0.99)	0.97 (CI: 0.96, 0.98)	0.94 (CI: 0.93, 0.95)	0.66 (CI: 0.63, 0.69)	0.68 (CI: 0.63, 0.73)	0.61 (CI: 0.59, 0.63)	RF1, RF3, CDF2, CDF4
Rumination	Model 9	0.98 (CI: 0.98, 0.98)	0.98 (CI: 0.97, 0.98)	0.90 (CI: 0.90, 0.91)	0.65 (CI: 0.63, 0.67)	0.66 (CI: 0.63, 0.70)	0.58 (CI: 0.56, 0.60)	RF1, RF2, RF3, CDF1, CDF4, CDF5
Feeding	Model 10	0.98 (CI: 0.97, 0.98)	0.97 (CI: 0.96, 0.98)	0.89 (CI: 0.88, 0.90)	0.67 (CI: 0.64, 0.70)	0.63 (CI: 0.57, 0.68)	0.66 (CI: 0.64, 0.69)	RF1, RF2, RF3
Feeding	Model 11	0.97 (CI: 0.97, 0.98)	0.95 (CI: 0.93, 0.97)	0.89 (CI: 0.88, 0.91)	0.87 (CI: 0.84, 0.91)	0.86 (CI: 0.76, 0.93)	0.72 (CI: 0.68, 0.77)	RF1
Body temperature	Model 12	0.99 (CI: 0.99, 0.99)	0.98 (CI: 0.97, 0.99)	0.95 (CI: 0.94, 0.96)	0.66 (CI: 0.60, 0.71)	0.55 (CI: 0.46, 0.65)	0.75 (CI: 0.72, 0.78)	RF1, RF3, CDF4
Climate	Model 13	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.97, 1.00)	0.95 (CI: 0.94, 0.96)	0.75 (CI: 0.71, 0.79)	0.71 (CI: 0.63, 0.77)	0.77 (CI: 0.72, 0.81)	RF1, RF2, RF3

Table 29: Best-performing regression models with LMS as the dependent variable, including performance, activity and one additional parameter class. The model formulas can be found in the appendices (AUC = Area under the curve, SN = Sensitivity, SP = Specificity)

Variables	Best model	Training			Test			Farms
		AUC	SN	SP	AUC	SN	SP	
Body weight and BCS	Model 14	0.99 (CI: 0.98, 0.99)	0.97 (CI: 0.90, 1.00)	0.95 (CI: 0.95, 0.96)	0.67 (CI: 0.60, 0.74)	0.27 (CI: 0.17, 0.40)	0.47 (CI: 0.42, 0.52)	RF1
Lying	Model 15	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.98, 1.00)	0.95 (CI: 0.95, 0.96)	0.78 (CI: 0.72, 0.84)	0.78 (CI: 0.65, 0.88)	0.72 (CI: 0.70, 0.74)	RF1, RF3, CDF2, CDF4
Rumination	Model 16	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.98, 1.00)	0.95 (CI: 0.94, 0.95)	0.70 (CI:0.66, 0.75)	0.69 (CI: 0.60, 0.76)	0.65 (CI: 0.63, 0.67)	RF1, RF2, RF3, CDF1, CDF4, CDF5
Feeding	Model 17	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.97, 1.00)	0.94 (CI: 0.93, 0.94)	0.80 (CI: 0.72, 0.88)	0.71 (CI: 0.54, 0.85)	0.83 (CI: 0.81, 0.85)	RF1, RF2, RF3
Feeding	Model 18	0.99 (CI: 0.99, 0.99)	0.98 (CI: 0.94, 1.00)	0.96 (CI: 0.95, 0.96)	0.85 (CI: 0.77, 0.94)	0.89 (CI: 0.67, 0.99)	0.66 (CI: 0.62, 0.70)	RF1
Body temperature	Model 19	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.97, 1.00)	0.94 (CI: 0.94, 0.95)	0.77 (CI: 0.73, 0.82)	0.88 (CI: 0.77, 0.95)	0.61 (CI: 0.58, 0.64)	RF1, RF3, CDF4
Climate	Model 20	1.00 (CI: 0.99, 1.00)	0.50 (CI: 0.44, 0.56)	0.97 (CI: 0.96, 0.97)	0.73 (CI: 0.64, 0.83)	0.73 (CI: 0.50, 0.89)	0.71 (CI: 0.67, 0.74)	RF1, RF2, RF3

5.1.4 Performance, activity and two additional parameter classes

In the subsequent analysis, two parameter classes were added to both activity and performance data. Only the models that demonstrated enhanced performance compared to models in Table 28 and Table 29 were included in the final evaluation. These models are detailed in Table 30 with C_LMS as the dependent variable and in Table 31 with LMS as the dependent variable.

Table 30: Best-performing regression models with C_LMS as the dependent variable, including performance, activity and two additional parameter classes. Only models surpassing the performance of corresponding single additional parameter class models are included. The model formulas can be found in the appendices (AUC = Area under the curve, SN = Sensitivity, SP = Specificity)

Variables	Best model	Training			Test			Farms
		AUC	SN	SP	AUC	SN	SP	
Lying, Body temperature	Model 21	0.99 (CI: 0.99, 0.99)	0.96 (CI: 0.94, 0.98)	0.95 (CI: 0.94, 0.96)	0.71 (CI: 0.67, 0.75)	0.85 (CI: 0.78, 0.91)	0.57 (CI: 0.53, 0.60)	RF1, RF3, CDF4
Feeding, BCS	Model 22	0.98 (CI: 0.98, 0.99)	0.95 (0.92, 0.97)	0.94 (0.93, 0.95)	0.90 (CI: 0.86, 0.94)	0.89 (CI: 0.77, 0.96)	0.82 (CI: 0.76, 0.88)	RF1
Feeding, Lying	Model 23	0.97 (CI: 0.96, 0.98)	0.95 (CI: 0.92, 0.97)	0.88 (CI: 0.87, 0.89)	0.91 (CI: 0.88, 0.95)	0.79 (CI: 0.69, 0.88)	0.88 (CI: 0.84, 0.91)	RF1
Feeding, Rumination	Model 24	0.99 (CI: 0.98, 0.99)	0.96 (CI: 0.94, 0.97)	0.91 (CI: 0.90, 0.92)	0.68 (CI: 0.64, 0.73)	0.70 (CI: 0.63, 0.76)	0.76 (CI: 0.73, 0.79)	RF1, RF2, RF3
Body temperature, Rumination	Model 25	0.99 (CI: 0.99, 0.99)	0.96 (CI: 0.94, 0.97)	0.95 (CI: 0.94, 0.96)	0.79 (CI: 0.75, 0.83)	0.68 (CI: 0.58, 0.77)	0.77 (CI: 0.74, 0.80)	RF1, RF3, CDF4

Table 31: Best-performing regression models with LMS as the dependent variable, including performance, activity and two additional parameter classes. Only models surpassing the performance of corresponding single additional parameter class models are included (AUC = Area under the curve, SN = Sensitivity, SP = Specificity)

Variables	Best model	Training			Test			Farms
		AUC	SN	SP	AUC	SN	SP	
Lying, Body temperature	Model 26	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.97, 1.00)	0.96 (CI: 0.95, 0.96)	0.82 (CI: 0.76, 0.87)	0.72 (CI: 0.61, 0.81)	0.80 (CI: 0.77, 0.83)	RF1, RF3, CDF4
Feeding, Lying	Model 27	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.96, 1.00)	0.95 (CI: 0.94, 0.96)	0.86 (CI: 0.81, 0.90)	0.84 (CI: 0.70, 0.93)	0.72 (CI: 0.69, 0.75)	RF1, RF3
Feeding, Lying	Model 28	0.99 (CI: 0.99, 0.99)	0.99 (CI: 0.96, 1.00)	0.96 (CI: 0.96, 0.97)	0.93 (CI: 0.86, 0.99)	0.89 (CI: 0.67, 0.99)	0.86 (CI: 0.83, 0.89)	RF1
Feeding, Rumination	Model 29	0.98 (CI: 0.98, 0.99)	0.98 (CI: 0.95, 0.99)	0.93 (CI: 0.93, 0.94)	0.77 (CI: 0.70, 0.84)	0.77 (CI: 0.61, 0.88)	0.71 (CI: 0.68, 0.73)	RF1, RF2, RF3

5.1.5 Performance, activity and three additional parameter classes

Only the best model for each of C_LMS and non-corrected LMS, including more than one farm as dependent variables, is presented in this context, except those that were developed solely based on the data of RF1 using the more detailed data on feeding behaviour.

The best C_LMS model included the parameter classes feeding, body temperature and climate, which could be recorded on RF1 and RF3, besides activity and performance, and achieved an AUC of 0.82 (CI: 0.77, 0.86) with an SN of 0.84 (0.75, 0.91) and an SP of 0.71 (0.65, 0.77) on the test data (Training: AUC (0.98), SN (0.99), SP (0.90)). The model contained the following predictors:

$$\begin{aligned} Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ LKV\_daily\_milk\_yield\ +\ Feeding \\ & +\ Smaxtec\_temp\_normal\_median\ +\ LKV\_daily\_milk\_yield{:}\ Season \\ & +\ Activity{:}\ LKV\_daily\_milk\_yield \\ & +\ +\ (Smaxtec\_temp\_without\_drink\_cycles\_median \mid FCN) \end{aligned}$$

Model 5: Best model for the corrected locomotion score (C_LMS) on different farms

In contrast, the best LMS model included the classes lying, body temperature and climate, which could be recorded on RF1, RF3 and CDF4, besides activity and performance, and presented as:

$$\begin{aligned} Claw\ health\ status_n \sim\ & Maximum\_milking\_interval\ +\ Lying \\ & +\ Activity{:}\ Lactation\_number\ LKV\_daily\_milk\_yield{:}\ Season \\ & +\ (Smaxtec\_temp\_without\_drink\_cycles\_median \mid FCN) \end{aligned}$$

Model 6: Best model for the non-corrected locomotion score (LMS) on different farms

The AUC for Model 6 was 0.89 (CI: 0.84, 0.95) on the test data with a SN of 0.83 (CI: 0.73, 0.90) and a SP of 0.90 (CI: 0.88, 0.92) and 0.99 (CI: 0.99, 0.99) on the training data with a SN of 0.98 (0.95, 1.00) and a SP of 0.95 (CI: 0.95, 0.96) (Figure 58).

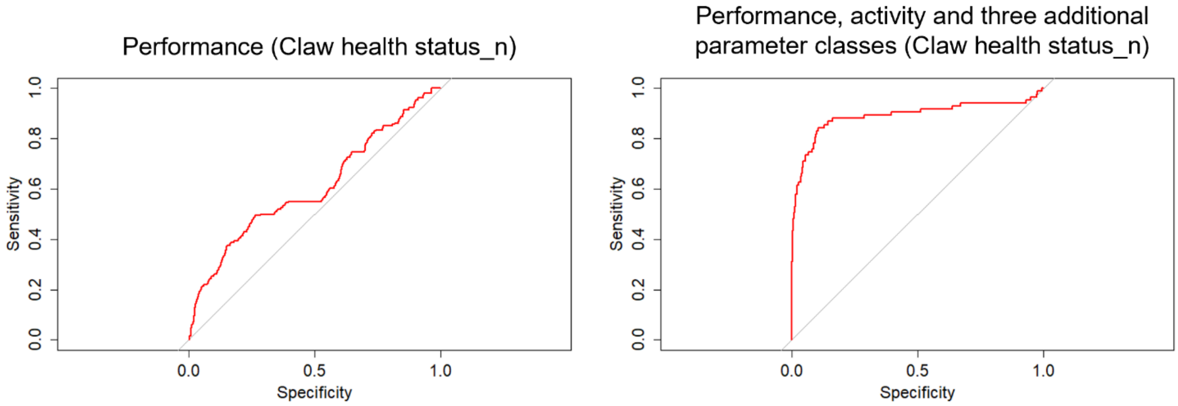


Figure 58: Receiver Operating Characteristic (ROC) curve of the best performance data model (Model 2) and the overall best model tested across multiple farms (Model 6)

VI. Discussion

1. Claw health

1.1 Locomotion scoring

The total number of locomotion scores varied significantly from one farm to another. This variation was partly due to differences in herd size across farms, but more notably due to the varying number of claw trimming dates conducted on the farms during the data collection period, as the frequency of claw trimming was set by each respective farm manager according to their preferences. Furthermore, some claw trimming dates could not be used due to camera failures as already mentioned in chapter V.1.1. The decision to conduct locomotion scoring based on video footage was made for logistical reasons, as the study included different farms across Bavaria and regular locomotion scoring on-site would have been time-consuming. Additionally, it reduces the impact on cow behaviour compared to scoring performed in the cow's direct presence (Lorenzini, 2019) and Schlageter-Tello et al. (2015a) observed a higher reliability of video locomotion scoring in experienced raters compared to live scoring. However, this approach comes with the inherent risk of data loss due to power outages, transmission errors, and hardware failures. The proper storage and preservation of video material on the NAS was found to be especially prone to issues in this study. Implementing more frequent automatic backups and integrating them with a cloud storage system could help to minimise the risk of data loss.

The detected lameness prevalence per farm on the day before claw trimming ranged from 1.9% to 10% and was lower than the figures reported in current studies (Table 1). However, this assessment only considered cows classified with an LMS3, indicating an irregular gait. The variability in reported prevalence rates across different studies can be dependent on the used locomotion score and the specific definition of lameness. For instance, Jensen et al. (2022) used the locomotion score system developed by Sprecher et al. (1997) to identify and count all cows with a score of 3 or higher, which signifies an arched back and shortened strides, in order to evaluate the prevalence of lameness. In contrast, Griffiths et al. (2018) applied a four-point scoring system and classified all cows with a score of 2 or above, indicating shortened strides and a noticeably affected limb, as lame. If the relatively high proportion of cows categorised as unsound (LMS2) (19.9%-26.7%) in the current study were included in the prevalence estimates, the reported prevalence would have been closer to 25%-36.7% and therefore would fall within the prevalence values presented in Table 1. The prevalence of lameness varied significantly across the farms, likely due to various factors contributing to lameness (II.2.3) that may be more pronounced on some farms than others. It is also essential to consider that the number of prevalence assessments differed between farms according to the count of claw trimmings, which may affect the comparison. LMS3 assessments varied not only from farm to farm but also within the same farm between the different claw trimming sessions. This could be attributed to seasonal climatic fluctuations, changes in management or husbandry practices, as well as adjustments in claw trimming procedures. On RF1, the claw trimmer changed after the initial two trimming dates, potentially resulting in the observed gradual reduction of LMS3 during the subsequent sessions. The relative share of locomotion scores documented during the whole data collection period was in the same range with 3.1% to 6.9% LMS3 and 10.9% to 20.09% LMS2 depending on the farm.

Regarding lameness development, all cases of lameness developed within two weeks, with the longest one taking 13 days. The median time between the last LMS1 and the first LMS3 was three days, which is slightly less than the median of five days observed by Lorenzini (2019). 61.8% of the cases developed in a short period of only one to three days, which could be due to the approach to use the latest LMS1 and the first LMS3. Previous transitions between LMS1 and LMS2 and back were not considered in this analysis, which may have prevented the detection of a potentially longer lameness development period with alternating better and worse days. Additionally, the sample size of 68 observations used to assess lameness development was relatively small. This limitation was due to restricting the data to the three weeks prior to claw trimming, resulting in many cows becoming lame or unsound before the start of the data collection period and remaining at LMS2 or LMS3 until the claw trimming date. Another reason could be that different claw diseases show different lameness progression periods. In this study, cows experiencing a prolonged lameness development phase were more likely to exhibit conditions such as WLD, WLA, or SU. Conversely, in cases where lameness emerged more rapidly, within one to three days, the lesions were more frequently associated with DD, IH or DS. This aligns with the analysis of farm-specific lameness development periods, where CDF1, with a median of nine days, significantly differs from the other farms with a median of one to four days. CDF1 showed an increased occurrence of WLF and WLA and no cases of DD at all and thus highlights possible differences in the duration of lameness development depending on the type of claw disease.

1.2 Pain test

The pain test was conducted to identify animals that, despite showing no visible signs, were still experiencing pain. The overall distribution of positive pain test results showed RF2 having the highest rate at 12.4%, followed by RF3 at 6.6% and RF1 at 6%. Out of the total aggregated value of 226 positive pain tests, no findings could be detected in 53 (23.5%) of these positive detections. Reflecting the overall distribution, most of the positive pain tests with no detectable findings were found on the research farms, accounting for 44 cases.

Claw diseases, such as sole haemorrhages, generally manifest as visible lesions 6 to 8 weeks following the onset of inflammation in the corium (Kofler, 2014). As a result, pain responses might be present before any clinical findings can be detected by the observer. One alternative reason for the high proportion of positive pain tests with no detectable findings on research farms could be that the initial three claw trimming dates, during which findings were recorded only by the claw trimmers, occurred on these farms. This could have resulted in incomplete documentation of findings. Moreover, other external stimuli, including the claw trimming conducted simultaneously by the claw trimmers on another foot, might have resulted in the cow exhibiting flinching behaviour, which could have been incorrectly interpreted as a pain response. Particularly on RF1, where two claw trimming chutes in combination with multiple claw trimmers were used in the initial two claw trimming sessions, the procedure was accompanied by increased ambient noise levels, which may have induced alternative defensive reactions in the respective cow. Additionally, as experience was gained over time, it is likely that distinguishing between pain responses and other involuntary movements became more accurate for the examiner in subsequent assessments. For future pain assessments, it is recommended that the examiner conducts multiple test runs in different environments beforehand. Furthermore, a calm ambient setting should be ensured, and simultaneous claw trimming on the other legs should be avoided during the pain assessment. The research farms also predominantly used rubber mats on their floors, while the majority of the commercial dairy farms employed concrete and slatted flooring without rubber mats. Manure generally drains better on slatted floors compared to solid floors (Fjeldaas et al., 2011) and concrete surfaces tend to retain less moisture than rubber flooring (Norberg, 2012). This difference in surface characteristics may have contributed to increased moisture on the walking areas of the research farms, potentially leading to softer claw horn in these settings (Fjeldaas et al., 2011) and therefore increased sensitivity to the pain tests.

Analysis of the percentage of positive and negative pain test results divided by the different claw diseases indicated that certain conditions were significantly less likely to induce a pain response. Specifically, in 80% or more of the cases, cows with any digital dermatitis stages, any kind of sole haemorrhages, WLD, HF, HHE, IH or BU did not exhibit a pain reaction. In contrast, cows with WLA, DS, OLU, SU, IP, TU or TN demonstrated a significantly higher proportion of pain reactions, with 38% or more showing positive pain test results. On the one hand, it is important to note that during the pain assessment with claw pliers, pressure was primarily applied to the wall and sole region. Therefore, lesions located in the bulb area, such as DD or BU, or in the interdigital space, such as IH, might not have led to a defensive reaction as no direct pressure was applied to these specific lesion sites. On the other hand, Tadich et al. (2010) identified distinct effects on locomotion associated with different claw diseases. No changes in locomotion could be observed in cases of DD, HHE, WLF, and SH, while SU, IP and DS were associated with significant gait alterations (Tadich et al., 2010). However, it remained unclear whether these lesions were associated with less pain or if the impact of these lesions could just not be adequately captured by the locomotion score. Holzhauer et al. (2008) observed that cows with DDM2 lesions were significantly more sensitive to palpation compared to other DD stages, but also only in 43% of DDM2 lesions the cows showed a pain response. Furthermore, the stress induced by fixation, like immobilising the cow in the cattle crush, could have potentially contributed to the suppression of a pain response in some cases (Herskin et al., 2004).

Upon examining the pain test in comparison to the locomotion score, it was observed that as the locomotion score increased, the percentage of pain reactions also increased. There was a significant rise from 24.1% positive tests in LMS2 cows to 53.2% positive tests in LMS3 cows. This disparity might be due to the fact that the pain response of cows in the LMS2 category might not be as pronounced or easily triggered as they are in the early stages of lameness development. Additionally, factors associated with LMS2, such as an arched back, can also be seen in other painful conditions such as the foreign body syndrome (Lakhpati et al., 2019) or mastitis.

To enhance the accuracy of pain response in future studies, simultaneous manipulations that may result in false-positive findings should be avoided and direct palpation of the bulb region should be included.

1.3 Growth in the sole centre

The growth in the sole centre was assessed as in the preceding study by Lorenzini (2019) some cows showed a pain reaction or unsound locomotion without displaying visible clinical findings. GSC3 accounted for the largest share of GSC recordings at 64.9%, while GSC2 was observed in only 34.6% of cases and GSC1 was only recorded 24 times. After aggregating the four individual values per cow into a median value, GSC3 made up the largest proportion at 49.3%, followed by GSC2 at 20.5% and GSC2.5 at 17.0%.

The great amount of a more pronounced growth in the sole centre could be explained by the frequency of claw trimming. This was also reflected in the comparison of different farms. CDF1, CDF2 and CDF5 showed the highest levels of GSC3, each exceeding 90%. On CDF1, claw trimming occurred only once a year, on CDF5 twice a year and on CDF2 before the cows were dried off. In contrast, farms with three claw trimming sessions per year, such as RF1, RF2, RF3 and CDF3, demonstrated a significantly more balanced distribution of GSC2 and GSC3. Smith et al. (2007) showed that more frequent claw trimming can be beneficial by observing that cows undergoing claw trimming three times a year, rather than just once, exhibited a 27% reduction in lameness and a 52% decrease in the risk for sole ulcers. Although claw trimming on CDF4 was also performed only twice a year, this farm showed lower GSC3 levels and higher GSC2 levels compared to other farms with fewer claw trimming dates. This might be attributed to differences in the claw trimming techniques employed by the claw trimmers. The sole centre could be trimmed more extensively on this farm compared to others, leading to a longer duration during which the sole centre remained unconsolidated. The type of flooring could also be a factor influencing the growth in the sole centre, as hard surfaces tend to result in increased claw growth, greater wear and decreased sole concavity compared to softer surfaces like rubber mats (Telezhenko, 2007). According to this, although rubber mats result in greater net growth, they also contribute to improved preservation of the sole cavity, which may have reduced the likelihood of GSC on research farms in this study.

The growth in the sole centre was compared with the results of the pain test, revealing that the mean values for those with a positive pain test were lower than those with a negative pain test. Special attention was given to GSC values in cows that had a positive pain test but showed no clinical findings, and this combination showed the lowest values, with a median of 2.3 and an average of 2.4. When GSC was analysed based on LMS, a gradual decrease in GSC was observed as LMS increased. While GSC3 remained the most prevalent across all LMS groups, the relative proportions of GSC2 and GSC3 became more similar in LMS3. Even though the relative share of GSC1.0 to 1.75 was generally very low, it was most pronounced in LMS3. These results might be explained by the study design, which involved collecting GSC data exclusively during the farm claw trimming sessions. As a result, lame animals or those with claw disorders may have been treated in-between these sessions, leading to a reduced GSC in the claws of these animals observed during the farm claw trimming. Specific claw diseases, such as laminitis, could also lead to the formation of inferior-quality and reduced horn (Nuss & Kofler, 2019), potentially resulting in a decreased GSC. Furthermore, the altered weight distribution observed in lame cows (Pastell et al., 2010) may influence horn growth patterns.

1.4 Clinical findings

SHD accounts for the largest share of the clinical findings, making up over 30% of the total findings, followed by DD and WLF. When evaluating individual farms, SHD was the most common disorder, except for CDF2 and CDF5, where WLF was more prevalent. The barn design could have contributed to this distribution, as features such as more edges or tighter corners could potentially favour the occurrence of WLF (Kofler, 2014). CDF1 also exhibited the highest incidence of WLA, with 14 cases documented during the claw trimming date. Moist walking surfaces could have contributed to the softening of claw horn (Rushen et al., 2004), thereby facilitating the penetration of foreign objects or bacteria. Since the barn was newly built in 2020, there might have been instability in the social herd structure and increased stress, leading to rank-related fights among the cows. This could also have resulted in slipping and subsequent injuries to the white line area. Additionally, the presence of a farmyard on CDF1 could have increased the risk of small stones being driven into the white line. High absolute numbers of WLF and WLA were also observed on CDF4, further supporting the theory, as this farm also employed a farmyard. Cows on CDF1, along with CDF4, showed the highest proportion of CSH at over 8%. CSH is often the precursor to SU (Nuss & Kofler, 2019) and CDF4 also exhibited the highest incidence of SU. However, no cases of SU were observed on CDF1. This absence of SU on this farm might be attributed to the fact that the cows on CDF1 were relatively young, with 2.1 lactations on average, while the average on CDF4 was 3.1 lactations. The risk of SU typically increases with age due to the reduced cushioning capacity of the bulb fat pad (Nuss & Kofler, 2019). This may explain why, on CDF1, the CSH lesions had not yet progressed to SU. Additionally, the high numbers of WLF, CSH or SU and sole haemorrhages on CDF1 and CDF4 could be interpreted as symptoms of laminitis, which can arise from a combination of various contributing factors, such as inadequate cow comfort or feeding issues (Nuss & Kofler, 2019). Unlike all other farms, CDF1 did not document a single case of DD. Factors such as genetics, the absence of acquisition of cows from external sources and especially hygiene may have played a significant role in this outcome (Nuss et al., 2019). RF3 had the highest proportion of DDM1 lesions at around 13%, RF2 recorded the highest share of DDM2 lesions at approximately 16% and CDF3 (16%), followed by RF1 (10%), had the most DDM4 lesions. Almost 50 cases of active DDM2 could also be recorded on CDF4 during only two claw trimming sessions. The generally higher incidence of DD cases on the research farms is likely attributable to the increased traffic in the barns due to visitors or educational activities, which can facilitate the introduction of pathogens. CDF3, similar to RF2, demonstrated a relatively high incidence of HHE at the same time, suggesting there might have been a generally moist environment, leading to maceration and entry of pathogens in the bulb area (Nuss et al., 2019). On RF1, the significant reduction in the number of active DDM2 lesions following the second claw trimming might have been due to the change of claw trimmers and the use of CZC for treating all lesions, whereas previously only CTC was used for treatment (Holzhauer et al., 2011). However, some active lesions might have progressed to a chronic stage, which could account for the increased occurrence of DDM4 lesions. RF2 showed an increase in DDM2 cases at the most recent trimming compared to the previous two sessions and RF3 reported a high incidence of DDM1 lesions. These numerous new or recurrent outbreaks of DD could be related to a compromised immune system in the animals due to external factors (Nuss et al., 2019). On CDF3, during the December claw trimming session, there was a significant rise in chronic DD cases compared to the other trimming dates. This could be due to seasonal factors, as winter conditions might lead to a higher risk of infectious claw diseases (Häggman & Juga, 2015) and therefore the healing process for these lesions might be less effective during the winter months. The majority of B were applied to cows on RF2, where also most SAP treatments were administered, primarily due to the high incidence of DDM2 lesions. Most CB were affixed to cows on CDF4 in response to the high prevalence of SU and WLA on this farm.

1.5 Distribution of test scores on individual extremities

The distribution of PT, GSC and the clinical findings across the four extremities was also investigated. For PT, the rate of positive pain reactions was notably higher in the hind feet (13.2%) compared to the front feet (9.8%). When examining the GSC, GSC3 occurred more frequently in the hind claws (over 67% on both left and right) than in the front claws (left 63%, right 61%). The most notable difference was found in the clinical findings, with 61.5% of the findings in the hind feet compared to 28.5% in the front feet. Somers, Schouten et al. (2005) and Sogstad et al. (2005) also reported a higher frequency of findings in the hind claws compared to the front claws, despite the primary weight bearing occurring on the front claws (Sogstad et al., 2005; Van der Tol et al., 2004). However, in comparison to the front claws, the weight distribution in the hind claws is highly uneven, with 80% of the load on the outer and only 20% on the inner claw (Sogstad et al., 2005; Van der Tol et al., 2004). The suspension system in the forelimbs by muscles and tendons may facilitate a more balanced weight distribution compared to the anatomical structures in the hind limb (Muggli et al., 2011; Sogstad et al., 2005).

The positive clinical findings for the hind legs were nearly equally distributed, but PT was more frequently positive in the left hind leg compared to the right. This could be explained by the fact that the PT was often started on the left hind leg, and the cows might have reacted sensitively not only to the affected leg but also to the pain in general. Consequently, they may have shown a pain reaction on the foot tested first, even though the claw disease itself was localised on a different one. Additionally, there could have been a random distribution of claw lesions with more painful findings on the left and fewer painful claw conditions on the right hind feet.

1.6 Validation of the locomotion scoring system

The three-level locomotion score was also validated in this study as, unlike in the previous project, significantly more actual LMS were generated instead of interpolated LMS, allowing for a more accurate validation. The score demonstrated a very high level of agreement in terms of the consistency of multiple scorings carried out by the same observer (intra-rater agreement) with over 90% PA and in terms of the reliability of scoring when compared to other observers (inter-rater agreement) with over 80% PA. According to Landis and Koch (1977), the intra-rater agreement achieved an "almost perfect" level, while the inter-rater agreement was rated as "substantial to almost” perfect and therefore both exceeded the minimum acceptance level of k = 0.6. The results surpassed those reported in the study by Schlageter-Tello et al. (2015b), which examined a five-point locomotion score by Flower and Weary (2006). In that study, the intra-rater agreement was k = 0.77 with a PA of 71.4%, and inter-rater agreement was k = 0.65 with a PA of 57.1%. Schlageter-Tello et al. (2015b) employed the linear weighted kappa method, whereas the present study used quadratic weighted kappa to account for larger deviations more strongly. Additionally, Schlageter-Tello et al. (2015b) involved experienced raters for the locomotion scoring, while Rater 1 in this study had no prior experience with locomotion scoring at the beginning. The study conducted by Gardenier et al. (2021) examined a 4-level locomotion scoring system, where an intra-observer agreement of 72% ($\kappa = 0.74$) and an inter-observer agreement of only 56% ($\kappa = 0.59$) were achieved. In the research by Rutherford et al. (2009), the inter-rater reliability was 67.2% ($\kappa = 0.69$) for a 4-level score but could be increased to 90.5% by reducing the 4 categories to a simple distinction between lame and sound. This indicates that, in comparison to the results of other researchers, the 3-level locomotion score used in this study exhibited notably better inter- and intra-rater reliability, and that reducing the number of scoring levels may enhance comparability. A further reduction of the locomotion score levels was not considered based on the findings of the previous project (Lorenzini, Grimm, Hertle et al., 2021), as a comparison of the different locomotion score groups revealed that most misclassifications occurred in animals with an LMS2 score. These animals could not be clearly assigned to either the LMS1 or LMS3 group, but nevertheless, a clear classification of these animals might be essential for practical purposes, as farmers need to know how to handle each specific case and whether they need to examine and treat the affected animals in the claw trimming chute.

To further validate the locomotion score in terms of its accuracy in reflecting claw lesions, a lesion score was also developed. In an initial analysis of two data sets, comparing lesion scores with locomotion scores from two claw trimming dates each, significant discrepancies were observed, with the PA ranging from 66.4% to 80% (Hertle et al., 2022). It was assumed that these differences may be explained by the fact that the first dataset used findings recorded by the claw trimmers, who might have documented the claw lesions in less detail, whereas the second one was based on the findings by a veterinarian who did not have to trim the claws and could thus concentrate only on documenting the findings (Hertle et al., 2022). But after finishing the locomotion scoring of all the claw trimming sessions, the overall locomotion scores were compared to the lesion scores, revealing only a moderate agreement between them. Significant variation in the level of agreement was also observed between the farms. Specifically, RF2 achieved a PA of only 48.9% (k = 0.24), while CDF2 (PA = 78.9%, k = 0.54) and CDF5 (PA = 69.5%, k = 0.58) showed notably better results. Since only the findings of the claw trimmers were included during the initial claw care trimming on RF2, this supports the hypothesis that these records were not sufficiently detailed to comprehensively reflect claw health. As mentioned before, the first claw trimmings occurred on research farms and initial misinterpretations of pain responses may have resulted in false positive PT outcomes. The especially high rate of positive PT on RF2 indicates that false positives may have distorted the lesion scores on this farm. Additionally, a growing familiarity of the observers with the procedures for conducting pain tests and recording findings may have led to more accurate results in subsequent claw care appointments. The differences in camera angles across farms could also have impacted, for example, the detection of an arched back, making it easier to notice on some farms compared to the others.

The deviations shown in Figure 42 suggest that especially animals with a lesion score (LS) higher than 1 often exhibited a sound locomotion (LMS1). According to this, not all painful or visibly apparent claw diseases might necessarily result in altered locomotion scores. Especially Simmental cattle exhibit a high degree of resilience and may show less pronounced pain responses compared to breeds such as Holstein-Friesians. Indeed, findings from Tadich et al. (2010), where some lesions, such as DD, did not lead to a significant increase in LMS, suggest that a locomotion score alone may not be sufficient to identify all types of claw diseases and their associated pain. Dyer et al. (2007) also reported that in 37.2% of cases, painful lateral claws were present, even though the locomotion score remained unchanged. Thomsen et al. (2012) demonstrated that when distinguishing between horn lesions like SU and skin lesions like DD, horn lesions showed a clearer correlation with the locomotion score. The high prevalence of DDM2 lesions observed at RF2 supports the theory that not all cows with acute digital dermatitis lesions might have altered their gait in this study. Blackie et al. (2013) were able to show that cows with SU are more likely to shorten their steps or adjust their spine, whereas cows with DD showed less of these changes but lifted their legs higher, likely due to the lesions being located on the sole for SU and in the heel area for DD. These specific changes might need to be incorporated into the locomotion score, although visual detection could be challenging. An animal might also have been scored as lame despite no visible findings or pain reactions if the issue was located in the upper leg rather than the claw or if other underlying health conditions were present, which could not be detected during the claw trimmings.

2. Automatically recorded parameters

2.1 General assessment and farm-specific variations

The analysis of the statistical summaries revealed that most of the mean values were within the normal ranges outlined in Table 3. The average values for the BCS (mean: 3.8) and body weight (mean: 741.5) in this study exceeded the mentioned averages in the table. This could be attributed to the fact that the animals in this study were predominantly of the Simmental breed, which have a higher mean live weight and BCS (Rittweg et al., 2023) than Holstein-Friesian cows. Additionally, factors related to breeding and management practices at RF1 might have contributed to higher BCS and body weight. Feeding took place via the weighing troughs on RF1, which resulted in shorter feeding durations and increased feeding pace on this farm. The average number of lying bouts on RF1, which exceeded 17, was notably higher than the average value of 9 to 11 lying bouts reported by Tucker et al. (2021), as well as the averages observed on the other farms. Accordingly, the average duration of each lying bout on RF1 was also lower at 52.6 minutes than the 60-99 minutes average noted in the study by Tucker et al. (2021). Weingut (2017) observed during the validation of these pedometers that more lying bouts were recorded by the pedometers than visually observed, indicating the issue could be related to the measurement of the pedometer. The limited cow-to-feeding-space ratio on RF1, with only 36 weighing troughs available for more than 60 cows, may also have led to these variations in lying behaviour. Other factors that could have influenced the farm-specific lying behaviour include high stocking density (Fregonesi et al., 2007), the design of cubicle surfaces (Tucker et al., 2003) or the relatively high humidity inside the barn (mean: 79.8) (Leliveld et al., 2022).

The average lactation number exhibited only minor variation across farms. CDF1 featured the youngest cows, with an average lactation number of 2.1, while the herds on CDF4 and CDF5 included older cows, with average lactation numbers of 3.1 and 3.2. Total milk yield per lactation varied from 5,955.8 kg on CDF1 to 11,847.4 kg on RF2. Notably, the daily average milk yield on CDF1 was substantially lower at 22.2 kg in the last lactation compared to 31.2 kg in the current lactation. This difference may be attributed to the herd's recent relocation to the new barn, which could have impacted milk production. The average milk temperature was lowest on CDF5, measuring 38.1°C, which significantly differed from the highest average of 39.2°C recorded on RF3. These higher average milk temperatures on RF3 could be explained by a greater number of mastitis cases (Maatje et al., 1992) or higher ambient temperatures (West et al., 2003) on this farm. Accordingly, on RF3, higher average outdoor temperatures were recorded at the weather station (mean: 11.4) compared to the other two farms, which also resulted in a warmer indoor barn climate (mean: 14.4) and, consequently, a higher indoor THI (mean: 57.5). The correlation analysis of the various automated parameters in this study also revealed strong correlation coefficients between milk temperature and ambient temperatures. Both, milk flow and maximum milk flow, exhibited substantial differences across farms. The significantly lower milk flow on the RF1 and CDF3 farms could be attributed to the use of different milking robots and, consequently, different preparation methods for the teats as milking practices could influence the milk flow (Sandrucci et al., 2007). Hogeveen et al. (2001) also found that milk flow decreases with shorter milking intervals, while Sandrucci et al. (2007) demonstrated that cows with a higher number of lactations and with less than 150 days in milk exhibit a stronger milk flow. However, these observations did not show a clear correlation in this study. Concentrate intake varied significantly according to farm-specific rations, ranging from an average of 2.1 kg on CDF4 to 5.6 kg on CDF5. The average feeding duration on RF3 at 270.7 minutes was significantly shorter compared to RF2 at 511.7 minutes. This could be attributed to different feeding management practices; for instance, according to DeVries & Keyserlingk (2005), the timing of feed distribution could influence feed intake durations. Moreover, on RF3, an additional sensor was also attached to the collar and the experience was made that its weight occasionally caused the feed intake sensor to be improperly positioned on the cow's neck, which led to inaccurate recording of feeding times. The higher temperatures on RF3 could also have influenced the results, as according to the Spearman's rank correlation coefficients, the feeding behaviour in this study showed a strong correlation with the climate. In contrast, the cows on RF2, with 271.7 minutes, exhibited a substantially lower average rumination time than on the other four farms, where the average rumination time was approximately 500 minutes. The time spent eating and ruminating can also be influenced by the diet's composition and its physical texture (Beauchemin, 2018). Furthermore, Herskin et al. (2004) demonstrated that cows respond to any stressors by reducing their rumination activity, which suggests that external disturbances may have also played a role in this context. The activity data from the various sensor systems were difficult to compare due to differences in measurement units, such as steps, activity units, or indices. Notable differences within the same sensor across the farms were primarily observed in the activity data collected by smaXtec, where higher values were recorded for RF1 (mean: 6.5) and RF3 (mean: 6.8) compared to the average value of 4.6 on CDF4. In contrast, an analysis of the corresponding pedometer activity values across the farms revealed no significant discrepancies. This could potentially be a sensor-specific issue, possibly due to difficulties in detecting activity due to specific housing conditions or rumen conditions on the farm. All other parameters showed no substantial deviations from one farm to another, which was also evident in the model analysis, where the calculated ICC indicated a low level of parameter variation explained by farm differences.

2.2 Lameness-induced alterations

Analysis revealed that the differences between the 'unsound' and 'lame' groups were more pronounced when examining the automatically recorded parameters by using the locomotion score (LMS), rather than the corrected locomotion score (C_LMS). On the one hand, this phenomenon could be explained by the fact that, with the C_LMS, a greater number of animals were categorised as C_LMS3 despite not showing a distinctly irregular gait but rather showing only features such as an arched back or an exaggerated head bob along with a positive pain response or visible findings. As a result, changes in behaviour and performance in these animals may be less pronounced compared to those with a clearly lame gait, leading to a less distinct separation between the two scoring categories. On the other hand, it is possible that animals classified with LMS2, despite lacking a positive pain response or other diagnostic findings, might already have experienced a subclinical claw health issue that impacted their behaviour at an early stage. This hypothesis is supported by the observation that after the locomotion score was adjusted to C_LMS, the statistical significance of differences between the 'sound' and 'unsound' groups remained relatively stable. Consequently, C_LMS1 and C_LMS2 animals continued to exhibit significant behavioural differences. Weigele et al. (2018) were one of the few who also investigated behavioural changes in moderately lame cows and identified significant deviations in behaviours such as lying patterns, feeding behaviour, and activity levels, even in these cases. Norring et al. (2014) demonstrated that the feeding duration and quantity of feed intake could already begin to decrease in the two weeks before visible gait impairment occurred. Similarly, Mazrier et al. (2006) observed that 45.7% of lame cows exhibited a decline in activity 7 to 10 days prior to the onset of clinical lameness. According to

Van Nuffel et al. (2015), most of the research on lameness detection has been predominantly focused on severely lame animals. As a result, there is a significant gap in knowledge on how behaviour and performance change at the initial stages of lameness, which needs to be further addressed to enable early lameness detection.

2.2.1 Breed

In this study, despite their lower representation on the farms, Holstein Friesian cows exhibited a significantly higher proportion of lameness cases (33%) compared to Simmental cows (16.7%). This aligns with other research, where Holstein cows have been found to be especially prone to certain claw disorders (Baird et al., 2009; Fürmann et al., 2024; Lusa et al., 2020). Simmental cows, conversely, are known for their longevity and higher resistance to diseases when compared with dairy breeds (Kucuk Baykan & Ozcan, 2019).

2.2.2 Milking parameters

2.2.2.1 Milk yield

When considering the daily milk yield recorded by the LKV and the milking robots, it becomes apparent that the various lameness groups are difficult to distinguish from one another. Based on the locomotion score alone, LMS2 animals exhibited a higher daily milk yield compared to the other groups. In contrast, with the C_LMS, a small increase in C_LMS3 was noticeable compared to C_LMS1. These varying results confirm the complex interactions between milk yield and lameness. Higher-producing cows inherently have a higher risk of lameness (O'Connor et al., 2020; Rutherford et al., 2009), which may explain the increased milk production seen in LMS2 animals, whereas possible negative effects of lameness on daily milk yield may become more evident in severe lameness cases (Olechnowicz & Jaskowski, 2010; Warnick et al., 2001), which could be why the average daily milk yield of LMS3 animals dropped back to the level of LMS1, despite their initially higher production levels. The analytical methods applied in this study did not account for the individual temporal progression of each animal's parameters. Consequently, it becomes difficult to clarify the causal relationship: whether high performance initially contributed to lameness or lameness itself led to a decline in milk yield in the first place. In the case of the C_LMS, more cows without visible gait alterations were identified as lame, which means they initially started with higher levels of milk yield, but they may not have been such severely lame that they were unable to maintain their previous milk output. As a result, an increase towards C_LMS3 is observed without a subsequent decline. In the study of Archer et al. (2010), comparable results were displayed, with a slightly higher milk yield in lame animals compared to healthy ones. The analysis of total milk yield during the previous lactation and the current lactation in this study showed a similar positive correlation. However, for the total milk yield during the previous lactation, neither the LMS nor the C_LMS revealed statistically significant differences between the 'unsound' and 'lame' groups. Nonetheless, there was an observable increase in milk yield compared to healthy cows, which could be attributed to the previously noted higher predisposition to lameness of higher-yielding animals. The odds ratio either did not demonstrate a statistically significant association or indicated no effect of lameness on milk performance, which might have been influenced by variations in the lactation performance across the different farms.

Some studies have also identified a correlation between lactation number and milk yield, revealing that lameness results in a significant reduction in milk production primarily in multiparous cows (Vlček et al., 2016; Warnick et al., 2001). The milk yield is thus influenced by various other parameters and, as documented by Grimm et al. (2019), showed a clear relationship with lameness only when analysed together with variables like lying and feeding behaviour, but not when considered independently. In the present study, milk yield also showed a strong correlation with feeding behaviour (0.41), as well as with performance parameter classes such as days in milk, milk content, and concentrated feed intake. Johnston and DeVries (2018) similarly found a connection between feeding behaviour and milk yield, demonstrating that an additional hour of feeding per day was associated with an average increase of 1.74 kg in milk yield. Furthermore, higher milk production was correlated with a greater number of feeding events and they attributed those findings to the relationship of these variables with dry matter intake. Azizi et al. (2009), however, observed that high-performing animals demonstrated a greater dry matter intake but showed shorter feeding durations and an elevated feeding pace. This suggests that while high-performing animals generally consume more feed, the duration over which this feed is ingested may vary depending on the feeding system and management practices.

At the farm-specific level, the relationship between daily milk yield and lameness revealed considerable variation. On farms RF1, RF3, CDF2, and CDF4, a significant positive correlation between milk production and lameness was observed. In contrast, CDF3 showed no statistically significant differences in daily milk yield from the milking robot, CDF1 lacked a statistically significant odds ratio, and both RF2 and CDF5 exhibited a negative correlation between daily milk yield and lameness. Additionally, RF2, unlike the other farms, demonstrated a negative relationship between milk yield in the last lactation and increasing C_LMS. A possible explanation for these findings might be the higher standard deviation of the daily milk yield on these farms, particularly on RF2 and CDF1, which might have led to less clear correlations due to fluctuations.

The intraclass correlation coefficient calculated between the milk yield parameters recorded by the milking robot and LKV showed a very high agreement of 0.9 for the total milk yield in the last lactation and 0.86 for the daily milk yield. This suggests that the monthly average recorded by the LKV is sufficiently accurate for corresponding analyses and a daily milk yield recorded by the milking robot is not always required.

2.2.2.2 Lactation metrics

The lactation number demonstrated a significant positive correlation with lameness, with the median lactation number being one unit higher in lame and unsound animals compared to healthy ones. This is consistent with the findings of most studies that report an increased risk of lameness with rising parity (Lean et al., 2023; Pötzsch et al., 2003; Rittweg et al., 2023). No statistically significant differences were observed for the lactation number between C_LMS2 and C_LMS3 cows, whereas there was a small rise from LMS2 to LMS3. A statistically significant association was found on all farms except CDF4, and a positive correlation was observed on all farms except CDF2 and CDF4. One possible explanation is that cows in their first lactation are especially prone to laminitis due to the numerous alterations surrounding calving, including factors like a new barn environment or feeding modifications (Bergsten, 2003) and show an increased risk for sole haemorrhages in the following months (Sogstad et al., 2005). This aligns with the high number of SHD, SHB, and CSH cases reported on CDF4.

The highest average number of days in milk was observed in C_LMS2 cows (median: 166, mean: 174), while the lowest was recorded in C_LMS3 cows (median: 150, mean: 153). A modest negative correlation and an odds ratio slightly below 1 could be observed. An analysis of the violin plot in Figure 47 reveals that C_LMS2 cows display two peaks, one around lactation day 50 and another around day 300. In contrast, C_LMS3 cows show a concentration primarily around 50 days in milk. According to the studies by Zlatanović et al. (2021), lesions such as digital dermatitis or laminitis typically manifest in the last third of lactation (days 201-305), while sole ulcers or interdigital hyperplasia predominantly occur in the period shortly after calving. In line with our findings, in their study, the proportion of severely lame cows was highest during the first third of lactation, whereas the rate of moderately lame cows peaked in the final third of lactation. This indicates that cases of digital dermatitis, which, as previously mentioned, may result in less severe gait alterations compared to other lesions, could be a factor contributing to the second peak in lameness observed during late lactation in C_LMS2 cows. Upon closer examination, a negative correlation between C_LMS and days in milk was found on all farms, except for CDF1 and CDF5, where the odds of lameness increased with advancing lactation. This may be attributed to the high prevalence of WLA and WLF on CDF1 and a significant number of WLF cases on CDF5. According to Van der Spek et al. (2015), white line lesions tend to appear predominantly in the later stages of lactation, which could explain the positive correlation between C_LMS and days in milk on these farms.

2.2.2.3 Milking frequency

When analysing the milking frequency data, it was observed that the median number of milkings per day was two across all C_LMS groups. However, the mean number of milkings decreased from 2.53 in C_LMS1 to 2.38 in C_LMS2 and 2.40 in C_LMS3. This suggests a difference, particularly between healthy and unsound cows, as well as between healthy and lame cows. The relatively small differences and the non-significant odds ratios observed on individual farms could be attributed to the fact that the majority of cows across all three groups showed two to three milkings per day, as can be seen in Figure 47. Matson et al. (2022) also stated that a higher milking frequency can be linked to a greater milk production, which in turn can be connected to the claw health status. This connection might then influence the reduction in milking frequency caused by lameness itself. Nevertheless, the overall odds ratio of 0.792 clearly indicated that with increasing milking frequency, the likelihood of lameness significantly decreased in the present study. Van den Borne et al. (2022) demonstrated that the number of milkings decreased in severely lame and mildly lame ones, which is consistent with the results of this study, but only the decrease in severe lameness cases also affected the milk yield. They also emphasised that 63% of the decline of milk performance due to lameness resulted from a diminished number of milkings and concluded that lameness leads to particularly large losses in farms with milking robots, where cows can actively control their milking frequency. The average maximum milking interval accordingly exhibited a steady increase with higher C_LMS levels, indicating longer milking intervals in lame cows. No statistically significant differences were observed in either the number of milkings or the maximum milking interval between C_LMS groups on RF1 and RF3. On these farms, the systematic practice of actively bringing lame animals to the milking robot might have led to less pronounced differences between lame and non-lame animals.

2.2.2.4 Milking contents

Milk protein showed the most distinct and consistent relationship with lameness, exhibiting a reduction in lame cows. This correlation was even stronger for the parameter recorded by the LKV. Differences in all other parameters were either minimal or barely detectable. These findings align with other studies that have examined changes in milk components (Malašauskienė et al., 2022; Slovák et al., 2021; Vlček et al., 2016), where a decline in milk protein associated with lameness was the most commonly observed outcome. It remains unclear whether the reduction in milk protein levels is primarily a consequence of lameness-induced changes in feeding behaviour, as outlined by Slovák et al. (2021), resulting in decreased feed intake and reduced nutrient absorption, or if an initial deficiency in dietary protein could be a contributing factor to the onset of lameness (Dippel et al., 2009). Lameness also leads to metabolic and immunological adjustments (Sun et al., 2015), which may result in metabolic energy being redirected from milk protein synthesis to support these processes and therefore in a reduced milk protein content. Lactose content only displayed a slight negative correlation with lameness, but increasing lactose content had a high negative influence on the likelihood of lameness according to the OR. This association of a decline in lactose content with lameness has also been demonstrated in several studies (Antanaitis, Juozaitienė, & Urbonavičius, 2021; Malašauskienė et al., 2022; Olechnowicz & Jaskowski, 2010).

There were no significant differences in urea levels at all among the C_LMS groups. Fat content showed a decrease with lameness in LKV data, while it increased in data from milking robots and accordingly the parameter fat-protein ratio behaved in the same manner. Somatic cell count showed no clear association with lameness, as in C_LMS analysis lame cows had the lowest, but in LMS analysis lame cows had the highest median somatic cell count. The varying correlation of fat and urea content across farms with lameness suggests that different farm-specific rations might have complicated the identification of more pronounced associations between these parameters and lameness. Malašauskienė et al. (2022) also found no clear differences in milk fat content between lame and non-lame cows, but they did observe higher somatic cell counts and concluded that lameness might be associated with a higher likelihood of developing mastitis. In contrast, Archer et al. (2011) found lower cell counts to be linked with higher locomotion scores. Singh et al. (2018) noted higher cell counts in lame cows, but like Yunta et al. (2012) and Pavlenko et al. (2011), they could not detect any changes in milk composition. In the study by Slovák et al. (2021), urea levels significantly decreased by 18-29.9%, depending on the lactation stage. Consequently, based on the results of this study and the existing literature, no clear association of the parameters fat, urea and somatic cell count with lameness could be established.

Some studies utilised monthly average values (Olechnowicz & Jaskowski, 2010) or total lactation summaries (Vlček et al., 2016) to quantify the association between claw health and milk composition. In this study, the monthly milk component values recorded by the LKV exhibited more pronounced deviations compared to the daily averages of milk components measured by the milking robot. This observation suggests that the effects of lameness on milk components might become more apparent over a longer period of time, indicating data aggregation may help in clarifying the relationship. Additionally, the correlations between milk components recorded by the LKV and those measured by the milking robot were relatively low. The strongest correlation was observed for milk protein (0.47), which is consistent with the similar patterns of association between LKV and robot values for lameness. This could be due to the potential inaccuracy of the robot's milk component measurements, or it might be that daily variability in milk components is so high that a monthly value is insufficient for accurate representation. However, the latter explanation is contradicted by the fact that the average standard deviation of the milking robot's measurements for milk contents was not greater than that of the LKV.

2.2.2.5 Other performance parameters

Milk temperature was significant between all C_LMS groups and showed a positive correlation with lameness on all farms and an OR >1, except for RF3. This could be due to the generally higher average milk temperatures observed on RF3 as a result of higher ambient temperatures (West et al., 2003), which may have masked the variations caused by lameness. The positive correlation between elevated milk temperature and lameness may be attributed to the observation that animals with claw diseases tend to exhibit increased body temperatures (Talvio, 2020), which are, to some extent, correlated with milk temperature (Pohl et al., 2014). In this studies, a correlation of 0.49 was observed between milk temperature and body temperature, very similar to the correlation of 0.52 reported by Pohl et al. (2014).

Regarding conductivity, varying results were observed. Standard conductivity measurements in mS/cm did not show any correlation with C_LMS. Conversely, conductivity recorded by the Lely milking robot in an alternate unit exhibited a slight positive correlation with lameness. Furthermore, a higher MDi was associated with an increased likelihood of lameness on RF1, while no effect was detected on CDF3. Antanaitis, Juozaitienė, and Urbonavičius (2021) also reported elevated conductivity values in all four quarters of the udder in lame animals, while Singh et al. (2018) revealed that a higher locomotion score was associated with a poorer udder health status and consequently, with mastitis. Malašauskienė et al. (2022) also observed that the conductivity values for lame animals deviated from the average of healthy animals (4 to 6 mS/cm), but with approximately 50% of lame animals exhibiting values above this range and 50% below. This indicates that while higher conductivity may occasionally be linked to claw diseases, variations in this association can occur and may depend on the specific udder health conditions present on each farm.

The maximum milk flow showed a positive correlation with lameness and an OR>1, whereas the normal milk flow, although slightly positively correlated, indicated that higher milk flow was associated with a lower likelihood of lameness. The considerable variability in milk flow across different farms and milking robots could have influenced this. Van Hertem et al. (2016) reported increased maximum milk flow values in lame animals, while Wieland et al. (2022) demonstrated lameness could increase the risk of developing a delayed milk flow. While on the one handy, high milk production can contribute to both lameness (O'Connor et al., 2020) and increased milk flow (Wieland et al., 2022), on the other hand, inflammatory processes resulting from claw diseases (Whay & Shearer, 2017) might negatively impact the milk flow (Wieland et al., 2022).

2.2.3 Constitution

The BCS of cows in the C_LMS3 group showed a decline, along with an overall negative correlation and an odds ratio greater than one, indicating that particularly severely lame animals tend to display a worse body condition. This raises the question of causality: whether lameness leads to a lower BCS or vice versa. A low BCS is typically associated with a reduced digital cushion thickness (Newsome et al., 2017), which can compromise claw support and increase susceptibility to lameness. But lame cows may also change their feeding behaviour and intake (Norring et al., 2014) and therefore experience a reduction in fat reserves or could suffer from muscle loss (Necula et al., 2022), for example, due to reduced activity. Despite these observations, C_LMS2 cows had the highest average BCS (3.91) of all C_LMS groups in this study. This aligns with other studies that have additionally found a higher baseline weight or BCS to be associated with an increased risk of lameness (Kranepuhl et al., 2021; Ristevski et al., 2017). Body weight also showed a positive relationship with lameness in this study, with unsound animals having the highest average weight among the three groups. Lorenzini (2019) also demonstrated that a higher BCS was associated with a lower likelihood of lameness, while a higher body weight was more strongly linked to a higher locomotion score. The discrepancy between BCS and body weight in relation to lameness led to the conclusion that animal-specific differences made it harder to determine a clear pattern. Furthermore, lameness and the associated calorie deficit, due to reduced feed intake (Norring et al., 2014), may primarily result in a higher loss of subcutaneous fat instead of muscle mass. Weber et al. (2015) indicated that weight loss following calving ceased significantly earlier, while BCS and back fat thickness continued to decline. They concluded that muscle mass and internal fat reserves must be replenished more rapidly than subcutaneous fat. As subcutaneous fat reserves diminish, the lower weight of fat relative to muscle could lead to a decline in BCS without a proportional reduction in body weight. In conclusion, although the kind of data analysis in this study could not establish causality, the animal's constitution seemed to be linked to the claw health status.

2.2.4 Feeding behaviour

The feeding duration recorded by the weighing troughs on RF1 showed a clear negative correlation with lameness and the likelihood of lameness significantly increased with a shorter feeding duration. In contrast to this gradual decrease with rising C_LMS, the pedometers on the same farm displayed a significant increase in feeding duration for cows with C_LMS2, before dropping again for cows with C_LMS3. Similarly, the number of trough visits and meals recorded by the weighing troughs decreased continuously with higher C_LMS, whereas the ENGS data also demonstrated a peak in the C_LMS2 group for the number of meals. This effect could not be observed in the study by Lorenzini (2019), where the ENGS parameters exhibited a clear negative correlation with lameness. In combination with the lack of statistically significant differences in many feeding behaviour parameters by ENGS, this might suggest that the ENGS data, collected from only one claw trimming date, was insufficient to establish a clear, traceable connection between feeding behaviour and lameness. Moreover, even with this single claw trimming session, it cannot be definitively stated that the induction loop under the rubber mats always remained in the same position during the whole three-week data collection period. A shift in the loop's position could have led to poor detection of some animals at the feeding trough, especially if individual cows tended to stand further away from the trough. For effective use of the induction loop in future experimental settings, a groove in the concrete floor is urgently needed to ensure that the cable remains installed securely and undamaged. The feeding duration recorded by Nedap also revealed a negative correlation, with a gradual decrease when using LMS as the reference. However, when C_LMS was taken as the reference, cows with C_LMS2 displayed a shorter feed intake duration compared to cows with C_LMS3. This implies that not all animals with an adjusted LMS due to PT or findings had necessarily experienced negative effects on their feeding behaviour yet. Meanwhile, some C_LMS2 animals, despite showing no visible signs or signs of pain, may have already been dealing with claw health problems that impacted their feeding duration. A reduction in feeding duration as well as in the feeding frequency has also been documented in various other studies (Antanaitis, Juozaitienė, Urbonavičius et al., 2021; Beer et al., 2016; Frondelius, Lindeberg et al., 2022; Grimm et al., 2019; Lorenzini, 2019). Schindhelm et al. (2017) explained this by noting that increased feeding duration also means more time spent standing, which lame animals naturally try to minimise. Additionally, each trip to the feeding trough is associated with renewed discomfort, which explains the reduction in the number of meals.

In contrast, feed intake itself demonstrated a positive association with lameness in this study, primarily driven by the higher intake observed in C_LMS2 animals. Norring et al. (2014) reported a decrease in silage intake among severely lame animals only, and similarly, in the present study, intake levels dropped again in C_LMS3 cows. Accordingly, the relationship between feed intake and lameness may be influenced by the fact that higher-yielding cows are at a greater risk of lameness (O'Connor et al., 2020), and cows with higher milk yields tend to consume more dry matter (Azizi et al., 2009). Based on Palmer et al. (2012), feed intake is also affected by lactation status, as lame animals showed a reduction in feed intake during early lactation, whereas no significant changes were observed during mid-lactation. According to Grimm et al. (2019), only high-producing cows exhibited a decrease in feed intake due to lameness, while no significant differences were observed in other cases. They were able to further highlight the complex relationships surrounding lameness in this context, as they found that for cows with above-average feed intake, the risk of lameness did not vary with milk production. However, for cows with below-average feed intake, a rise in lameness odds could be observed with higher milk yields. Proudfoot et al. (2010) observed an increase in feed intake associated with lameness, as cows that developed claw disease in mid-lactation showed a rise in feed intake, particularly during the 24 hours following calving. Additionally, they noted that lame animals significantly increased their feeding rate in the two weeks prior to calving. In the same way, this study reveals a strong positive correlation between feeding pace and lameness, suggesting that lame animals attempt to consume as much feed as possible in the limited time they are willing to spend standing at the feed trough.

In line with the findings by Lorenzini (2019), feed intake per meal and visit increased notably with lameness in this study. The duration of individual trough visits also rose with worsening claw health, similar to the study of Lorenzini (2019), whereas meal duration displayed a negative correlation with lameness. This could be related to the tendency of lame animals to avoid making frequent short feeding stops. Once they make the effort to reach the feed trough, they interrupt their feed intake less often, leading to larger quantities consumed in overall shorter meals. The comparison between day and night values revealed no noteworthy differences in feeding behaviour.

Kofler et al. (2023) examined the consequences of subacute ruminal acidosis induced by high levels of concentrate feed and observed a decline of claw health in severe cases, along with a higher occurrence of white line disease. Accordingly, higher concentrate feed rations can promote symptoms associated with laminitis. Conversely, a reduced milking frequency due to lameness (Van den Borne et al., 2022) can lead to a decreased concentrate feed intake, as it is primarily offered through the milking robot. In this study, there was no correlation between concentrate feed intake and lameness, even though lame animals left more concentrate feed unclaimed compared to healthy animals. This lack of correlation may be due to the considerable variability in concentrate feed rations across farms, with about half showing a positive correlation between concentrate intake and lameness, while the other half exhibited a negative correlation. Furthermore, it is possible that the incidence of feeding-related laminitis symptoms on the project farms was relatively low.

2.2.5 Rumination

Regarding rumination, the systems displayed varying tendencies depending on lameness. The smaXtec system showed no significant correlation with lameness, while rumination duration in more severely lame animals slightly decreased with the SCR sensors and showed a significant decrease with Nedap collars. The bolus and collar systems on RF1 both showed a decrease in rumination for lame animals, while on RF3, the bolus rumination parameter was positively associated with lameness, unlike the collar. According to smaXtec (2024), the bolus measures the duration of rumination based on reticuloruminal contractions, which could result in discrepancies compared to the head movements recorded by collars. In contrast, Capuzzello et al. (2023) reported a relatively high correlation of 0.72 between rumination durations recorded by the bolus and a collar. However, their study was limited to just six cows, which may have prevented the identification of individual or farm-specific variations. Since reticulorumen contractions are classified as continuous processes rather than discrete episodes of rumination (Hamilton et al., 2019), deriving accurate rumination duration from these contractions can be challenging. The discrepancies observed in the bolus measurements might therefore be attributed to variations in the intensity of reticulorumen contractions among individual cows or animal-specific differences in how these contractions correlate with rumination duration. Antanaitis, Juozaitienė, Urbonavičius et al. (2021) were able to detect a decrease in rumination activities as early as seven days before the onset of clinical symptoms of lameness, whereas Magrin et al. (2022) observed only a slight reduction in rumination time in lame animals. Many other studies failed to establish a clear connection between rumination and lameness. For example, Pavlenko et al. (2011) investigated SU and DD lesions and noted that animals with these claw issues showed no differences in overall rumination duration. Likewise, Weigele et al. (2018) studied the rumination behaviour of moderately lame animals and detected no significant changes in the number, duration or speed of rumination episodes. These results, along with our own findings, suggest that lameness does not always negatively affect rumination, possibly because rumination primarily occurs during the lying periods, which cause less discomfort for the claws. Significant reductions in rumination duration may only be evident in animals in more severe lameness stages.

2.2.6 Lying behaviour

In the analysis of lying behaviour, it became evident that using C_LMS as a reference revealed no significant differences in the lying durations recorded by ENGS and Nedap across the score groups. However, when LMS was used as the reference, distinct differences emerged between the groups. With LMS, the average lying duration initially decreased in unsound cows, followed by a marked increase in LMS3 cows. In contrast, when using C_LMS, the increase in lying duration among lame cows mostly disappeared, resulting in a negative correlation with lameness. These findings suggest that lying duration significantly increased only in cases of clear lameness, whereas cows with claw diseases that have not yet impacted gait did not exhibit clear changes in lying behaviour. In contrast, the Lemmer-Fullwood pedometer data indicated a clear and progressive rise in lying duration for both unsound and lame animals, regardless of the reference score used. The discrepancy in lying times for unsound cows between CDF2 and CDF4 versus RF1 and RF3 might be explained by differences in measurement techniques of the pedometers, variations in housing conditions (Ito et al., 2010) or animal-specific variations. It might be anticipated that already cows with a beginning claw problem would increase their lying time as a compensatory mechanism to reduce pressure on their claws and alleviate associated discomfort. Accordingly, Weigele et al. (2018) reported an average increase of up to 45 minutes in lying time already for moderately lame cows and Lorenzini (2019) noted a gradual rise in lying time as LMS increased. Yunta et al. (2012), on the other hand, in line with our results, observed that moderate lameness does not significantly influence the total lying time of cows but identified other significant patterns, such as moderately lame cows rising later for feeding and lying down earlier thereafter. Notably, the parameters derived from the ENGS values, especially the day-night ratio of lying time as well as the daytime lying duration, exhibited a strong positive correlation with lameness, along with an odds ratio exceeding 1. This indicates that in unsound cows, daytime lying time may increase initially, while total lying time remains largely unchanged. These findings align with those of Blackie et al. (2011), who detected a significantly higher lying time in the evening and thus a greater daytime lying duration in lame cows. Grimm et al. (2019) already demonstrated in their study that the day-night ratio of specific parameters can be highly indicative for the detection of developing lameness. They also found a relationship with milk yield, revealing that high performance increased the risk of lameness only when the total lying time of the cow was below the average (Grimm et al., 2019). Consequently, it is essential to consider other influencing factors, such as climate (Thompson et al., 2019) or lactation number (Thompson et al., 2019), when assessing lying behaviour. This study demonstrated a significant correlation between lying duration and body temperature. The latter might in turn be affected by a hot barn climate and may lead cows to spend more time standing in the aisles to help regulate their body temperature (Allen et al., 2015). These additional effects could potentially play an even greater role in the lying behaviour of unsound cows than the claw condition itself.

Consistent with findings from numerous other studies (Bernhard et al., 2020; Hut et al., 2021; Solano et al., 2016), this research documented an increase in the duration of individual lying bouts by ENGS associated with lameness. Bernhard et al. (2020) stated that the strain on claws might be particularly intense during the processes of getting up and lying down, prompting lame animals to try to reduce this discomfort. But in terms of the number of lying bouts in this study, the data from Nedap and ENGS revealed a contrasting pattern compared to results from Lemmer-Fullwood pedometers. Both Nedap and ENGS values demonstrated a reduction in lying events as claw health status worsened, while the Lemmer-Fullwood sensors showed a positive association with lameness and an increase, especially in the C_LMS2 cows. The literature also presents an inconsistent picture of the relationship between lying bouts and lameness, with some studies showing an increase (Frondelius, Lindeberg et al., 2022; King et al., 2017), others a reduction (Bernhard et al., 2020; Lorenzini, 2019), and some displaying no significant correlation (Navarro et al., 2013; Thompson et al., 2019; Yunta et al., 2012). Grimm et al. (2019) attributed it to the fact that interactions of lying behaviour with other parameters like feeding behaviour were often not considered in other studies. In their study, lame cows only exhibited longer durations of individual lying bouts when their total feeding duration was simultaneously reduced or when the proportion of daily feeding duration was increased. Parity could also be an influencing factor, as cows in their first lactation typically demonstrate fewer and shorter lying bouts (Solano et al., 2016).

2.2.7 Activity and heat behaviour

Among all seven sensor systems used in this study to monitor cow activity, a reduction in activity associated with lameness was observed. Walking as well as standing increases the pressure on the claws, which cows suffering from claw health issues might try to avoid. Accordingly, numerous other studies also reported a reduction in activity levels for animals affected by claw disorders (Hut et al., 2021; Magrin et al., 2022; Neirurerová et al., 2021; Van Hertem et al., 2016). In this study, the activity reduction due to lameness was more pronounced in some systems, such as the pedometers and the DeLaval and SCR neck collars, compared to others like the bolus. Furthermore, the bolus detected on average an increase in activity among unsound cows. The activity measured by the bolus on RF1, similar to the rumination data, showed an opposite correlation with lameness compared to other farms. Thus, farm-specific conditions and, particularly since not all animals on RF1 were equipped with a bolus, animal-specific differences could have led to these discrepancies. The less pronounced correlation in some sensors could also be attributed to differences in sensor placement and measurement methods. For example, the bolus might struggle to accurately assess activity due to interference from other reticuloruminal movements, compared to a pedometer mounted directly on the leg of the cow. Furthermore, the DeLaval and Nedap neck collars, along with the ENGS and Lemmer-Fullwood pedometers, did not reveal significant differences between unsound and lame animals. On one hand, a reason could be that cows that do not yet show a clear impaired gait only slightly reduce their activity, regardless of whether findings or pain are present. On the other hand, activity levels might already decline in the development of lameness and may therefore not necessarily be markedly distinct in cases of clear, visible lameness. The inactive time recorded by Nedap increased significantly in C_LMS2 cows in this study, indicating already unsound cows demonstrated less head movement. Weigele et al. (2018) documented a reduction of activity and neck activity in moderately lame cows, with significantly lower activity levels compared to healthy cows in the hour following feeding. Schindhelm (2016) did not observe a strong impact of lameness on activity, which was attributed to the large individual variations in activity levels among animals. King et al. (2017) demonstrated that lower activity can be linked to a higher lactation number and that cows with a low BCS tend to move more during the day, while those with a high BCS are more active at night. Additionally, activity levels decreased over the course of lactation and were associated with both milk yield and lying behaviour (King et al., 2017). In this study, activity also demonstrated strong correlations with other factors, including climate, body weight and feeding behaviour. Furthermore, it is noticeable that often the day-night ratio and always the activity during daytime displayed a stronger negative correlation with lameness than the total activity per day, which might suggest that lameness primarily leads to a reduction in daytime activity. This observation is consistent with those of King et al. (2017), who observed an increased night-to-day activity ratio with lameness, and with Van Hertem et al. (2016), where daytime activity was integrated as the most significant activity parameter in the model.

No differences were observed between lame and healthy animals in the oestrus probability calculated by SCR. However, the restlessness factor by Lemmer-Fullwood was significantly higher on average in healthy cows compared to unsound or lame cows, suggesting that some animals may exhibit their oestrus symptoms less distinctly due to claw diseases.

2.2.8 Body temperature

Almost all body temperature parameters from the bolus showed a positive correlation with lameness, indicating an increase in body temperature with the occurrence of claw diseases. Notably, the average body temperature was particularly high in the C_LMS2 group across all parameters. Tadich et al. (2010) also observed a higher rectal body temperature in lame animals, but conversely, this effect was only evident in cases of severe lameness. Talvio (2020) demonstrated that cows with SU had elevated rectal body temperatures compared to healthy animals and these temperatures approached those of healthy animals as the lesions healed over time. They concluded that SU not only leads to a local inflammatory reaction but also induces a systemic response in the body. Harris-Bridge et al. (2018) used infrared thermography and observed that in the case of a DD lesion, not only was the temperature of the affected foot elevated, but also that of the contralateral hind foot. They also concluded that a systemic inflammatory response triggered by these lesions could lead to an increased body temperature. The observation that temperature was highest in unsound cows may be attributable to the fact that certain inflammatory processes occur during the development of lameness and prior to its manifestation. For example, sole haemorrhages typically become apparent six to eight weeks after the initial inflammation of the corium (Kofler, 2014).

Since the boluses account for drinking behaviour in the body temperature parameters, drinking could also be approximately compared within the different C_LMS groups. The temperature differences between temperature without and temperature with drinking cycles showed statistically significant differences, with an increase in C_LMS2 and a subsequent decrease in C_LMS3 animals. This could be explained by the distinct association of different claw diseases with drinking behaviour. According to Pavlenko et al. (2011), cows with DD exhibited a significantly higher number of drinking events than healthy cows, while no significant difference was observed between cows with SU and healthy animals. Antanaitis, Juozaitienė, Urbonavičius et al. (2021) observed a significant decrease in drinking time in lame animals, which may reflect the reduction of water intake in lame cows detected in this study. This could be attributed to the reluctance of these cows to put weight on their painful claws, thereby reducing drinking time in a similar manner to the reduction in feeding time.

2.2.9 Climate

When considering the different seasons, this study actually showed that in winter the highest percentage of C_LMS3 was observed. Autumn followed, while the lowest rate of lame cows was observed in summer. This result contrasts with other studies, which reported higher lameness prevalence during the summer months (Cook et al., 2007; Jewell et al., 2021; Sanders et al., 2009). Cook et al. (2007) attributed this effect to the increased load on the claws due to longer standing times as a result of heat stress during the summer months. Most researchers that detected higher lameness prevalence during the winter focused on pasture-based housing systems (Clarkson et al., 1996; Olechnowicz & Jaskowski, 2015), which are not really comparable to the housing systems of the farms studied in this research. In housed cattle without access to pasture, seasonal variations in lameness prevalence are often reported to be minimal or absent, reflecting a more consistent level of claw health throughout the year (Sjöström et al., 2018; Tillack et al., 2024). Cook (2003), on the other hand, identified a higher prevalence of lameness in winter in free-stall systems without sand. They attributed this increase to the slower drying of walking surfaces in winter and the particular challenges of managing slurry under cold temperatures. Häggman and Juga (2015) observed seasonal variations between infectious and non-infectious claw diseases, with infectious conditions being 18-53% more likely during winter months, while non-infectious conditions were more common in summer and autumn. Similarly, Armbrecht et al. (2018) found that cattle without pasture access had a higher incidence of DD, DS, IH, and WLD in winter, while HHE, SH, and SU were more apparent in the summer. It should also be noted that this study recorded significantly fewer LMS and C_LMS data in winter compared to the other three seasons, which might also have contributed to the observed higher lameness percentages in this season. Additionally, scoring sessions conducted in summer could have taken place before the peak heat stress, meaning that any resulting deterioration in claw health may only have become apparent at the following claw trimming date in autumn or winter. In conclusion, it is important to highlight that these findings are primarily hypothetical, as data collection spanned only 1.5 years, limiting the representation of all seasons within this study. To enable clearer and more definitive conclusions, future research should aim to include at least two representations of each season.

Consistent with the results regarding seasonality, temperature and THI inside and outside the barn showed a negative correlation with lameness, indicating that lameness was more likely to occur at lower temperatures and lower THI values. Conversely, lower air humidity levels had a protective effect against lameness. King et al. (2016) observed similar results, with each 10-degree increase in temperature correlating with a reduction in lameness prevalence of over 6%. They also concluded that the higher lameness prevalence in winter could be related to the development of claw diseases during the summer months and the delayed impact on the cow's walking behaviour. Unlike other countries, where the highest relative humidity might be observed during the summer (Sanders et al., 2009), summers in Germany tend to be relatively dry. This difference could help to explain the higher frequency of lameness observed in autumn and winter, as in this study the average humidity levels in these two seasons were significantly higher compared to spring and summer.

3. Regression models

In indirect automatic lameness detection, where lameness is identified using animal-specific sensor data, regression models have proven effective across various studies. For instance, the first of the two preceding studies of this project achieved a high AUC of 0.94 with an ENET beta model, demonstrating a sensitivity of 0.92 and a specificity of 0.83 (Grimm et al., 2019). In the follow-up study by Lorenzini (2019), the same modelling approach, however, yielded significantly worse results when applied to data across different farms. This led to the adoption of generalised linear mixed regression models to account for random effects, which provided a better fit for the animals-in-farms data structure and were thus also applied in the present study. Following further development of the models, Lorenzini, Grimm, and Haidn (2021) were able to attain an AUC of 0.82 by using this regression method.

Similar to Lorenzini (2019), in this study the farm as a random effect only explained a small, negligible proportion of the data's variation. In contrast, incorporating individual animal variance had a significant impact on the performance of the models. This is likely due to individual animal differences being more pronounced across farms than the farm-specific differences themselves, a finding supported by the observations of other studies that highlighted considerable variability at the individual animal level (Alsaaod et al., 2012; Kramer et al., 2009; Thorup et al., 2015; Weigele et al., 2018). Weigele et al. (2018) incorporated different random effects as well and demonstrated that the variation between farms was less pronounced compared to the variability observed between individual cows.

In the different models, three additional parameters could be identified as the random slopes that most effectively improved the fit of the regression models: milk yield, days in milk, and body temperature. Accordingly, these parameters exhibit considerable individual variability in their association with lameness. Each cow may have a different baseline milk production, not every cow with high milk production necessarily faces an increased risk of lameness, nor does lameness always need to cause a uniform decline in milk yield for each cow. Similarly, certain cows might be more susceptible to claw diseases at different times, such as shortly after calving or towards the end of lactation. Additionally, for some cows, an increased body temperature might be linked to lameness, while others may react to elevated external temperatures or other diseases.

Across nearly all models, the observation was consistent that models using C_LMS as a reference showed poorer performance compared to models using LMS. This could be explained by the fact that C_LMS might classify animals as lame even if they do not yet exhibit a clearly altered gait but only suspicious characteristics such as an arched back or a compensatory posture. In these cases, the claw lesions might be so mildly pronounced that they do not necessarily affect the cows' behaviour yet. Behavioural changes caused by chronic lameness tend to emerge slowly and vary during the developing period (González et al., 2008), which could have also led to an inadequate detection in this study. Additionally, claw diseases, which are harder to identify based on the locomotion score, such as DD (Tadich et al., 2010), might also have a less or diverse impact on the behaviour and performance of cows (Amory et al., 2008). Furthermore, false classification of healthy animals as lame, particularly due to the pain test, could have also contributed to this discrepancy.

Examining the best models based solely on performance data (Model 1, Model 2) or on performance data combined with activity data (Model 3, Model 4), it became evident that several parameters were consistently featured. These parameters included milking frequency as the number of milkings or the maximum milking interval, lactation data such as days in milk or lactation number and the milk yield. The interaction parameter between lactation number and milk protein accounted for the fact that in this study animals with a higher lactation number exhibited higher milk protein levels, an observation that aligns with the findings by Vlček et al. (2016). The analysis of the interaction between activity and lactation number revealed that cows with higher lactation numbers generally exhibited lower activity levels, with activity declining more significantly due to lameness compared to cows in earlier lactations. Garcia et al. (2014) also observed that the impact of lameness on performance and behaviour, especially activity, may vary considerably depending on the lactation number.

The accuracy of the models based exclusively on performance data (Model 1, Model 2) was limited, with an AUC of approximately 60%, and they demonstrated a very low sensitivity, making it difficult to identify lame animals effectively. Similarly, Van Hertem et al. (2016) used a regression model incorporating solely performance parameters such as milk yield, milk flow or milking order and yielded comparable results, with an AUC of 0.603 and very low sensitivity. Lemmens et al. (2023) assessed a random forest model using AMS and performance data to detect mild lameness cases and achieved an AUC of 0.629. This suggests that performance data alone, both in this study and in the literature, were not sufficient to detect lameness with adequate accuracy. The variations in milk parameters do not seem to be significant enough to indicate lameness without the inclusion of additional behavioural parameters.

Behaviour parameters thus needed to be incorporated in the model and activity was selected as the first additional behavioural parameter. This approach was pursued as the most used sensor systems on farms are those designed for heat detection and activity is the parameter generally monitored by most animal-attached sensor systems. The activity model with C_LMS as a reference (Model 3) showed almost no improvement compared to the performance model, while the model with LMS as a reference (Model 4) demonstrated a significant enhancement, with an AUC of 0.7. This observation, combined with the results of the bivariate analysis, where no significant differences in activity were observed between most sensors for C_LMS2 and C_LMS3, suggests that the activity patterns of lame cows in the LMS model (Model 4), all showing an asymmetric gait, differed more significantly from healthy cows than those of unsound walking animals, irrespective of pain reactions or visible lesions. Consequently, relying solely on activity as the only behavioural parameter in the lameness detection model appeared inadequate, as the aim must be to detect lame animals before they show obvious signs of gait alteration. Moreover, the better LMS model (Model 4) also displayed significant weaknesses, as with a specificity of 53%, only half of the healthy cows would be correctly identified and farmers would receive too many false-positive lameness notifications. The individual differences in baseline activity among cows (Müller & Schrader, 2005) may have complicated the accurate detection of lameness when relying solely on this behavioural parameter. Van Hertem et al. (2016) also achieved only a marginal increase in the AUC of their model up to 0.669 by combining activity and milking data. The model presented by Kamphuis et al. (2013), which was based on milking order and activity, reached an AUC of 0.676. While their model accuracy aligns with the result of this study, they observed only a slight reduction in accuracy when mild lameness cases were incorporated (AUC: 0.664). In contrast, de Mol et al. (2013) achieved high sensitivity and specificity, both above 80%, by employing a cow-specific model that accounted for day-to-day alterations in activity and milking parameters. Similarly, Taneja et al. (2020), using an alternative approach that categorised cows into distinct activity groups, were able to detect lameness with an accuracy of 87% and could identify lame animals up to three days prior to the appearance of visible symptoms.

These findings indicate that while activity and performance parameters may not be suitable in a generalised model applied to all animals, as explored in this study, clustering methods or animal-specific models could lead to a significant improvement in lameness detection accuracy.

The inclusion of one single additional behavioural parameter enhanced the performance of all models. The best-performing model, which included performance, activity, and a supplemental behavioural parameter, was a feeding model incorporating feeding behaviour data from the weighing troughs on RF1 (Model 11, Model 18). This model showed strong results on test data for both LMS (AUC: 0.85) (Model 11) and C_LMS (AUC: 0.87) (Model 18) as references. In particular, the behavioural parameters feeding pace and weighing trough visits had a significant impact on the model's strong performance. However, this model had two notable limitations. First, it was tested on only one farm, and second, it relied on data from weighing troughs, an expensive system typically reserved for research farms. Despite these limitations, the results highlight the importance of a more nuanced assessment of feeding behaviour using sensor systems that go beyond simply measuring feeding duration. The models, including only feeding duration (Model 10, Model 17), which could be measured on three different farms performed significantly worse, especially with C_LMS as a reference (Model 10). Technologies like the ENGS pedometers, which unfortunately could not be used for consistently monitoring feeding behaviour in our case but were successfully employed in the previous study (Lorenzini, 2019), may offer good potential for commercial dairy farms under different conditions. Many other studies have also emphasised the significance of feeding behaviour recordings in relation to lameness (González et al., 2008; Grimm et al., 2019; Lorenzini, 2019; Thorup et al., 2016; Weigele et al., 2018). In the study by Lemmens et al. (2023), a model based solely on feeding duration, performance data and activity patterns achieved a comparable AUC of 0.695, similar to the findings in this study.

Among the other regression models adding an individual behavioural parameter, it is notable that after feeding behaviour, with LMS as the outcome variable, the models including lying behaviour (Model 15) or body temperature (Model 19) achieved the highest AUC, while for C_LMS, the models based on constitution (Model 7), meaning BCS and body weight, or climate (Model 13) yielded the best performance. These observations further highlight that cows with early-stage claw diseases, which are not yet visibly lame, showed different deviations in parameters compared to those that were clearly lame. It is crucial to note that, for the C_LMS models, the interaction between BCS and body weight was particularly significant, but this parameter combination could only be detected on one single farm. However, other studies have similarly shown that integrating BCS or body weight could elevate the AUC of their models to between 0.72 and 0.85 (Borghart et al., 2021; Kamphuis et al., 2013; Lemmens et al., 2023). This underscores the potential of these constitution-related parameters to enhance lameness detection models across different farm settings. Furthermore, since climatic conditions differ by location, the impact of climate on the lameness probability in the C_LMS model (Model 13) observed in this study in Bavaria may not be universally applicable to other regions. But as Lavrova et al. (2023) were also able to find a strong influence of season and thus climatic conditions on lameness in their studies on six other dairy farms in Germany, there seems at least to be a correlation in the local climate zone. The lying behaviour in the C_LMS model (Model 8) performed significantly worse than in the LMS model (Model 15), as anticipated from the bivariate analysis. This discrepancy underlines the assumption that lying behaviour might change significantly only with more pronounced lameness. Neupane et al. (2024) attributed the minor variations in lying behaviour in their study to the observation that lying times for lame cows were either very high or very low, which, according to the findings of this study, may also be associated with different severity grades of lameness. The least effective behaviour parameter for both LMS (Model 16) and C_LMS (Model 9) was rumination, with many other studies also failing to find a significant association between rumination and the likelihood of lameness (Lemmens et al., 2023; Thorup et al., 2016; Weigele et al., 2018).

Conversely, incorporating another additional parameter notably enhanced the AUC of the C_LMS rumination model (Model 9) up to 0.78 when combining rumination with body temperature (Model 25). This implies that even a less significant single behavioural parameter like rumination can indeed contribute to the detection of lameness if combined with other parameters. Similarly, the combination of lying behaviour and body temperature in the C_LMS model (Model 21) yielded improved results, indicating that body temperature, when considered alongside other behavioural parameters, can provide more accurate outcomes, particularly in cases where lameness is not yet clearly detectable. Additionally, also for the LMS models, the combination of lying behaviour and body temperature (Model 26) significantly increased the model's AUC. The best accuracies, with an AUC of 90% or more, were achieved by combining feeding behaviour and lying behaviour in the C_LMS (Model 23) and the LMS models (Model 27, Model 28) or condition with feeding behaviour in the C_LMS model (Model 22). However, as noted earlier, these models, except for Model 27, are solely based on weighing trough data from a single farm.

The best models, which could be tested across multiple farms and did not include the more detailed feeding behaviour data provided solely by weighing troughs, included performance, activity, body temperature, climate, and for C_LMS feeding behaviour, as well as lying behaviour for LMS. In this case, the LMS model (Model 6) attained an AUC of 0.89 on test data, whereas the C_LMS model (Model 5) achieved an AUC of 0.82. The interaction term including milk yield and season was incorporated in both models, highlighting that the increased risk of lameness in high-producing cows seems to be more pronounced in winter and spring. In contrast, during summer and autumn, the combination of heat stress and lameness may further intensify the negative effects on milk yield. Lavrova et al. (2023) similarly integrated various parameter classes like activity, lying behaviour, performance, and climate into a mixed effects regression model, achieving a sensitivity of 77%. Besides, other studies using different modelling approaches and combining multiple parameter classes demonstrated similar outcomes as well. For example, Lemmens et al. (2023) obtained an AUC of 0.72 with a random forest model, while the time series model by Neupane et al. (2024) accurately identified the need for therapeutic claw trimming with an AUC of 0.80.

The results of this study also align with the accuracy reported in the two preceding studies, which achieved an AUC of 0.94 on a single farm (Grimm et al., 2019) and 0.82 across five farms (Lorenzini, Grimm, & Haidn, 2021). In both studies, the combination of feeding behaviour and lying behaviour with performance parameters proved to be particularly significant in the regression models, a pattern that was also confirmed by this study. However, when sensors only capture feeding duration without more detailed feeding behaviour data, additional parameters such as climate or body temperature become essential. Notably, while body temperature has not yet been explored in relation to lameness detection models, this study demonstrated that it can significantly contribute to lameness detection when combined with other behavioural parameters.

VII. Conclusion

In conclusion, the results of this study indicate that lameness continues to be a significant issue in dairy farming, also affecting Simmental cows in Bavaria. The pain test used in this study revealed that nearly a quarter of the cows in pain showed no visible signs of claw disease, indicating that some claw conditions may cause pain before they become visibly detectable. The three-level LMS demonstrated good reliability, but several cows with pain or lesions were not classified as lame, which suggests that not all claw diseases may have an equally pronounced effect on the gait of the animals. These results emphasise the need for a multi-component reference system, as used in this study, to ensure accurate detection of claw health issues.

Many of the behaviour and performance parameters recorded in this study either influenced lameness or were affected by it, including factors such as lactation status, milking frequency, feeding behaviour or body temperature. However, the challenge of distinguishing between cause and effect, which is particularly complex in parameters such as milk yield or body condition score, often complicates the interpretation of the relationship between claw health, behaviour and performance. Animals with mild or early-stage claw disorders, without visible impairments in gait, may differ in their behavioural changes compared to visibly lame animals, for example, potentially showing an altered body condition rather than changes in lying behaviour. In addition, there was a notable variation among individual animals in the way the parameters changed in relation to lameness. These factors need to be considered when modelling data for lameness detection.

In this study, data from various sensor systems covering behaviour, performance, physiology, and climate were successfully applied in generalised linear mixed models to detect lameness. A lameness detection model based solely on performance data or a combination of performance and activity data proved ineffective in this study, but adding even a single additional behavioural parameter significantly improved the detection of lame animals. However, in the end, it was the combination of various parameters, including performance, behaviour, physiology and climate data, that allowed for highly accurate identification of lame cows. Particularly, parameters related to feeding behaviour, lying behaviour, body temperature, climate and constitution showed promising results for integration into lameness detection models. The increased use of sensor technology on dairy farms and the promising results of this study show that it is possible to help farmers automatically detect lame animals using data collected for other purposes, thus enabling earlier treatment and more awareness of the claw health situation on the farm.

VIII. Outlook

The next step would be to investigate whether the lameness detection models could also identify claw health issues before they become visible to an observer in either the animal’s gait or stance. Given that previous studies have demonstrated early alterations in behaviour parameters (Mazrier et al., 2006; Norring et al., 2014; Taneja et al., 2020), indirect automatic lameness detection might be suitable for an early diagnosis. For this purpose, the models would need to be implemented on a farm where manual locomotion scoring by a farmer or veterinary professional is conducted on a regular basis to evaluate whether the models alert for lameness before the observer and, if so, to determine how much sooner they could detect a change in claw health status. Another approach would be to investigate whether different lameness detection models tailored for specific claw diseases, such as one for horn-associated lesions and another for claw skin-associated lesions, could improve the overall detection of claw diseases. Furthermore, efforts should be directed towards improving the performance accuracy of lameness detection. The data collected in this study might be suitable for time series analyses, as multiple measurements were taken over equivalent time periods. Time series analysis enables the comparison of an individual animal's behaviour across various time periods (Neupane et al., 2024), facilitating the identification of deviations. In contrast to a model that evaluates all animals at a single point in time, time series analysis could provide a more nuanced understanding of each animal's specific changes and trends (Neupane et al., 2024).

IX. Summary

Lameness continues to be a widespread, global issue and represents one of the most significant production-related diseases in dairy farming, alongside udder diseases and fertility issues. Investigating the aetiology of lameness demands the consideration of individual cow factors such as age, breed or performance, as well as management practices and housing conditions. Since lameness is a manifestation of pain, it significantly impacts animal welfare and can influence various behaviours in cows, including their activity levels, feeding behaviour, and lying patterns, thereby preventing them from engaging in their natural behaviours. From an economic perspective, lameness imposes substantial costs on dairy farmers due to treatment costs, production losses or potential culling of affected animals.

Regular and systematic visual lameness detection in livestock demands a considerable amount of time, which farmers often struggle to spare in their daily routines. Moreover, the accuracy of manual lameness detection is significantly influenced by the observer's expertise and experience. But early detection of claw health issues is critical, as it enables timely intervention and helps to prevent further deterioration of the condition.

In this context, automated lameness detection systems present a promising solution for achieving a more objective and precise identification of lame animals. The field of Precision Livestock Farming (PLF) is gaining increasing attention, with sensor systems and digital technologies being deployed in various ways within and around barns to, for instance, enhance animal health and ease the daily workload of farmers. While these systems may present potential challenges, such as system failures, data security concerns and high investment costs, they can also alleviate certain tasks for farmers, streamline herd monitoring and facilitate the identification of various health issues.

Unlike simpler systems such as automatic heat detection, automated lameness detection presents a greater complexity as it involves numerous interrelated factors that both contribute to and result from lameness. Automated lameness detection systems can be categorised into direct systems, which rely on kinetic, kinematic, or thermographic methods, and indirect systems, which use performance and behavioural data recorded by animal-specific sensor systems. The latter offer the benefit of utilising sensor systems already installed in the barn to monitor various health conditions, enabling farmers to avoid additional investments.

The two preceding studies regarding indirect automatic lameness detection, also conducted at the Institute for Agricultural Engineering and Animal Husbandry of the Bavarian State Research Centre for Agriculture (LfL), revealed that developed algorithms containing behaviour and performance data could accurately distinguish between lame and non-lame cows with a probability of 82% or greater. In these studies, the only animal-attached sensors utilised were pedometers, which recorded activity, lying, and feeding behaviours.

The objective of this study, as part of the experimental field DigiMilch, was to refine and enhance these algorithms using data from various sensor systems installed on eight Bavarian dairy farms. It was aimed to determine which parameters from different sensor systems or their combinations were best suited for indirect automatic lameness detection. Furthermore, an additional aim was to validate the three-level locomotion score (LMS) created in the previous project with the new data.

With three research farms and five commercial farms involved, more farms participated in the investigation than in the preceding projects. All farms utilised milking robots by different manufacturers along with varying sensor systems attached to the animals. Data from three different pedometers, three neck tags, a bolus, a BCS camera, scales, weighing troughs and the LKV could be incorporated into the study alongside the milking robot data.

The necessary reference data regarding claw health were collected during 20 claw trimming dates conducted between March 2021 and October 2022. During the claw trimming itself, visible findings were documented and a pain test was performed on each claw to identify animals that were experiencing pain without any visible signs. Additionally, the growth in the sole centre was evaluated using a three-level scoring system. Furthermore, the cow's gait was assessed through video recordings by using the three-level LMS. Cameras were accordingly installed at the exit of the milking robot, allowing a retrospective locomotion scoring for up to 21 days prior to the claw trimming date to track the developments of lameness cases. Both intra-rater and inter-rater reliability were calculated for the three-level LMS. Furthermore, a lesion score (LS) was developed for additional validation, based on a combination of visible findings and the pain assessment. The reference data were ultimately consolidated into a corrected locomotion score (C_LMS), where all LMS2 cases were elevated to LMS3 if accompanied by either a positive pain test or visible findings.

Sensor data were either automatically transferred to an SQL database, depending on interface availability, or manually exported. These data were then merged with the reference data in RStudio to create daily datasets for each farm, which were later used to generate daily records based on different parameter categories. The best possible generalised linear mixed regression models were developed for each parameter class, using both the LMS and the C_LMS as a reference.

The lameness prevalence ranged from 1.9% to 10% when only visibly lame animals were considered. However, due to the large number of LMS2 cases, the prevalence increased to 25%-36.7% when all non-sound animals were included. Lameness developed in all cases within two weeks, with a median onset of three days. In total, the pain test was positive in 226 cases, 23.5% of which showed no visible signs of findings. Excessive sole centre overgrowth could be documented in 64.9% of all claws. The most frequent findings were diffuse sole haemorrhages with a percentage of 30%, followed by digital dermatitis and white line fissures. The majority of findings, pain responses and overgrown sole centres was detected in the hind legs.

The LMS exhibited high intra-rater (κ_w = 0.89, CI: 0.84-0.94) and inter-rater reliability (κ_w = 0.72, CI: 0.64-0.81) in this study. However, only moderate agreement was achieved between the LS and the LMS (κ_w = 0.44, CI: 0.40-0.50). In particular, many cows with a higher LS, indicating a pain reaction and/or visible findings, were classified as sound based on the LMS.

The automatically recorded parameters were analysed for differences between the LMS and C_LMS groups. The results indicated that most of the automatically recorded parameters, such as milking frequency, feeding behaviour and body temperature, differed in lame animals significantly from those in healthy animals. However, the same differences were not always observed when comparing the LMS and C_LMS groups. For instance, animals with a noticeably irregular gait (LMS3) exhibited a statistically significant increase in lying duration compared to those classified as healthy. This difference disappeared when animals without visible lameness, but with findings or a positive pain test, were included in this group (C_LMS3).

The generalised linear mixed regression models that included only performance data achieved an area under the curve (AUC) of approximately 0.6. This could only be improved to a maximum of 0.7 by adding activity data. However, the inclusion of just one additional automatically recorded parameter increased the accuracy to over 80%. The best models across multiple farms incorporated not only performance and activity parameters but also the parameter classes feeding behaviour or lying behaviour in combination with body temperature and climate, achieving an AUC of 0.82 for C_LMS and 0.89 for LMS. The overall best performance for both C_LMS (AUC: 0.91) and LMS (AUC: 0.93) was attained using the weighing trough data on RF1 in combination with lying behaviour. In the C_LMS model, the combination of constitution and feeding behaviour also yielded particularly good results on the same farm (AUC: 0.90).

The results provide insights into the prevalence of lameness in Bavarian dairy farms and the most commonly occurring claw diseases. The fact that almost a quarter of the painful animals showed no visible findings suggests that some claw diseases may cause pain before they are visually detectable by the observer. The LMS demonstrated high comparability; however, the relatively large proportion of animals with pain or findings that were not identified as lame may be attributed to the fact that certain claw diseases, such as digital dermatitis, could have a less pronounced impact on the LMS.

Developing claw lesions or mild cases might have different effects on automatically recorded parameters compared to clearly visible lameness. For example, lying time may only increase in cases of advanced lameness, whereas body condition score and body weight in combination might provide an earlier indication of lameness.

Models relying solely on performance data or those that include both performance and activity data failed to achieve adequate accuracy, likely due to significant individual variation in activity levels among the animals. However, by adding further parameters, a high level of performance in the automated lameness detection models was achieved. The most successful models incorporated parameters such as feeding pace and trough visits, indicating that a more detailed recording of feeding behaviour by sensor systems could significantly improve automatic lameness detection. Even the inclusion of single additional parameters like feeding behaviour, lying behaviour or body temperature already enhanced model accuracy, but it was the combination of various parameters that most effectively identified lame animals. These results highlight the critical need for integrating data from various sensors for complex health concerns such as lameness, as a multifaceted approach is essential for the accurate detection and management of this condition.

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X. Zusammenfassung

Lahmheiten stellen nach wie vor ein weit verbreitetes, globales Problem dar und gehören neben Eutererkrankungen und Fruchtbarkeitsproblemen zu den bedeutendsten produktionsbedingten Erkrankungen in der Milchwirtschaft. Die Suche nach auslösenden Faktoren erfordert die Berücksichtigung sowohl tierindividueller Faktoren wie Alter, Rasse oder Milchleistung als auch von Managementpraktiken und Haltungsbedingungen. Da Lahmheiten eine Ausdrucksform von Schmerz sind, haben sie erhebliche Auswirkungen auf das Tierwohl und können verschiedenste Verhaltensweisen der Kühe beeinflussen, einschließlich Aktivitätsniveau, Fress- und Liegeverhalten, wodurch diese daran gehindert werden, ihren natürlichen Verhaltensweisen nachzugehen. Aus wirtschaftlicher Sicht verursachen Lahmheiten erhebliche Kosten für Landwirte durch Behandlungen, Leistungsausfälle oder die manchmal notwendige Keulung der betroffenen Tiere.

Die regelmäßige und systematische visuelle Lahmheitserkennung bei Nutztieren erfordert einen erheblichen Zeitaufwand, dem die Landwirte in ihrem täglichen Arbeitsalltag oft nur schwer nachkommen können. Darüber hinaus wird die Genauigkeit der manuellen Lahmheitserkennung erheblich von der Sachkenntnis und Erfahrung des Beobachters beeinflusst. Eine frühzeitige Erkennung von Klauengesundheitsproblemen ist jedoch von entscheidender Bedeutung, da sie ein rechtzeitiges Eingreifen ermöglicht und dazu beiträgt, eine weitere Verschlechterung des Zustands zu verhindern.

In diesem Zusammenhang stellen automatische Lahmheitserkennungssysteme eine vielversprechende Lösung für eine objektivere und präzisere Identifikation lahmer Tiere dar. Der Bereich der Präzisionslandwirtschaft (PLF) gewinnt zunehmend an Bedeutung, wobei Sensorsysteme und digitale Technologien auf unterschiedliche Weise in Innen- und Außenwirtschaft eingesetzt werden, um zum Beispiel die Tiergesundheit zu verbessern oder die tägliche Arbeitsbelastung der Landwirte zu reduzieren. Während diese Systeme potenzielle Herausforderungen hinsichtlich Systemausfällen, Datensicherheit und hoher Investitionskosten mit sich bringen, können sie den Landwirten auch bestimmte Aufgaben abnehmen, die Herdenüberwachung optimieren und die Erkennung verschiedener Gesundheitsprobleme erleichtern.

Im Gegensatz zu einfacheren Systemen wie der automatischen Brunsterkennung ist die automatische Lahmheitserkennung komplexer, da sie zahlreiche zusammenhängende Faktoren umfasst, die sowohl eine Lahmheit begünstigen als auch daraus resultieren können. Automatische Lahmheitserkennungssysteme lassen sich in direkte Systeme, die sich auf kinetische, kinematische oder thermografische Methoden stützen, und indirekte Systeme unterteilen, die Leistungs- und Verhaltensdaten nutzen, die von tierindividuellen Sensorsystemen aufgezeichnet werden. Letztere bieten den Vorteil, dass vorhandene Sensorsysteme im Stall genutzt werden können, um verschiedene Gesundheitszustände zu überwachen, und somit zusätzliche Investitionen vermieden werden können.

Die beiden vorangegangenen Studien zur indirekten automatischen Lahmheitserkennung, die ebenfalls am Institut für Landtechnik und Tierhaltung der Bayerischen Landesanstalt für Landwirtschaft (LfL) durchgeführt wurden, ergaben, dass die mit Hilfe von Verhaltens- und Leistungsdaten entwickelten Algorithmen mit einer Wahrscheinlichkeit von 82 % oder mehr zwischen lahmen und nicht lahmen Kühen unterscheiden konnten. In diesen Studien wurden als einzige am Tier angebrachte Sensoren Pedometer verwendet, die die Aktivität sowie das Liege- und Fressverhalten aufzeichneten.

Ziel dieser Studie im Rahmen des Experimentierfelds DigiMilch war es, diese Algorithmen mit Hilfe von Daten aus verschiedenen Sensorsystemen, die in acht bayerischen Milchviehbetrieben installiert waren, zu verfeinern und zu verbessern. Es sollte ermittelt werden, welche Parameter aus den unterschiedlichen Sensorsystemen oder deren Kombinationen sich am besten zur indirekten automatischen Lahmheitserkennung eignen. Ein weiteres Ziel war es, den im Vorgängerprojekt entwickelten dreistufigen Locomotionscore (LMS) mit den neuen Daten zu validieren.

Mit drei Versuchsbetrieben und fünf Praxisbetrieben konnten mehr Betriebe in die Untersuchung miteinbezogen werden als in den vorhergehenden Projekten. Alle Betriebe verwendeten Melkroboter verschiedener Hersteller in Verbindung mit unterschiedlichen an den Tieren angebrachten Sensorsystemen. So konnten neben den Melkroboterdaten auch Daten von drei verschiedenen Pedometern, drei Halsbandsensoren, einem Bolus, einer BCS-Kamera, Waagen, Wiegetrögen und dem LKV in die Studie einfließen.

Die erforderlichen Referenzdaten zur Klauengesundheit wurden innerhalb von 20 Klauenpflegeterminen im Zeitraum vom März 2021 bis Oktober 2022 erhoben. Bei der Klauenpflege selbst wurden die sichtbaren Befunde dokumentiert und es wurde ein Schmerztest an jeder Klaue durchgeführt, um Tiere zu identifizieren, die trotz Abwesenheit sichtbarer Klauenläsionen schmerzhaft waren. Außerdem wurde das Überwachsen der Hohlkehlung anhand eines dreistufigen Punktesystems bewertet. Der Gang der Kuh wurde anhand von Videoaufzeichnungen mit Hilfe des dreistufigen LMS bewertet. Dementsprechend wurden Kameras am Ausgang des Melkroboters installiert, die eine retrospektive Beurteilung des Gangbilds bis zu 21 Tage vor dem Klauenpflegetermin ermöglichten, um auch die Entwicklung der Lahmheiten nachverfolgen zu können. Sowohl die Intra-Rater- als auch die Inter-Rater-Reliabilität wurden für den dreistufigen LMS berechnet. Darüber hinaus wurde zur zusätzlichen Validierung ein Läsions-Score (LS) entwickelt, der auf einer Kombination aus sichtbaren Befunden und der Schmerzprobe beruhte. Die Referenzdaten wurden schließlich zu einem korrigierten Locomotionscore (C_LMS) konsolidiert, bei dem alle LMS2-Fälle auf LMS3 hochgestuft wurden, wenn sie mit einem positiven Schmerztest oder sichtbaren Befunden einhergingen.

Die Sensordaten wurden je nach Verfügbarkeit der Schnittstelle entweder automatisch in eine SQL-Datenbank übertragen oder manuell exportiert. Diese Daten wurden dann in RStudio mit den Referenzdaten zusammengeführt, um Tagesdatensätze für jeden Betrieb zu erstellen, die später in Tagesdatensätze basierend auf den verschiedenen Parameterkategorien umgewandelt wurden. Für jede Parameterklasse wurden die bestmöglichen generalisierten linearen gemischten Regressionsmodelle entwickelt, wobei sowohl der LMS als auch der C_LMS als Referenz verwendet wurden.

Die Lahmheitsprävalenz reichte von 1,9 % bis 10 %, wenn nur deutlich lahme Tiere berücksichtigt wurden. Aufgrund der großen Anzahl an LMS2-Fällen stieg die Prävalenz jedoch auf 25 % bis 36,7 %, wenn alle nicht gesunden Tiere miteinbezogen wurden. Eine Lahmheit entwickelte sich in allen Fällen innerhalb von zwei Wochen, im Median dauerte es drei Tage. Insgesamt war der Schmerztest in 226 Fällen positiv, wobei 23,5 % der schmerzhaften Tiere keine sichtbaren Anzeichen einer Klauenerkrankung zeigten. Eine stark überwachsene Hohlkehlung konnte bei 64,9 % aller Klauen dokumentiert werden. Die am häufigsten auftretenden Befunde waren diffuse Sohlenblutungen mit einem Anteil von 30 %, gefolgt von Dermatitis digitalis und Weiße-Linie-Defekten. Die meisten Befunde, Schmerzreaktionen und überwachsene Hohlkehlungen konnten an den Hinterbeinen festgestellt werden.

Der LMS zeigte in dieser Studie eine hohe Intra-Rater- (κ_w = 0,89, KI: 0,84-0,94) und Inter-Rater-Reliabilität (κ_w = 0,72, KI: 0,64-0,81). Es wurde jedoch nur eine moderate Übereinstimmung zwischen dem LS und dem LMS erzielt (κ_w = 0,44, KI: 0,40-0,50). Insbesondere wurden viele Kühe trotz eines höheren LS aufgrund einer Schmerzreaktion und/oder sichtbaren Befunden auf der Grundlage des LMS als gesund eingestuft.

Die automatisch erfassten Parameter wurden auf Unterschiede zwischen den LMS- und C_LMS-Gruppen untersucht. Die Ergebnisse zeigten, dass sich die meisten der automatisch aufgezeichneten Parameter, wie Melkfrequenz, Fressverhalten und Körpertemperatur, bei lahmen Tieren signifikant von denen gesunder Tiere unterschieden. Beim Vergleich der LMS- und C_LMS-Gruppen wurden jedoch nicht immer die gleichen Unterschiede beobachtet. So wiesen Tiere mit einem sichtbar unregelmäßigen Gang (LMS3) eine statistisch signifikant höhere Liegedauer auf als die als gesund eingestuften Tiere. Dieser Unterschied ging jedoch verloren, wenn Tiere ohne sichtbare Lahmheit, aber mit Befund oder positivem Schmerztest in diese Gruppe aufgenommen wurden (C_LMS3).

Die generalisierten linearen gemischten Regressionsmodelle, die nur Leistungsdaten enthielten, erreichten eine Fläche unter der Kurve (AUC) von etwa 0,6. Dieser Wert konnte durch Hinzufügen von Aktivitätsdaten nur auf maximal 0,7 verbessert werden. Die Einbeziehung von nur einem zusätzlichen automatisch erfassten Parameter konnte die Genauigkeit jedoch auf über 80 % erhöhen. Die besten Modelle über mehrere Betriebe hinweg beinhalteten nicht nur Leistungs- und Aktivitätsparameter, sondern auch die Parameterklassen Fressverhalten oder Liegeverhalten in Kombination mit Körpertemperatur und Klima und erreichten eine AUC von 0,82 für den C_LMS und 0,89 für den LMS als Referenz. Die insgesamt beste Leistung sowohl für C_LMS (AUC: 0,91) als auch für LMS (AUC: 0,93) wurde mit den Wiegetrogdaten von RF1 in Kombination mit dem Liegeverhalten erreicht. Im C_LMS-Modell lieferte außerdem die Kombination aus Konstitution und Fressverhalten auf demselben Betrieb besonders gute Ergebnisse (AUC: 0,90).

Die Ergebnisse geben Aufschluss über die Prävalenz von Lahmheiten in bayerischen Milchviehbetrieben und die am häufigsten auftretenden Klauenerkrankungen. Die Tatsache, dass fast ein Viertel der schmerzhaften Tiere keine sichtbaren Befunde zeigte, deutet darauf hin, dass einige Klauenerkrankungen Schmerzen verursachen können, bevor sie für den Beobachter visuell erkennbar sind. Der LMS wies eine hohe Vergleichbarkeit auf; der relativ große Anteil an Tieren mit Schmerzen oder Befunden, die nicht als lahm identifiziert werden konnten, könnte jedoch darauf zurückzuführen sein, dass bestimmte Klauenkrankheiten, wie z. B. die Dermatitis digitalis, einen weniger ausgeprägten Einfluss auf den LMS haben.

Lahmheiten beeinflussen viele verschiedene Aspekte im Leben einer Kuh, doch das Hauptproblem liegt oft in der schwierigen Unterscheidung zwischen Ursache und Wirkung. Sich entwickelnde Klauenläsionen oder leichte Fälle könnten außerdem andere Auswirkungen auf die automatisch erfassten Parameter haben als deutlich sichtbare Lahmheiten. So zeigte in dieser Studie beispielsweise die Liegezeit nur bei fortgeschrittener Lahmheit eine Verlängerung, während der Body-Condition-Score und das Körpergewicht in Kombination frühere Hinweise auf Klauenerkrankungen lieferten.

Modelle, die sich ausschließlich auf Leistungsdaten stützten, oder solche, die sowohl Leistungs- als auch Aktivitätsdaten enthielten, erreichten keine ausreichende Genauigkeit, was unter anderem auf die erheblichen individuellen Unterschiede im Aktivitätsniveau der Tiere zurückzuführen sein kann. Durch Hinzufügen weiterer Parameter wurde jedoch ein hohes Leistungsniveau der automatischen Lahmheitserkennungsmodelle erreicht. Die erfolgreichsten Modelle enthielten Parameter wie Fressgeschwindigkeit und Trogbesuche, was darauf hindeutet, dass eine detailliertere Aufzeichnung des Futteraufnahmeverhaltens durch Sensorsysteme die automatische Lahmheitserkennung erheblich verbessern könnte. Selbst die Einbeziehung einzelner zusätzlicher Parameter wie Futteraufnahmeverhalten, Liegeverhalten oder Körpertemperatur verbesserte bereits die Modellgenauigkeit, aber es war die Kombination verschiedener Parameter, die am effektivsten lahme Tiere identifizierte. Diese Ergebnisse verdeutlichen, wie wichtig die Integration von Daten aus verschiedenen Sensoren für komplexe Gesundheitsprobleme wie Lahmheit ist, da ein multifaktorieller Ansatz für die genaue Erkennung und Behandlung dieser Erkrankung unerlässlich ist.

Die Förderung des Vorhabens erfolgt aus Mitteln des Bundesministeriums für Ernährung und Landwirtschaft (BMEL) aufgrund eines Beschlusses des deutschen Bundestages. Die Projektträgerschaft erfolgt über die Bundesanstalt für Landwirtschaft und Ernährung (BLE) im Rahmen des Programms Experimentierfelder in der Landwirtschaft.

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XII. Appendices

Table 32: Claw trimming dates used for data analysis

	2021	2022
RF1	11/03, 13/07, 29/11	04/04, 11/10
RF2	06/05	03/02, 02/06
RF3	11/05, 21/09	02/02, 14/07
CDF1	/	24/05
CDF2	/	07/02
CDF3	20/09, 15/12	15/07
CDF4	18/11-19/11	11/04-12/04
CDF5	/	21/02-22/02

Table 33: All parameters recorded manually and automatically during the study

Code	Parameter	Description	Format	Unit	Data sources	Farms
Animal Characteristics						
CowID	Cow number	Short identification number of the cow on the specific farm	factor		LKV, HIT, every system	All farms
ETN	Ear Tag number	Unique identification number on the ear tag of the cow	factor		LKV, HIT, every system	All farms
Date	Date	Date of the data collection	date	YYYY-mm-dd	Every system	All farms
Breed	Breed	Breed of the cow	factor		LKV, number was assigned to each breed	All farms
Date_of_birth	Date of birth	Birth date of the cow	date	YYYY-mm-dd	LKV, HIT	All farms
Milking						
Status_of_reproduction	Status of reproduction	The reproductive status of the cow, for example lactating or dry	character		Calculated based on daily milk yield, lactation number and days in milk	All farms

Code	Parameter	Description	Format	Unit	Data sources	Farms
Lactation_number	Parity/Lactation number	Number of the current lactation of the cow	integer	n	LKV	All farms
Days_in_milk	Days in milk	Number of days since calving	integer	n	Calculated based on last calving date	All farms
Last_date_of_calving	Last calving date	Last calving date of the cow	date	YYYY-mm-dd	LKV	All farms
LKV_milk_yield_in_last_lactation	Milk yield in last lactation	Total milk yield of the cow in the last lactation measured during the Milk performance tests	numeric	kg	LKV	Except for CDF1
LKV_test_date	Milk performance test date	Date of the respective milk performance testing	date	YYYY-mm-dd	LKV	All farms
LKV_daily_milk_yield	Daily milk yield	Average daily milk yield as a result of the monthly milk performance testing	numeric	kg	LKV	All farms
LKV_urea	Urea	Average daily urea content in milk as a result of the monthly milk performance testing	integer	ppm (parts per million)	LKV	All farms
LKV_somatic_cell_count	Somatic cell count	Average daily somatic cell count of the milk as a result of the monthly milk performance testing	integer	thousand cells/ml	LKV	All farms

Code	Parameter	Description	Format	Unit	Data sources	Farms
LKV_fat	Fat	Average daily fat content in milk as a result of the monthly milk performance testing	numeric	%	LKV	All farms
LKV_protein	Protein	Average daily protein content in milk as a result of the monthly milk performance testing	numeric	%	LKV	All farms
LKV_fat_protein_ratio	Fat-protein ratio	Average daily fat-protein ratio in milk as a result of the monthly milk performance testing	numeric		Calculated based on the fat and protein content in the milk measured during the milk performance testing by LKV	All farms
LKV_lactose	Lactose	Average daily lactose content in milk as a result of the monthly milk performance testing	numeric	%	LKV	All farms
Milkings	Milkings	Number of milkings on current day	integer	n	Milking robot	All farms
Maximum_milking_interval	Maximum milking interval	Longest interval between two consecutive milkings on current day	integer	mins	Calculated based on milking visits of the milking robot	All farms
Robot_daily_milk_yield	Daily milk yield	Sum of all milkings on current day	numeric	kg	Milking Robot	All farms

Code	Parameter	Description	Format	Unit	Data sources	Farms
Robot_milk_yield_in_current_lactation	Total milk yield in current lactation	Accumulated milk yields within the current lactation until the respective day	numeric	kg	Milking robot	RF1
Robot_milk_yield_in_last_lactation	Total milk yield in last lactation	Accumulated milk yields within the last lactation	numeric	kg	Milking robot	RF2, RF3, CDF1, CDF2, CDF3, CDF4, CDF5
Robot_daily_milk_yield_in_last_lactation	Daily milk yield in last lactation	Average daily milk yield within the last lactation	numeric	kg	Milking robot	RF2, RF3, CDF1, CDF5
Robot_fat	Fat	Average daily fat content in milk	numeric	%	Milking robot	RF2, RF3, CDF1, CDF2, CDF4, CDF5
Robot_protein	Protein	Average daily protein content in milk	numeric	%	Milking robot	RF2, RF3, CDF1, CDF2, CDF4, CDF5
Robot_fat_protein_ratio	Fat-protein ratio	Average daily fat-protein ratio in milk	numeric		Calculated based on the fat and protein content in the milk measured by the milking robot	RF2, RF3, CDF1, CDF2, CDF4, CDF5
Robot_lactose	Lactose	Average daily lactose content in milk	numeric	%	Milking robot	RF2, RF3, CDF1, CDF2, CDF4, CDF5
Robot_somatic_cell_count	Somatic cell count	Average daily somatic cell count in milk	numeric	thousand cells/ml	Milking robot	RF2, RF3, CDF1

Code	Parameter	Description	Format	Unit	Data sources	Farms
Robot_effect_of_scc	Effect of the somatic cell count	Index displaying the effect of the somatic cell count of the cow on the whole herd	numeric		Milking robot	RF2, RF3, CDF1
Robot_blood	Blood in milk	Amount of blood in the milk	numeric	cells/µL percent	Milking robot	RF1, CDF3
Robot_blood_percent	Blood in milk	Amount of blood in the milk	numeric	%	Milking robot	CDF2, CDF4
Colour_lv, Colour_rv, Colour_lh, Colour_rh	Milk colour	Colour of the milk of every milk quarter	factor		Milking robot, number was assigned to each possible milk colour	RF2, RF3, CDF1, CDF5
Milking_temperature	Milk temperature	Average daily temperature of the milk	numeric	° C	Milking robot	RF2, RF3, CDF1, CDF5
MDi	Mastitis-Detection-Index	Index combining blood in milk, milking interval and conductivity	numeric		Milking robot (DeLaval)	RF1, CDF3
Milking_flow	Average milking flow	Average rate of milk expulsion from the udder during the milking process	numeric	kg/min	Milking robot	RF1, RF2, RF3, CDF1, CDF3, CDF5
Max_milking_flow	Maximum milking flow	Maximum rate of milk expulsion from the udder during the milking process	numeric	kg/min	Milking robot	RF1, RF2, RF3, CDF1, CDF3, CDF5
Conduct_lv, Conduct_rv, Conduct_lh, Conduct_rh	Median conductivity of the milk in every quarter	Ability of milk to conduct electrical current, reflecting its composition	numeric	mS/cm	Milking robot	RF1, CDF2, CDF3, CDF4

Code	Parameter	Description	Format	Unit	Data sources	Farms
Conduct_lely_lv, Conduct_lely_rv, Conduct_lely_lh, Conduct_lely_rh	Median conductivity of the milk in every quarter	Ability of milk to conduct electrical current, reflecting its composition	integer	proprietary measurement unit	Milking robot (Lely)	RF2, RF3, CDF1, CDF5
Constitution						
Robot_BCS	Body condition score	Numerical assessment of the body fat reserves of the cow on a scale from 1 to 5	numeric		Milking robot (DeLaval)	RF1
Body_weight	Body weight	Total body weight of the cow	numeric	kg	Weighing troughs, milking robot	RF1, CDF5
Feeding						
WT_feed_intake	Feed intake	Total of individual feed intake amounts	numeric	kg	Weighing Troughs	RF1
Concentrated_feed_intake	Intake of concentrated feed	Intake amount of concentrated feed	numeric	kg	Milking robot	All farms
Concentrated_feed_remains	Remaining concentrated feed	Remaining amount of concentrated feed	numeric	kg	Milking robot	RF2, RF3, CDF1, CDF5
WT_feeding_duration	Feeding duration	Total duration of all visits to the feeding throughs	numeric	mins	Weighing Troughs	RF1
WT_feeding_duration_day	Feeding duration during daytime	Duration of all visits to the feeding throughs during daytime	numeric	mins	Weighing Troughs (Calculated)	RF1
WT_feeding_duration_day_night	Feeding duration (day/night)	Ratio of the feeding duration during daytime to the total feeding duration	numeric		Weighing Troughs (Calculated)	RF1

Code	Parameter	Description	Format	Unit	Data sources	Farms
WT_feeding_pace	Feeding pace	Amount of feed intake per feeding duration	numeric	kg/min	Weighing Troughs (Calculated)	RF1
WT_trough_visits	Number of weighing trough visits	Total number of visits to the weighing trough	integer	n	Weighing Troughs	RF1
WT_trough_visits_day	Number of weighing trough visits during daytime	Number of visits to the weighing trough during daytime	integer	n	Weighing Troughs (Calculated)	RF1
WT_trough_visits_day_night	Number of weighing trough visits (day/night)	Ratio of the number of visits to the weighing trough during daytime to the total number of visits to the weighing trough	numeric		Weighing Troughs (Calculated)	RF1
WT_number_of_meals	Number of meals	Total number of meals	integer	n	Weighing Troughs (Calculated)	RF1
WT_number_of_meals_day	Number of meals during daytime	Number of meals during daytime	integer	n	Weighing Troughs (Calculated)	RF1
WT_number_of_meals_day_night	Number of meals (day/night)	Ratio of the number of meals during daytime to the total number of meals	numeric		Weighing Troughs (Calculated)	RF1
WT_feed_intake_per_meal	Feed intake per meal	Average feed intake per meal	numeric	kg	Weighing Troughs (Calculated)	RF1
WT_feeding_duration_per_meal	Feeding duration per meal	Average feeding duration per meal	numeric	mins	Weighing Troughs (Calculated)	RF1
WT_feeding_duration_per_visit	Feeding duration per visit	Average feeding duration per weighing trough visit	numeric	mins	Weighing Troughs (Calculated)	RF1

Code	Parameter	Description	Format	Unit	Data sources	Farms
WT_feed_intake_per_visit	Feed intake per visit	Average feed intake per weighing trough visit	numeric	kg	Weighing Troughs (Calculated)	RF1
ENGS_feeding	Feeding duration	Total duration of all meals	integer	mins	ENGS	RF1
ENGS_feeding_day	Feeding duration during daytime	Duration of all meals during daytime	integer	mins	ENGS (Calculated)	RF1
ENGS_feeding_day_night	Feeding duration (day/night)	Ratio of the feeding duration during daytime to the total feeding duration	numeric		ENGS (Calculated)	RF1
ENGS_number_of_meals	Number of meals	Total number of meals	integer	n	ENGS	RF1
ENGS_number_of_meals_day	Number of meals during daytime	Number of meals during daytime	integer	n	ENGS (Calculated)	RF1
ENGS_number_of_meals_day_night	Number of meals (day/night)	Ratio of the number of meals during daytime to the total number of meals	numeric		ENGS (Calculated)	RF1
ENGS_feeding_duration_per_meal	Feeding duration per meal	Average feeding duration per meal	numeric	mins	ENGS (Calculated)	RF1
Nedap_feeding	Feeding duration	Total feeding duration per day	integer	mins	Nedap	RF2, RF3
Rumination						
Smaxtec_rum	Duration of rumination	Total duration of rumination	numeric	mins	smaXtec	RF1, RF3, CDF4
SCR_rum	Duration of rumination	Total duration of rumination	integer	mins	SCR, Milking robot	RF1, RF3, CDF1, CDF5
SCR_rum_day	Duration of rumination during daytime	Duration of rumination during daytime	integer	mins	SCR (Calculated)	RF1

Code	Parameter	Description	Format	Unit	Data sources	Farms
SCR_rum_day_night	Duration of rumination (day/night)	Ratio of duration of rumination during daytime to the total duration of rumination	numeric		SCR (Calculated)	RF1
Nedap_rum	Duration of rumination	Total duration of rumination	integer	mins	Nedap	RF2, RF3
Heat behaviour						
SCR_heat_probability	Heat probability	Probability of an occurring heat in a cow	factor		SCR, Milking robot (Lely)	RF3, CDF1, CDF5
SCR_heat_probability_day	Heat probability during daytime	Probability of an occurring heat in a cow during daytime	factor		SCR, Milking robot (Lely)	RF3, CDF1, CDF5
Lemmer_factor_of_restlessness	Factor of restlessness	Factor of restlessness, depending on the cows' activity	factor		Milking robot (Lemmer-Fullwood)	CDF2, CDF4
Lying behaviour						
ENGS_lying	Lying duration	Total lying duration	integer	mins	ENGS	RF1
ENGS_lying_day	Lying duration during daytime	Lying duration during daytime	integer	mins	ENGS (Calculated)	RF1
ENGS_lying_day_night	Lying duration (day/night)	Ratio of lying duration during daytime to the total lying duration	numeric		ENGS (Calculated)	RF1
ENGS_lying_bouts	Lying bouts	Total number of lying events	integer	n	ENGS	RF1
ENGS_lying_bouts_day	Lying bouts during daytime	Number of lying events during daytime	integer	n	ENGS (Calculated)	RF1
ENGS_lying_bouts_day_night	Lying bouts (day/night)	Ratio of lying bouts during daytime to the total number of lying bouts	numeric		ENGS (Calculated)	RF1

Code	Parameter	Description	Format	Unit	Data sources	Farms
ENGS_lying_duration_per_bout	Lying duration per bout	Average lying duration per lying bout	numeric	mins	ENGS (Calculated)	RF1
Nedap_lying	Lying duration	Total lying duration	integer	mins	Nedap	RF3
Nedap_get_ups	Lying bouts	Total number of lying events	integer	n	Nedap	RF3
Lemmer_lying	Lying duration	Total lying duration	integer	mins	Milking robot (Lemmer-Fullwood)	CDF2, CDF4
Lemmer_get_ups	Lying bouts	Total number of lying events	integer	n	Milking robot (Lemmer-Fullwood)	CDF2, CDF4
Activity						
ENGS_act	Activity units	Total activity	integer		ENGS	RF1
ENGS_act_day	Activity units during daytime	Activity during daytime	integer		ENGS (Calculated)	RF1
ENGS_act_day_night	Activity units (day/night)	Ratio of total activity to activity during daytime	numeric		ENGS (Calculated)	RF1
Smaxtec_act	Activity index	Total activity	numeric		smaXtec	RF1, RF3, CDF4
Smaxtec_act_day	Activity index during daytime	Activity during daytime	numeric		smaXtec (Calculated)	RF1, RF3, CDF4
Smaxtec_act_day_night	Activity index (day/night)	Ratio of total activity to activity during daytime	numeric		smaXtec (Calculated)	RF1, RF3, CDF4
SCR_act	Activity index	Total activity	numeric		SCR, Milking robot (Lely)	RF1, RF3, CDF1, CDF5
SCR_act_day	Activity index during daytime	Activity during daytime	numeric		SCR, Milking robot (Lely) (Calculated)	RF1, RF3, CDF1, CDF5

Code	Parameter	Description	Format	Unit	Data sources	Farms
SCR_act_day_night	Activity index (day/night)	Ratio of total activity to activity during daytime	numeric		SCR, Milking robot (Lely) (Calculated)	RF1, RF3, CDF1, CDF5
Nedap_act	Step count	Total activity	integer		Nedap	RF3
Nedap_inactive	Inactive time	Total inactive time without any head movements	integer	mins	Nedap	RF2, RF3
Nedap_act_foot_median	Median step count	Median step count in a two-hour interval	numeric		Nedap	RF3
Nedap_act_foot_sum_day	Step count during daytime	Total activity during daytime	integer		Nedap (Calculated)	RF3
Nedap_act_foot_median_day	Median step count during daytime	Median step count in a two-hour interval during daytime	numeric		Nedap (Calculated)	RF3
Nedap_act_foot_sum_day_night	Step count (day/night)	Ratio of total activity to activity during daytime	numeric		Nedap (Calculated)	RF3
Nedap_act_foot_median_day_night	Median step count (day/night)	Ratio of median activity in a two-hour interval during daytime to daily average activity in a two-hour interval	numeric		Nedap (Calculated)	RF3
Nedap_act_collar_sum	Neck activity	Total heat-associated neck movements	integer		Nedap (Calculated)	RF2, RF3
Nedap_act_collar_median	Median of neck activity	Median heat-associated neck movements in a two-hour interval	numeric		Nedap (Calculated)	RF2, RF3

Code	Parameter	Description	Format	Unit	Data sources	Farms
Nedap_act_collar_sum_day	Neck activity during daytime	Heat-associated neck movements during daytime	integer		Nedap (Calculated)	RF2, RF3
Nedap_act_collar_median_day	Median of neck activity during daytime	Median heat-associated neck movements in a two-hour interval during daytime	numeric		Nedap (Calculated)	RF2, RF3
Nedap_act_collar_sum_day_night	Neck activity (day/night)	Ratio of heat-associated neck movements during daytime to total heat-associated neck movements	numeric		Nedap (Calculated)	RF2, RF3
Nedap_act_collar_median_day_night	Median of neck activity (day/night)	Ratio of median heat-associated neck movements in a two-hour interval during daytime to daily average heat-associated neck movements in a two-hour interval	numeric		Nedap (Calculated)	RF2, RF3
Lemmer_act	Hourly average step count	Hourly average step count	integer		Milking robot (Lemmer-Fullwood)	CDF2, CDF4
Delaval_act_avg	Activity index	Average daily activity index	integer		Milking robot (DeLaval)	CDF3
Delaval_act_rel	Relative activity	Current activity level of the cow compared to its individual average	integer	%	Milking robot (DeLaval)	CDF3

Code	Parameter	Description	Format	Unit	Data sources	Farms
Delaval_act_rel_min	Minimum relative activity	Lowest value of the cow's activity compared to its individual average	integer	%	Milking robot (DeLaval)	CDF3
Delaval_act_rel_max	Maximum relative activity	Highest value of the cow's activity compared to its individual average	integer	%	Milking robot (DeLaval)	CDF3
Body temperature						
Smaxtec_temp_normal_median	Normal body temperature	Individual normal body temperature of the cow based on the last 5 days	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_temp_min	Minimum body temperature	Minimum body temperature of the cow	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_temp_max	Maximum body temperature	Maximum body temperature of the cow	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_temp_median	Median body temperature	Median body temperature of the cow	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_temp_without_drink_cycles_min	Minimum body temperature without drink cycles	Minimum body temperature adjusted for temperature declines resulting from drinking	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_temp_without_drink_cycles_max	Maximum body temperature without drink cycles	Maximum body temperature adjusted for temperature declines resulting from drinking	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_temp_without_drink_cycles_median	Median body temperature without drink cycles	Median body temperature adjusted for temperature declines resulting from drinking	numeric	°C	smaXtec	RF1, RF3, CDF4

Code	Parameter	Description	Format	Unit	Data sources	Farms
Climate						
Smaxtec_climate_temp_min	Minimum temperature	Minimum ambient temperature	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_climate_temp_max	Maximum temperature	Maximum ambient temperature	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_climate_temp_median	Average temperature	Median ambient temperature	numeric	°C	smaXtec	RF1, RF3, CDF4
Smaxtec_climate_hum_min	Minimum humidity	Minimum ambient humidity	numeric	%	smaXtec	RF1, RF3, CDF4
Smaxtec_climate_hum_max	Maximum humidity	Maximum ambient humidity	numeric	%	smaXtec	RF1, RF3, CDF4
Smaxtec_climate_hum_median	Median humidity	Median ambient humidity	numeric	%	smaXtec	RF1, RF3, CDF4
Smaxtec_thi_min	Minimum THI	Minimum Temperature-Humidity-Index	numeric		smaXtec (Calculated)	RF1, RF3, CDF4
Smaxtec_thi_max	Maximum THI	Maximum Temperature-Humidity-Index	numeric		smaXtec (Calculated)	RF1, RF3, CDF4
Smaxtec_thi_median	Median THI	Median Temperature-Humidity-Index	numeric		smaXtec (Calculated)	RF1, RF3, CDF4
WS_thi_min	Minimum THI	Minimum Temperature-Humidity-Index	numeric		Weather station (Calculated)	RF1, RF2, RF3
WS_thi_max	Maximum THI	Maximum Temperature-Humidity-Index	numeric		Weather station, (Calculated)	RF1, RF2, RF3
WS_thi_median	Median THI	Median Temperature-Humidity-Index	numeric		Weather station (Calculated)	RF1, RF2, RF3
WS_temp_2m_med	Median temperature in 2 m height	Median temperature in 2 m height	numeric	°C	Weather station	RF1, RF2, RF3
WS_temp_2m_min	Minimum temperature in 2 m height	Minimum ambient temperature in 2 m height	numeric	°C	Weather station	RF1, RF2, RF3

Code	Parameter	Description	Format	Unit	Data sources	Farms
WS_temp_2m_max	Maximum temperature in 2 m height	Maximum ambient temperature in 2 m height	numeric	°C	Weather station	RF1, RF2, RF3
WS_temp_20cm_med	Median temperature in 20 cm height	Median ambient temperature in 20 cm height	numeric	°C	Weather station	RF1, RF2, RF3
WS_temp_20cm_min	Minimum temperature in 20 cm height	Minimum ambient temperature in 20 cm height	numeric	°C	Weather station	RF1, RF2, RF3
WS_temp_20cm_max	Maximum temperature in 20 cm height	Maximum ambient temperature in 20 cm height	numeric	°C	Weather station	RF1, RF2, RF3
WS_soil_temp_5cm_med	Median soil temperature in 5 cm depth	Median soil temperature in 5 cm depth	numeric	°C	Weather station	RF1, RF2, RF3
WS_soil_temp_5cm_min	Minimum soil temperature in 5 cm depth	Minimum soil temperature in 5 cm depth	numeric	°C	Weather station	RF1, RF2, RF3
WS_soil_temp_5cm_max	Maximum soil temperature in 5 cm depth	Maximum soil temperature in 5 cm depth	numeric	°C	Weather station	RF1, RF2, RF3
WS_soil_temp_20cm_med	Median soil temperature in 20 cm depth	Median soil temperature in 20 cm depth	numeric	°C	Weather station	RF1, RF2, RF3
WS_soil_temp_20cm_min	Minimum soil temperature in 20 cm depth	Minimum soil temperature in 20 cm depth	numeric	°C	Weather station	RF1, RF2, RF3
WS_soil_temp_20cm_max	Maximum soil temperature in 20 cm depth	Maximum soil temperature in 20 cm depth	numeric	°C	Weather station	RF1, RF2, RF3
WS_rel_hum_med	Median relative humidity	Median relative humidity	numeric	%	Weather station	RF1, RF2, RF3
WS_rel_hum_min	Minimum relative humidity	Minimum relative humidity	numeric	%	Weather station	RF1, RF2, RF3

Code	Parameter	Description	Format	Unit	Data sources	Farms
WS_rel_hum_max	Maximum relative humidity	Maximum relative humidity	numeric	%	Weather station	RF1, RF2, RF3
WS_wind_velocity_med	Median wind velocity	Median wind velocity	numeric	m/s	Weather station	RF1, RF2, RF3
WS_wind_velocity_min	Minimum wind velocity	Minimum wind velocity	numeric	m/s	Weather station	RF1, RF2, RF3
WS_wind_velocity_max	Maximum wind velocity	Maximum wind velocity	numeric	m/s	Weather station	RF1, RF2, RF3
WS_rain_med	Median precipitation	Median precipitation	numeric	mm	Weather station	RF1, RF2, RF3
WS_rain_min	Minimum precipitation	Minimum precipitation	numeric	mm	Weather station	RF1, RF2, RF3
WS_rain_max	Maximum precipitation	Maximum precipitation	numeric	mm	Weather station	RF1, RF2, RF3
WS_global_rad_med	Median global radiation	Median global radiation	numeric	Wh/m²	Weather station	RF1, RF2, RF3
WS_global_rad_min	Minimum global radiation	Minimum global radiation	numeric	Wh/m²	Weather station	RF1, RF2, RF3
WS_global_rad_max	Maximum global radiation	Maximum global radiation	numeric	Wh/m²	Weather station	RF1, RF2, RF3
Season	Season	Current season of the claw trimming	integer		Manual, number assigned for each season	All farms
Claw health						
LMS	Locomotion score	Three-step Locomotion score	integer		Manual	All farms
C_LMS	Corrected Locomotion score	Locomotion score, corrected for pain test and findings	integer		Manual	All farms
GSC	Growth in the sole centre	Three-step score for growth in the sole centre	integer		Manual	All farms
PT	Pain test	Positive or negative pain test	integer		Manual	All farms

Code	Parameter	Description	Format	Unit	Data sources	Farms
Findings	Findings and treatments	Clinical findings and treatments of the claw trimming	character		Manual	All farms

Table 34: Classification of the claw trimming dates into seasons

Season	Months	Number
Spring	March, April, May	1
Summer	June, July, August	2
Autumn	September, October, November	3
Winter	December, January, February	4

Table 35: Count and percentage of locomotion scores (LMS) on the different claw trimming dates (CT)

	CT 1	CT 2	CT 3	CT 4	CT 5	Farm
LMS1	33 (58.9%)	45 (77.6%)	39 (68.4%)	43 (78.2%)	39 (66.1%)	RF1
LMS2	15 (26.8%)	8 (13.8%)	12 (21.0%)	7 (12.7%)	17 (28.8%)	RF1
LMS3	8 (14.3%)	5 (8.6%)	6 (10.5%)	5 (9.1%)	3 (5.1%)	RF1
LMS1	38 (84.4%)	28 (65.1%)	31 (72.1%)	/	/	RF2
LMS2	6 (13.3%)	10 (23.3%)	10 (23.3%)	/	/	RF2
LMS3	1 (2.2%)	5 (11.6%)	2 (4.7%)	/	/	RF2
LMS1	42 (66.7%)	38 (67.9%)	40 (76.9%)	40 (75.5%)	/	RF3
LMS2	12 (19.0%)	16 (28.6%)	6 (11.5%)	11 (20.8%)	/	RF3
LMS3	9 (14.3%)	2 (3.6%)	6 (11.5%)	2 (3.8%)	/	RF3
LMS1	46 (74.2%)	/	/	/	/	CDF1
LMS2	13 (21.0%)	/	/	/	/	CDF1
LMS3	3 (4.8%)	/	/	/	/	CDF1
LMS1	39 (75.0%)	/	/	/	/	CDF2
LMS2	12 (23.1%)	/	/	/	/	CDF2
LMS3	1 (1.9%)	/	/	/	/	CDF2
LMS1	17 (58.6%)	20 (62.5%)	20 (69.0%)	/	/	CDF3
LMS2	8 (27.6%)	8 (25.0%)	8 (27.6%)	/	/	CDF3
LMS3	4 (13.8%)	4 (12.5%)	1 (3.5%)	/	/	CDF3
LMS1	80 (69.6%)	93 (75.6%)	/	/	/	CDF4
LMS2	21 (18.3%)	27 (22.0%)	/	/	/	CDF4
LMS3	14 (12.2%)	3 (2.4%)	/	/	/	CDF4
LMS1	94 (72.9%)	/	/	/	/	CDF5
LMS2	28 (21.7%)	/	/	/	/	CDF5
LMS3	7 (5.4%)	/	/	/	/	CDF5

Table 36: Median lameness development period between last locomotion score (LMS) 1 and first LMS3 and standard deviation on each farm

Farm	Median days between last LMS1 and first LMS3	Standard deviation
RF1	3	3.45
RF2	4	1.56
RF3	1	0.76
CDF1	9	4.32
CDF2	3	6.43
CDF3	2	0.84
CDF4	2	2.41
CDF5	3	2.50

Table 37: Count and percentage of pain tests (PT) on the different claw trimming dates (CT)

	CT1	CT2	CT3	CT4	CT5	Farm
PT-	163 (86.7%)	212 (91.4%)	217 (95.2%)	218 (99.1%)	228 (96.6%)	RF1
PT+	25 (13.3%)	20 (8.6%)	11 (4.8%)	2 (0.9%)	8 (3.4%)	RF1
PT-	135 (75.0%)	161 (93.6%)	163 (94.8%)	/	/	RF2
PT+	45 (25%)	11 (6.4%)	9 (5.2%)	/	/	RF2
PT-	221 (87.7%)	213 (95.1%)	199 (95.7%)	204 (96.2%)	/	RF3
PT+	31 (12.3%)	11 (4.9%)	9 (4.3%)	8 (3.8%)	/	RF3
PT-	242 (97.6%)	/	/	/	/	CDF1
PT+	6 (2.4%)	/	/	/	/	CDF1
PT-	202 (97.1%)	/	/	/	/	CDF2
PT+	6 (2.9%)	/	/	/	/	CDF2
PT-	107 (92.2%)	122 (95.3%)	113 (97.4%)	/	/	CDF3
PT+	9 (7.8%)	6 (4.7%)	3 (2.6%)	/	/	CDF3
PT-	433 (94.1%)	479 (98.2%)	/	/	/	CDF4
PT+	27 (5.9%)	9 (1.8%)	/	/	/	CDF4
PT-	496 (96.1%)	/	/	/	/	CDF5
PT+	20 (3.9%)	/	/	/	/	CDF5

Table 38: Count and percentage of the growth in the sole centre (GSC) on the different claw trimming dates (CT)

	CT1	CT2	CT3	CT4	CT5	Farm
GSC1	4 (2.1%)	1 (0.4%)	3 (1.3%)	0 (0%)	0 (0%)	RF1
GSC2	154 (81.9%)	144 (62.1%)	97 (42.6%)	25 (11.4%)	57 (24.2%)	RF1
GSC3	30 (16.0%)	87 (37.5%)	128 (56.1%)	195 (88.6%)	179 (75.8%)	RF1
GSC1	1 (0.6%)	0 (0%)	0 (0%)	/	/	RF2
GSC2	144 (80.0%)	6 (3.5%)	49 (28.5%)	/	/	RF2
GSC3	35 (19.4%)	166 (96.5%)	123 (71.5%)	/	/	RF2
GSC1	0 (0%)	1 (0.4%)	4 (1.9%)	4 (1.9%)	/	RF3
GSC2	187 (74.2%)	127 (56.7%)	77 (37.0%)	53 (25.0%)	/	RF3
GSC3	65 (25.8%)	96 (42.9%)	127 (61.1%)	155 (73.1%)	/	RF3
GSC1	0 (0%)	/	/	/	/	CDF1
GSC2	21 (8.5%)	/	/	/	/	CDF1
GSC3	227 (91.5%)	/	/	/	/	CDF1
GSC1	0 (0%)	/	/	/	/	CDF2
GSC2	5 (2.4%)	/	/	/	/	CDF2
GSC3	203 (97.6%)	/	/	/	/	CDF2
GSC1	2 (1.7%)	4 (3.1%)	0 (0%)	/	/	CDF3
GSC2	93 (80.2%)	51 (39.9%)	8 (6.9%)	/	/	CDF3
GSC3	21 (18.1%)	73 (57.0%	108 (93.1%)	/	/	CDF3
GSC1	0 (0%)	0 (0%)	/	/	/	CDF4
GSC2	284 (61.7%)	38 (7.8%)	/	/	/	CDF4
GSC3	176 (38.3%)	450 (92.2%)	/	/	/	CDF4
GSC1	0 (0%)	/	/	/	/	CDF5
GSC2	44 (8.5%)	/	/	/	/	CDF5
GSC3	472 (91.5%)	/	/	/	/	CDF5

Table 39: Count of the total findings and treatments on each farm and percentages of the findings and treatments (abbreviations explained in Table 7 and Table 8)

	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5	Total	Percentage
Findings										
TU	1	0	0	1	0	0	0	2	4	0.14
OLU	4	5	0	0	0	2	1	1	13	0.44
IP	5	1	0	0	1	0	0	2	9	0.31
SU	10	6	3	0	1	5	17	5	47	1.58
DDM1	38	10	59	0	2	13	0	2	124	4.20
DDM2	30	56	59	0	7	22	49	27	250	8.46
DDM3	0	0	0	0	0	0	0	0	0	0.00
DDM4	64	11	5	0	5	54	15	3	157	5.31
DDM4.1	3	1	0	0	0	8	4	0	16	0.54
HHE	10	10	2	2	1	9	1	35	70	2.37
CSH	36	12	22	14	3	11	53	21	172	5.82
SHD	204	148	200	83	12	120	269	79	1,115	37.73
SHC	85	13	17	2	12	0	70	13	212	7.17
WLF	116	55	55	43	18	65	79	81	512	17.33
WLA	10	6	4	14	6	4	29	9	82	2.78
HF	13	6	4	0	3	2	7	1	36	1.22
IH	25	7	18	1	1	11	12	10	85	2.88
DS	16	3	7	5	3	5	7	3	49	1.66
TN	0	1	0	0	0	0	0	0	1	0.03
BU	1	0	0	0	0	0	0	0	1	0.03
Total	671	351	455	165	75	331	613	294	2,955	100.00
Treatments										
B	48	67	58	5	2	32	45	41	298	30.07
SAP	17	62	57	0	2	31	13	40	222	22.40
CTC	0	62	0	3	11	34	41	45	196	19.78
CB	27	12	7	4	11	2	33	0	96	9.69
SAPO	0	0	0	4	0	0	25	0	29	2.93
CZC	84	0	66	0	0	0	0	0	150	15.13
Total	176	203	188	16	26	99	157	126	991	100.00

Table 40: Count and percentage of findings and treatments on the different claw trimming dates (CT) on RF1 (abbreviations explained in Table 7 and Table 8)

	CT1		CT2		CT3		CT4		CT5	
	Count	Percentage	Count	Percentage	Count	Percentage	Count	Percentage	Count	Percentage
Findings										
TU	0	0.00	0	0.00	1	0.50	0	0.00	0	0.00
OLU	0	0.00	0	0.00	1	0.50	2	0.82	1	0.53
IP	0	0.00	3	13.64	0	0.00	1	0.41	1	0.53
SU	1	6.25	3	13.64	2	1.00	0	0.00	4	2.13
DDM 1	0	0.00	0	0.00	8	3.98	14	5.74	16	8.51
DDM 2	5	31.25	5	22.73	10	4.98	2	0.82	8	4.26
DDM 3	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
DDM 4	0	0.00	0	0.00	28	13.93	20	8.20	16	8.51
DDM 4.1	0	0.00	0	0.00	0	0.00	1	0.41	2	1.06
HHE	0	0.00	0	0.00	10	4.98	0	0.00	0	0.00
CSH	0	0.00	0	0.00	11	5.47	10	4.10	15	7.98
SHD	2	12.50	0	0.00	63	31.34	86	35.25	53	28.19
SHC	0	0.00	0	0.00	36	17.91	38	15.57	11	5.85
WLF	2	12.50	1	4.55	16	7.96	56	22.95	41	21.81
WLA	0	0.00	4	18.18	1	0.50	0	0.00	5	2.66
HF	0	0.00	2	9.09	4	1.99	5	2.05	2	1.06
IH	4	25.00	0	0.00	8	3.98	7	2.87	6	3.19
DS	2	12.50	4	18.18	2	1.00	1	0.41	7	3.72
TN	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
BU	0	0.00	0	0.00	0	0.00	1	0.41	0	0.00
Total	16	100.00	22	100.00	201	100.00	244	100.00	188	100.00
Treatments										
B	9	90	10	50.00	8	14.81	10	18.87	11	28.21
SAP	0	0	0	0.00	6	11.11	3	5.66	8	20.51
CTC	0	0	0	0.00	0	0.00	0	0.00	0	0.00
CB	1	10	10	50.00	8	14.81	2	3.77	6	15.38
SAP O	0	0	0	0.00	0	0.00	0	0.00	0	0.00
CZC	0	0	0	0.00	32	59.26	38	71.70	14	35.90
Total	10	100.00	20	100.00	54	100.00	53	100.00	39	100.00

Table 41: Count and percentage of findings and treatments on the different claw trimming dates (CT) on RF2 (abbreviations explained in Table 7 and Table 8)

	CT1		CT2		CT3	
	Count	**Percentage**	**Count**	**Percentage**	**Count**	**Percentage**
Findings						
TU	0	0.00	0	0.00	0	0.00
OLU	0	0.00	0	0.00	5	2.13
IP	0	0.00	1	1.09	0	0.00
SU	1	4.17	4	4.35	1	0.43
DDM1	1	4.17	1	1.09	8	3.40
DDM2	16	66.67	15	16.30	25	10.64
DDM3	0	0.00	0	0.00	0	0.00
DDM4	0	0.00	9	9.78	2	0.85
DDM4.1	0	0.00	0	0.00	1	0.43
HHE	0	0.00	2	2.17	8	3.40
CSH	0	0.00	3	3.26	9	3.83
SHD	0	0.00	28	30.43	120	51.06
SHC	0	0.00	3	3.26	10	4.26
WLF	3	12.50	17	18.48	35	14.89
WLA	2	8.33	3	3.26	1	0.43
HF	0	0.00	0	0.00	6	2.55
IH	1	4.17	3	3.26	3	1.28
DS	0	0.00	2	2.17	1	0.43
TN	0	0.00	1	1.09	0	0.00
BU	0	0.00	0	0.00	0	0.00
Total	24	100.00	92	100.00	235	100.00
Treatments						
B	16	31.37	24	36.36	27	31.40
SAP	16	31.37	20	30.30	26	30.23
CTC	16	31.37	17	25.76	29	33.72
CB	3	5.88	5	7.58	4	4.65
SAPO	0	0.00	0	0.00	0	0.00
CZC	0	0.00	0	0.00	0	0.00
Total	51	100.00	66	100.00	86	100.00

Table 42: Count and percentage of findings and treatments on the different claw trimming dates (CT) on RF3 (abbreviations explained in Table 7 and Table 8)

	CT1		CT2		CT3		CT4	
	Count	Percentage	Count	Percentage	Count	Percentage	Count	Percentage
Findings								
TU	0	0.00	0	0.00	0	0.00	0	0.00
OLU	0	0.00	0	0.00	0	0.00	0	0.00
IP	0	0.00	0	0.00	0	0.00	0	0.00
SU	0	0.00	1	1.32	1	1.06	1	0.50
DDM1	22	25.58	11	14.47	18	19.15	8	4.02
DDM2	23	26.74	14	18.42	7	7.45	15	7.54
DDM3	0	0.00	0	0.00	0	0.00	0	0.00
DDM4	0	0.00	0	0.00	0	0.00	5	2.51
DDM4.1	0	0.00	0	0.00	0	0.00	0	0.00
HHE	0	0.00	0	0.00	0	0.00	2	1.01
CSH	0	0.00	3	3.95	9	9.57	10	5.03
SHD	27	31.40	33	43.42	32	34.04	108	54.27
SHC	6	6.98	0	0.00	5	5.32	6	3.02
WLF	3	3.49	5	6.58	11	11.70	36	18.09
WLA	1	1.16	2	2.63	1	1.06	0	0.00
HF	0	0.00	3	3.95	0	0.00	1	0.50
IH	3	3.49	1	1.32	8	8.51	6	3.02
DS	1	1.16	3	3.95	2	2.13	1	0.50
TN	0	0.00	0	0.00	0	0.00	0	0.00
BU	0	0.00	0	0.00	0	0.00	0	0.00
Total	86	100.00	76	100.00	94	100.00	199	100.00
Treatments								
B	19	31.67	14	31.82	8	72.73	17	29.82
SAP	19	31.67	14	31.82	8	72.73	16	28.07
CTC	0	0.00	0	0.00	0	0.00	0	0.00
CB	2	3.33	2	4.55	3	27.27	0	0.00
SAPO	0	0.00	0	0.00	0	0.00	0	0.00
CZC	20	33.33	14	31.82	8	72.73	24	42.11
Total	60	100.00	44	100.00	11	100.00	57	100.00

Table 43: Count and percentage of findings and treatments on the different claw trimming dates (CT) on CDF1 (abbreviations explained in Table 7 and Table 8)

	CT1	
	Count	**Percentage**
Findings		
TU	1	0.61
OLU	0	0.00
IP	0	0.00
SU	0	0.00
DDM1	0	0.00
DDM2	0	0.00
DDM3	0	0.00
DDM4	0	0.00
DDM4.1	0	0.00
HHE	2	1.21
CSH	14	8.48
SHD	83	50.30
SHC	2	1.21
WLF	43	26.06
WLA	14	8.48
HF	0	0.00
IH	1	0.61
DS	5	3.03
TN	0	0.00
BU	0	0.00
Total	165	100.00
Treatments		
B	5	31.25
SAP	0	0.00
CTC	3	18.75
CB	4	25.00
SAPO	4	25.00
CZC	0	0.00
Total	16	100.00

Table 44: Count and percentage of findings and treatments on the different claw trimming dates (CT) on CDF2 (abbreviations explained in Table 7 and Table 8)

	CT1	
	Count	**Percentage**
Findings		
TU	0	0.00
OLU	0	0.00
IP	1	1.33
SU	1	1.33
DDM1	2	2.67
DDM2	7	9.33
DDM3	0	0.00
DDM4	5	6.67
DDM4.1	0	0.00
HHE	1	1.33
CSH	3	4.00
SHD	12	16.00
SHC	12	16.00
WLF	18	24.00
WLA	6	8.00
HF	3	4.00
IH	1	1.33
DS	3	4.00
TN	0	0.00
BU	0	0.00
Total	75	100.00
Treatments		
B	2	7.69
SAP	2	7.69
CTC	11	42.31
CB	11	42.31
SAPO	0	0.00
CZC	0	0.00
Total	26	100.00

Table 45: Count and percentage of findings and treatments on the different claw trimming dates (CT) on CDF3 (abbreviations explained in Table 7 and Table 8)

	CT1		CT2		CT3	
	Count	**Percentage**	**Count**	**Percentage**	**Count**	**Percentage**
Findings						
TU	0	0.00	0	0.00	0	0.00
OLU	0	0.00	0	0.00	2	1.02
IP	0	0.00	0	0.00	0	0.00
SU	2	6.06	2	1.98	1	0.51
DDM1	2	6.06	0	0.00	11	5.58
DDM2	7	21.21	10	9.90	5	2.54
DDM3	0	0.00	0	0.00	0	0.00
DDM4	2	6.06	36	35.64	16	8.12
DDM4.1	0	0.00	6	5.94	2	1.02
HHE	2	6.06	2	1.98	5	2.54
CSH	0	0.00	6	5.94	5	2.54
SHD	12	36.36	26	25.74	82	41.62
SHC	0	0.00	0	0.00	0	0.00
WLF	3	9.09	10	9.90	52	26.40
WLA	1	3.03	0	0.00	3	1.52
HF	1	3.03	1	0.99	0	0.00
IH	1	3.03	2	1.98	8	4.06
DS	0	0.00	0	0.00	5	2.54
TN	0	0.00	0	0.00	0	0.00
BU	0	0.00	0	0.00	0	0.00
Total	33	100.00	101	100.00	197	100.00
Treatments						
B	8	33.33	14	33.33	10	30.30
SAP	8	33.33	13	30.95	10	30.30
CTC	8	33.33	14	33.33	12	36.36
CB	0	0.00	1	2.38	1	3.03
SAPO	0	0.00	0	0.00	0	0.00
CZC	0	0.00	0	0.00	0	0.00
Total	24	100.00	42	100.00	33	100.00

Table 46: Count and percentage of findings and treatments on the different claw trimming dates (CT) on CDF4 (abbreviations explained in Table 7 and Table 8)

	CT1		CT2	
	Count	**Percentage**	**Count**	**Percentage**
Findings				
TU	0	0.00	0	0.00
OLU	0	0.00	1	0.22
IP	0	0.00	0	0.00
SU	11	6.63	6	1.34
DDM1	0	0.00	0	0.00
DDM2	18	10.84	31	6.94
DDM3	0	0.00	0	0.00
DDM4	0	0.00	15	3.36
DDM4.1	0	0.00	4	0.89
HHE	0	0.00	1	0.22
CSH	2	1.20	51	11.41
SHD	57	34.34	212	47.43
SHC	28	16.87	42	9.40
WLF	13	7.83	66	14.77
WLA	20	12.05	9	2.01
HF	6	3.61	1	0.22
IH	5	3.01	7	1.57
DS	6	3.61	1	0.22
TN	0	0.00	0	0.00
BU	0	0.00	0	0.00
Total	166	100.00	447	100.00
Treatments				
B	18	26.47	27	30.34
SAP	13	19.12	0	0.00
CTC	14	20.59	27	30.34
CB	23	33.82	10	11.24
SAPO	0	0.00	25	28.09
CZC	0	0.00	0	0.00
Total	68	100.00	89	100.00

Table 47: Count and percentage of findings and treatments on the different claw trimming dates (CT) on CDF5 (abbreviations explained in Table 7 and Table 8)

	CT1	
	Count	**Percentage**
Findings		
TU	2	0.68
OLU	1	0.34
IP	2	0.68
SU	5	1.70
DDM1	2	0.68
DDM2	27	9.18
DDM3	0	0.00
DDM4	3	1.02
DDM4.1	0	0.00
HHE	35	11.90
CSH	21	7.14
SHD	79	26.87
SHC	13	4.42
WLF	81	27.55
WLA	9	3.06
HF	1	0.34
IH	10	3.40
DS	3	1.02
TN	0	0.00
BU	0	0.00
Total	294	100.00
Treatments		
B	41	32.54
SAP	40	31.75
CTC	45	35.71
CB	0	0.00
SAPO	0	0.00
CZC	0	0.00
Total	126	100.00

Table 48: Statistical summaries over all farms (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1.1	1	6	0.6	24,583
Lactation_number	0	1	2	2.7	4	12	1.8	24,583
Days_in_milk	0	73	152	160.3	230	530	103.7	24,253
LKV_milk_yield_in_last_lactation	3,194	7,851	9,317	9,727.1	11,350	21,193	2,704.9	12,064
LKV_daily_milk_yield	6.5	23.2	29.3	29.5	35.6	61.1	8.4	22,494
LKV_urea	30	140	184	184.3	229	454	65.2	21,752
LKV_somatic_cell_count	10	24	55	201.3	144	9,999	653.4	22,281
LKV_fat	2.1	3.6	4.1	4.2	4.6	8	0.8	22,482
LKV_protein	2.4	3.3	3.5	3.5	3.8	4.9	0.4	22,494
LKV_fat_protein_ratio	0.6	1	1.2	1.2	1.3	2.4	0.2	22,470
LKV_lactose	3.6	4.8	4.9	4.9	5	5.4	0.2	22,225
Milkings	1	2	2	2.5	3	9	0.7	23,652
Maximum_milking_interval	18.8	495	567	586.3	654	1420	133.3	22,279
Robot_daily_milk_yield	0.1	22.1	28.6	28.9	35.5	72.5	9.6	23,642
Robot_milk_yield_in_current_lactation	2.2	2,296.1	5,063.2	5,325.8	7,728.5	15,874	3,509.5	5,137
Robot_milk_yield_in_last_lactation	635	7,338	8,867	9,200.6	10,759	20,148	2,724.1	11,822
Robot_daily_milk_yield_in_last_lactation	12	25.3	28.8	29.2	33.6	43	5.9	7,174
Robot_fat	0.9	3.8	4.2	4.4	4.8	13.1	1	16,676
Robot_protein	2.5	3.3	3.4	3.4	3.6	5.6	0.3	16,675
Robot_fat_protein_ratio	0.2	1.1	1.2	1.3	1.4	3.5	0.3	16,678
Robot_lactose	2.9	4.6	4.8	4.7	4.9	5.2	0.2	16,669
Robot_somatic_cell_count	1	30	53	117.4	99	3,920.5	279.1	7,491
Robot_effect_of_scc	0	0.6	1	1.8	1.7	43.6	3.2	7,491
Milking_temperature	35.9	38.2	38.6	38.7	39.1	41.5	0.7	10,713
MDi	1	1	1.1	1.2	1.1	4.2	0.3	6,912
Milking_flow	0	1.2	2	2.1	2.9	7.1	1.1	16,650
Max_milking_flow	0.5	2.9	4	4.1	5.2	11.8	1.7	16,650
Conduct_lv	0	4.3	4.6	4.6	5	8	0.7	12,560
Conduct_rv	0	4.4	4.7	4.8	5.2	9.3	0.7	12,457
Conduct_lh	0	4.4	4.7	4.8	5.2	8.9	0.7	10,867
Conduct_rh	0	4.3	4.5	4.6	4.9	7.7	0.7	12,439
Conduct_lely_lv	59	66.5	69	69.6	71.5	128.5	5	10,524
Conduct_lely_rv	59	66.5	69	69.5	71	138	5.3	10,631

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Conduct_lely_lh	60	67	69	69.5	71	166	4.8	10,553
Conduct_lely_rh	59	67	69	69.4	71	152.5	5	10,552
Concentrated_feed_intake	0	1.9	3.7	3.7	5.3	10.6	2.2	22,788
Concentrated_feed_remains	0	0.1	0.1	0.4	0.3	6	0.6	10,752
Robot_BCS	2.5	3.6	3.9	3.8	4.1	4.6	0.3	4,770
Body_weight	444.4	641.5	742.3	741.5	820.8	1,151.6	118.7	6,782
WT_feed_intake	0	35.7	44.7	44.2	53.9	92.2	14.5	5,437
WT_feeding_duration	10	96	128	133.9	164	792	59.4	5,413
WT_feeding_duration_day	0	70	95	100.4	124	769	48.5	5,413
WT_feeding_duration_day_night	0	0.7	0.8	0.8	0.8	1	0.1	5,413
WT_feeding_duration_per_visit	0.4	2.5	3.4	3.9	4.7	70.3	3	5,443
WT_feed_intake_per_visit	0	0.8	1.1	1.4	1.7	13	1.1	5,443
WT_feeding_pace	0.06	0.25	0.35	0.36	0.43	2.14	0.13	5,439
WT_trough_visits	1	25	39	42.6	55	222	25	5,445
WT_trough_visits_day	0	19	29	32.8	42	178	20.2	5,445
WT_trough_visits_day_night	0	0.7	0.8	0.8	0.9	1	0.1	5,445
WT_number_of_meals	1	7	9	9.4	11	23	3.1	5,151
WT_number_of_meals_day	0	5	7	7	9	20	2.6	5,151
WT_number_of_meals_day_night	0	0.7	0.8	0.7	0.8	1	0.1	5,151
WT_feed_intake_per_meal	0.8	3.7	4.9	5.3	6.4	23.9	2.3	5,151
WT_feed_intake_per_visit	0	0.8	1.1	1.4	1.7	13	1.1	5,443
ENGS_feeding	1	48	83	89.8	124	288	54.9	1,266
ENGS_feeding_day	0	36	61	67.3	94	220	42.7	1,266
ENGS_feeding_day_night	0	0.7	0.8	0.8	0.9	1	0.2	1,266
ENGS_number_of_meals	0	6	9	8.7	11	25	3.6	1,266
ENGS_number_of_meals_day	0	5	6	6.5	8	18	2.8	1,266
ENGS_number_of_meals_day_night	0	0.7	0.8	0.8	0.9	1	0.2	1,238

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
ENGS_feeding_duration_per_meal	1	5.9	9.4	10.8	14.4	63	6.8	1,238
Nedap_feeding	10	252	374	372	504	806.4	157.8	6,433
Smaxtec_rum	188	490.5	532.1	526.1	569.2	735.1	65.3	6,892
SCR_rum	11	517	561	551.7	599	751	73.9	8,864
SCR_rum_day	2	305	343	338	379	545	63.1	4,224
SCR_rum_day_night	0	0.6	0.6	0.6	0.7	1	0.1	4,224
Nedap_rum	10	273.6	388.8	383.8	504	820.8	145.2	6,463
SCR_heat_probability	-35	-3.5	-1.5	-0.6	0.5	92	7.7	4,472
SCR_heat_probability_day	-36	-4	-1	-0.4	1	100	8.9	4,449
Lemmer_factor_of_restlessness	53	210.6	301.7	421.8	439.4	30,501.8	809.7	5,670
ENGS_lying	4	576	688	677.1	789	1,258	174.9	5,091
ENGS_lying_day	0	311	389	385.5	464	835	124.1	5,091
ENGS_lying_day_night	0	0.5	0.6	0.6	0.6	1	0.1	5,091
ENGS_lying_bouts	1	11	15	17.1	20	109	10.6	5,093
ENGS_lying_bouts_day	0	7	9	11	13	60	6.9	5,091
ENGS_lying_bouts_day_night	0	0.6	0.7	0.6	0.7	1	0.1	5,093
ENGS_lying_duration_per_bout	1.6	32.3	45.6	52.6	61.8	719	41.7	5,091
Nedap_lying	156	633	723	716.9	809	1,131	135.1	2,151
Nedap_get_ups	1	8	10	10.1	12	29	3.8	2,223
Lemmer_get_ups	1	7	9	9.3	11	40	3.9	5,669
Lemmer_lying	12	528	636	630	732	1,254	2.8	5,672
ENGS_act	30	1,689	2,153	2,213.1	2,635	8,735	885.4	5,088
ENGS_act_day	0	1,293	1,667	1,724.9	2,060.2	7,471	717	5,088
ENGS_act_day_night	0	0.7	0.8	0.8	0.8	1	0.1	5,088
Smaxtec_act	0.3	3.9	4.9	5.6	7	21.4	2.4	9,039
Smaxtec_act_day	0.4	4.8	5.9	6.4	7.8	23.7	2.5	9,035
Smaxtec_act_day_night	0.4	1.1	1.1	1.2	1.3	2.5	0.2	9,034
SCR_act	21.5	35.5	39.5	40.6	44	150	8.2	8,804
SCR_act_day	20.5	37.5	42	43.6	48	151	9.6	8,799
SCR_act_day_night	0.6	1	1.1	1.1	1.1	2.2	0.1	8,807
Nedap_act	1,284	2,556.8	3,268.5	3,525.8	4,203.2	14,174	1,365.1	2,224
Nedap_inactive	225	563	655	676.5	769	1378	164.9	6,441

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Nedap_act_foot_median	72.5	197.5	245	259.2	307	1,207	92.5	2,222
Nedap_act_foot_median_day	86	222.5	282.5	308	367.5	1,501.5	131	2,237
Nedap_act_foot_sum_day	774	1,881	2,460	2,710.9	3,289.8	12,174	1185.1	2,238
Nedap_act_foot_median_day_night	0.4	1	1.1	1.2	1.3	3.5	0.2	2,231
Nedap_act_foot_sum_day_night	0.2	0.7	0.8	0.8	0.8	1	0.1	2,230
Nedap_act_collar_median	0	4.5	7	8	10.5	71	4.9	6,476
Nedap_act_collar_sum	9	62	93	107.1	137	859	64.1	6,472
Nedap_act_collar_median_day	0	5	8	9.3	12	89.5	6.4	6,481
Nedap_act_collar_sum_day	6	45	69	80.1	102	737	51.4	6,481
Nedap_act_collar_median_day_night	0.1	1	1.1	1.2	1.3	5.5	0.3	6,474
Nedap_act_collar_sum_day_night	0.2	0.7	0.8	0.7	0.8	1	0.1	6,473
Lemmer_act	37	97	126	144.4	165	858	84.6	5,965
Delaval_act_avg	10	23	29	30	36	89	10.1	1,515
Delaval_act_rel	44	89	99	100.2	108	293	19.4	1,515
Delaval_act_rel_min	39	80.8	88	88.3	95	191	13.5	1,436
Delaval_act_rel_max	59	100	109	111.2	118	255	21.1	1,436
Smaxtec_temp_normal_median	39	39.3	39.4	39.4	39.5	40	0.2	9,046
Smaxtec_temp_min	27	32.9	33.8	33.8	34.7	39.3	1.3	9,104
Smaxtec_temp_max	39	39.6	39.8	39.8	39.9	42.4	0.3	9,105
Smaxtec_temp_median	38.5	39	39.1	39.2	39.3	40.6	0.2	9,102
Smaxtec_temp_without_drink_cycles_min	37.7	38.5	38.6	38.6	38.8	40	0.2	9,063
Smaxtec_temp_without_drink_cycles_max	39	39.6	39.7	39.8	39.9	42.3	0.3	9,056
Smaxtec_temp_without_drink_cycles_median	38.7	39.1	39.3	39.3	39.4	40.8	0.2	9,059
Smaxtec_climate_temp_median	2.4	8.9	10.9	11.8	14.5	24.3	5	11,340
Smaxtec_climate_temp_min	-0.3	5.3	8.4	8.7	11.7	19.6	4.3	11,340

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Smaxtec_climate_temp_max	4	10.8	14.1	15	18.3	29.6	6	11,340
Smaxtec_climate_hum_median	46.5	67.4	73.7	74	81.3	100	11.2	10,936
Smaxtec_climate_hum_min	1.2	50	63	62.1	76.8	98.8	16.2	10,936
Smaxtec_climate_hum_max	62.4	77.2	82.1	82.7	85.6	100	7.5	10,936
Smaxtec_thi_median	28.1	46.2	51.6	52	58	71.8	9.7	10,936
Smaxtec_thi_min	35.5	45.1	48.8	49.6	54.5	65.3	6.4	10,936
Smaxtec_thi_max	39.4	52	57.1	58.8	65	83.1	9.9	10,936
WS_thi_med	27.2	38.7	48.7	48.9	59.8	70.8	11.7	12,790
WS_thi_min	22.6	35.9	42.5	43	51.4	61.1	9.4	12,790
WS_thi_max	30.7	44.1	58.8	57.6	69.6	91.7	15.3	12,790
WS_temp_2m_med	-3.4	3.1	8.5	9.2	15.5	23.3	6.8	12,790
WS_temp_2m_min	-7.9	-0.6	2.5	4.2	9.3	16.4	5.9	12,790
WS_temp_2m_max	-0.7	6.7	14.9	14.3	20.9	33.4	8.5	12,790
WS_temp_20cm_med	-3.9	2.7	7.7	8.8	15.5	23.5	6.9	12,790
WS_temp_20cm_min	-9.6	-2	1.2	2.6	7.6	16.2	6.2	12,790
WS_temp_20cm_max	-0.4	8	16.9	15.6	23.3	33	9	12,790
WS_soil_temp_5cm_med	0.7	4.3	9.2	10.2	16.3	22.6	6.6	12,790
WS_soil_temp_5cm_min	0.5	2.6	7.2	8.6	14.5	19.5	6.1	12,790
WS_soil_temp_5cm_max	1	6.2	11.9	12.2	18.2	28.5	7.3	12,790
WS_soil_temp_20cm_med	1.6	4.5	9	10.2	15.7	20.4	6	12,790
WS_soil_temp_20cm_min	1.5	4	8.5	9.8	15.2	19.7	5.9	12,790
WS_rel_hum_med	41.8	73.8	87.5	84.4	98.2	100	14.9	12,790
WS_rel_hum_min	17.8	40.2	58.7	62.8	90.3	100	25.9	12,790
WS_wind_velocity_med	0.5	1.1	1.5	1.8	2.1	5.7	1	12,790
WS_wind_velocity_min	0	0	0	0.2	0.2	3.3	0.5	12,790
WS_wind_velocity_max	1.6	2.7	3.5	4	4.7	12.7	2	12,790
WS_rain_med	0	0	0	0	0	0.2	0	12,790
WS_rain_min	0	0	0	0	0	0	0	12,790
WS_rain_max	0	0	0	0.3	0.3	12.2	1.1	12,790

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
WS_global_rad_med	5.6	54	141.8	147.1	222.4	359.3	98.3	12,790
WS_global_rad_min	0	0	0	0.1	0	2	0.3	12,790
WS_global_rad_max	41	339	689	612.3	855	1,164	303.3	12,790
Season	1	1	2	2.2	3	4	1	24,583
LMS	1	1	1	1.3	1	3	0.6	24,583
C_LMS	1	1	1	1.4	1	3	0.7	24,583
GSC	0	2.2	3	2.7	3	3	0.4	24,394
PT	0	0	0	0.2	0	1	0.4	24,373

Table 49: Statistical summaries of RF1 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1	1	2	0.2	5,842
LMS	1	1	1	1.3	1	3	0.6	5,842
C_LMS	1	1	1	1.4	1	3	0.8	5,842
Lactation_number	0	1	2	2.6	3	10	1.9	5,842
Days_in_milk	0	63	156	160.5	235	481	106.2	5,660
LKV_milk_yield_in_last_lactation	6,201	8,644	10,423	10,653.6	12,290	18,962	2,543.1	3,661
LKV_daily_milk_yield	8.1	24	29.7	30	35.8	52.7	7.8	5,196
LKV_urea	30	128.8	190	183.8	239	454	77.6	4,740
LKV_somatic_cell_count	10	25	62	191.9	144	7,099	549.9	5,133
LKV_fat	2.1	3.6	4.2	4.1	4.6	7.4	0.9	5,184
LKV_protein	2.5	3.3	3.5	3.5	3.8	4.6	0.4	5,196
LKV_fat_protein_ratio	0.6	1	1.2	1.2	1.3	2.4	0.3	5,196
LKV_lactose	3.6	4.8	4.9	4.9	5	5.4	0.2	5,097
Milkings	1	2	3	2.5	3	5	0.7	5,137
Maximum_milking_interval	203	501	570	584.8	651	1,059	118.7	4,954
Robot_daily_milk_yield	2.8	24	30	30.6	37	69.2	8.9	5,130
Robot_milk_yield_in_current_lactation	2.2	2,296.1	5,063.2	5,325.8	7,728.5	15,874	3,509.5	5,137
MDi	1	1	1.1	1.2	1.1	4.2	0.3	5,095
Milking_flow	0.3	0.8	1	1	1.2	2	0.3	4,117
Max_milking_flow	2	4.8	5.6	5.8	6.7	11.8	1.4	4,117
Conduct_rv	0	4.2	4.4	4.4	4.7	9.3	0.7	4,990
Conduct_lv	0	4.2	4.4	4.3	4.7	7.7	0.7	5,032
Conduct_rh	0	4.2	4.4	4.4	4.6	7.5	0.7	4,907
Conduct_lh	0	4.2	4.4	4.4	4.7	8.2	0.7	4,799
Robot_BCS	2.5	3.6	3.9	3.8	4.1	4.6	0.3	4,770
Body_weight	444.4	721.4	776.7	783.3	835	1,151.6	95.5	5,363

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Concentrated_feed_intake	0	2.7	5	4.6	6.4	9.4	2.2	4,432
WT_feed_intake	0	35.7	44.7	44.2	53.9	92.2	14.5	5,437
WT_feeding_duration	10	96	128	133.9	164	792	59.4	5,413
WT_feeding_duration_day	0	70	95	100.4	124	769	48.5	5,413
WT_feeding_duration_day_night	0	0.7	0.8	0.8	0.8	1	0.1	5,413
WT_feeding_duration_per_visit	0.4	2.5	3.4	3.9	4.7	70.3	3	5,443
WT_feed_intake_per_visit	0	0.8	1.1	1.4	1.7	13	1.1	5,443
WT_feeding_pace	0.06	0.25	0.35	0.36	0.43	2.14	0.13	5,439
WT_trough_visits	1	25	39	42.6	55	222	25	5,445
WT_trough_visits_day	0	19	29	32.8	42	178	20.2	5,445
WT_trough_visits_day_night	0	0.7	0.8	0.8	0.9	1	0.1	5,445
WT_number_of_meals	1	7	9	9.4	11	23	3.1	5,151
WT_number_of_meals_day	0	5	7	7	9	20	2.6	5,151
WT_number_of_meals_day_night	0	0.7	0.8	0.7	0.8	1	0.1	5,151
WT_feed_intake_per_meal	0.8	3.7	4.9	5.3	6.4	23.9	2.3	5,151
WT_feed_intake_per_visit	0	0.8	1.1	1.4	1.7	13	1.1	5,443
ENGS_lying	4	576	688	677.1	789	1258	174.9	5,091
ENGS_lying_day	0	311	389	385.5	464	835	124.1	5,091
ENGS_lying_day_night	0	0.5	0.6	0.6	0.6	1	0.1	5,091
ENGS_lying_bouts	1	11	15	17.1	20	109	10.6	5,093
ENGS_lying_bouts_day	0	7	9	11	13	60	6.9	5,091
ENGS_lying_bouts_day_night	0	0.6	0.7	0.6	0.7	1	0.1	5,093
ENGS_lying_duration_per_bout	1.6	32.3	45.6	52.6	61.8	719	41.7	5,091
ENGS_act	30	1,689	2,153	2,213.1	2,635	8,735	885.4	5,088
ENGS_act_day	0	1,293	1,667	1,724.9	2,060.2	7,471	717	5,088

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
ENGS_act_day_night	0	0.7	0.8	0.8	0.8	1	0.1	5,088
ENGS_feeding	1	48	83	89.8	124	288	54.9	1,266
ENGS_feeding_day	0	36	61	67.3	94	220	42.7	1,266
ENGS_feeding_day_night	0	0.7	0.8	0.8	0.9	1	0.2	1,266
ENGS_number_of_meals	0	6	9	8.7	11	25	3.6	1,266
ENGS_number_of_meals_day	0	5	6	6.5	8	18	2.8	1,266
ENGS_number_of_meals_day_night	0	0.7	0.8	0.8	0.9	1	0.2	1,238
ENGS_feeding_duration_per_meal	1	5.9	9.4	10.8	14.4	63	6.8	1,238
Smaxtec_rum	188	473	506	503	543	643	61.5	712
Smaxtec_act	1.7	4.7	6.3	6.5	8.1	15.2	2.2	1,293
Smaxtec_act_day	1.9	5.5	6.9	7.1	8.4	16.6	2.1	1,293
Smaxtec_act_day_night	0.7	1	1.1	1.1	1.2	2.3	0.1	1,293
Smaxtec_temp_min	28.1	32.7	33.6	33.5	34.4	38.4	1.3	1,357
Smaxtec_temp_max	39.2	39.7	39.8	39.8	40	41.5	0.3	1,356
Smaxtec_temp_median	38.7	39	39.2	39.2	39.3	40	0.2	1,356
Smaxtec_temp_without_drink_cycles_min	37.9	38.5	38.7	38.7	38.8	39.4	0.2	1,315
Smaxtec_temp_without_drink_cycles_max	39.2	39.7	39.8	39.8	40	40.8	0.2	1,307
Smaxtec_temp_without_drink_cycles_median	38.8	39.2	39.3	39.3	39.5	40.2	0.2	1,314
Smaxtec_temp_normal_median	39	39.4	39.5	39.5	39.6	40	0.2	1,309
Smaxtec_climate_temp_median	2.4	8.9	11.2	10.7	12.6	15.7	3	2,323
Smaxtec_climate_temp_min	0.9	4	6.7	6.7	9	12.9	3.3	2,323
Smaxtec_climate_temp_max	4.1	12.1	15.7	14.7	17.3	21.9	3.7	2,323
Smaxtec_climate_hum_median	51.7	56.1	88.2	79.8	95.4	100	18.4	1,919

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Smaxtec_climate_hum_min	1.2	40.2	63.3	61.5	83.3	98.8	24.6	1,919
Smaxtec_climate_hum_max	68.5	80	98.8	91.8	100	100	10.4	1,919
Smaxtec_thi_median	28.1	32.8	41.6	42	50.2	58.6	9.9	1,919
Smaxtec_thi_min	35.5	44.2	45.9	46.4	49.3	54.7	4.2	1,919
Smaxtec_thi_max	39.4	52.9	59.6	58	62.8	71.4	6.9	1,919
SCR_act	22.5	36.5	41	42.4	46	150	10	4,224
SCR_act_day	20.5	39.5	45	46.4	51	151	11.3	4,224
SCR_act_day_night	0.6	1	1.1	1.1	1.1	2.2	0.1	4,224
SCR_rum	11	495	545	535.5	591	739	83	4,224
SCR_rum_day	2	305	343	338	379	545	63.1	4,224
SCR_rum_day_night	0	0.6	0.6	0.6	0.7	1	0.1	4,224
WS_thi_med	29.3	39.2	47.6	47.6	54.1	69.8	10.2	5,842
WS_thi_min	23.5	35.9	41.4	41.9	46.4	61.1	8.9	5,842
WS_thi_max	31.1	46.5	56.3	56	64.3	87.6	12.5	5,842
WS_temp_2m_med	-1.5	3.9	7.8	8.3	12.1	22.3	5.9	5,842
WS_temp_2m_min	-6.7	-1.4	2.3	3.5	7.9	16.4	5.9	5,842
WS_temp_2m_max	-0.5	8	13.5	13.4	18	30.9	7	5,842
WS_temp_20cm_med	-1.8	2.9	6.2	7.7	11.4	22.1	6.1	5,842
WS_temp_20cm_min	-8.6	-4.2	-0.1	1.2	5.8	16.1	6.4	5,842
WS_temp_20cm_max	-0.2	8.9	15.3	14.8	20	32.2	7.5	5,842
WS_soil_temp_5cm_med	2.6	4.4	6.1	9.2	12.4	21.2	6.1	5,842
WS_soil_temp_5cm_min	0.9	2.6	4.9	7.6	11.8	19.3	6	5,842
WS_soil_temp_5cm_max	3.6	6.5	8.3	11.2	13.9	28.5	6.2	5,842
WS_soil_temp_20cm_med	2.5	4.6	6.6	9.5	13.3	19.8	5.7	5,842
WS_soil_temp_20cm_min	2.2	4.1	6.4	9.1	13	19.4	5.7	5,842
WS_soil_temp_20cm_max	3	5.1	6.8	9.9	13.6	20.3	5.7	5,842
WS_rel_hum_med	46.3	80.6	92.5	87.8	99.5	100	14	5,842
WS_rel_hum_min	17.8	47.3	67.9	68.6	97.3	100	26.2	5,842
WS_rel_hum_max	67.1	99.6	100	99.1	100	100	3.5	5,842
WS_wind_velocity_med	0.5	1.1	1.4	1.6	1.9	3.7	0.6	5,842

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
WS_wind_velocity_min	0	0	0	0.1	0	1	0.2	5,842
WS_wind_velocity_max	1.6	2.6	3.5	3.7	4.4	10.1	1.5	5,842
WS_rain_med	0	0	0	0	0	0.2	0	5,842
WS_rain_min	0	0	0	0	0	0	0	5,842
WS_rain_max	0	0	0	0.3	0.3	4.1	0.8	5,842
WS_global_rad_med	15.2	57	126.8	135.9	199.7	343	88.5	5,842
WS_global_rad_min	0	0	0	0.1	0	2	0.4	5,842
WS_global_rad_max	78	351	577	571.8	728	1,164	273.4	5,842
Season	1	1	2	2	3	3	0.9	5,842
GSC	1.2	2	2.5	2.6	3	3	0.4	5,653
PT	0	0	0	0.2	0	1	0.4	5,653

Table 50: Statistical summaries of RF2 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1.5	1	6	1.3	2,727
LMS	1	1	1	1.3	1	3	0.5	2,727
C_LMS	1	1	1	1.4	1	3	0.8	2,727
Lactation_number	1	1	2	2.4	3	7	1.5	2,727
Days_in_milk	7	105	168	203.9	287	530	127.1	2,716
LKV_milk_yield_in_last_lactation	6,038	10,195	11,582	11,847.4	12,690	2,1193	2,972.9	1,705
LKV_daily_milk_yield	11.8	24.7	30.4	31.5	36.8	57.4	8.4	2,650
LKV_urea	64	162	204	205.1	243	334	53.8	2,641
LKV_somatic_cell_count	10	17	34	80.9	68	3258	268.3	2,644
LKV_fat	2.6	3.8	4.2	4.4	4.8	7	0.8	2,650
LKV_protein	2.7	3.5	3.8	3.7	4	4.9	0.4	2,650
LKV_fat_protein_ratio	0.8	1	1.1	1.2	1.2	2.1	0.2	2,650
LKV_lactose	4.4	4.8	4.9	4.9	5	5.3	0.2	2,641
Milkings	1	2	3	2.8	3	6	0.8	2,716
Maximum_milking_interval	78.7	452.5	508.6	525.1	574.8	1,172.1	111	2,637
Robot_daily_milk_yield	10.2	24.4	30.1	31.1	37.4	61	8.9	2,716
Robot_milk_yield_in_last_lactation	635	8,340	10,406	10,382.9	11,808	20,148	3,682.4	1,705
Robot_daily_milk_yield_in_last_lactation	20.8	27.3	31.4	31.3	35.5	43	5.2	1,705
Robot_fat	2.1	3.8	4.3	4.4	5	7.9	0.9	2,716
Robot_protein	3	3.5	3.6	3.6	3.8	4.4	0.2	2,716

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Robot_fat_protein_ratio	0.6	1.1	1.2	1.2	1.4	2	0.2	2,716
Robot_lactose	4.4	4.8	4.9	4.9	5	5.1	0.1	2,716
Robot_somatic_cell_count	1	31	57	101.2	102	3725	220.4	2,409
Robot_effect_of_scc	0	0.9	1.4	2.2	2.3	43.6	3.3	2,409
Milking_temperature	36.7	38.1	38.5	38.4	38.8	40.6	0.5	2,716
Milking_flow	0.9	1.9	2.4	2.4	2.9	4.9	0.7	2,716
Max_milking_flow	1	2.8	3.5	3.5	4.1	6.9	0.9	2,715
Conduct_lely_lv	59	67	69.5	69.6	72	88	4.1	2,653
Conduct_lely_rv	60	67	69	69.3	71.5	89.5	3.9	2,694
Conduct_lely_lh	60.5	67	69	69.4	71	94	3.6	2,674
Conduct_lely_rh	59	66.5	69	69.7	71.5	152.5	7.2	2,695
Concentrated_feed_intake	0	2.4	4.4	4.5	6.2	10	2.1	2,716
Concentrated_feed_remains	0	0.1	0.1	0.2	0.2	6	0.3	2,669
Nedap_rum	10	206	277	271.7	344	746	100.4	2,727
Nedap_feeding	144	446.4	518.4	511.7	576	806.4	93.5	2,705
Nedap_inactive	225	550	634	643.7	723	1167	137.9	2,705
Nedap_act_collar_median	0	6	9	9.9	12.5	71	5.7	2,704
Nedap_act_collar_sum	11	83	124	132.6	164	859	73.7	2,704
Nedap_act_collar_median_day	0	6.5	10.5	11.5	14.5	89.5	7.6	2,704
Nedap_act_collar_sum_day	6	59	90	98	121	737	59.3	2,704
Nedap_act_collar_median_day_night	0.2	1	1.1	1.1	1.2	5.2	0.3	2,703
Nedap_act_collar_sum_day_night	0.3	0.7	0.7	0.7	0.8	1	0.1	2,704
WS_thi_med	27.2	36	47.2	46.7	56.3	66.2	10.9	2,727
WS_thi_min	22.6	36.1	41.7	41.6	47.6	56.6	7.6	2,727
WS_thi_max	31.8	39.2	55.6	54.5	66.4	91.7	15.6	2,727
WS_temp_2m_med	-3.4	1.5	7.1	7.6	13.3	19.6	6.4	2,727
WS_temp_2m_min	-7.9	-0.5	0.9	2.5	6.2	13.3	4.6	2,727
WS_temp_2m_max	-0.1	4	13	12.5	19.5	33.4	8.8	2,727
WS_temp_20cm_med	-3.9	1.7	7.2	7.5	13	19.3	6.1	2,727
WS_temp_20cm_min	-9.6	-1.2	0.4	1.5	4.4	11.6	4.2	2,727
WS_temp_20cm_max	0.1	5	15.2	13.9	21.8	30.8	9.1	2,727

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
WS_soil_temp_5cm_med	1.3	2.6	8.9	9	15.3	18.8	5.7	2,727
WS_soil_temp_5cm_min	1.1	2.1	6.2	7.1	12.1	15.4	4.8	2,727
WS_soil_temp_5cm_max	1.8	3.4	11.4	11.1	18.5	24.4	6.9	2,727
WS_soil_temp_20cm_med	2.8	3.5	8.7	8.8	14.2	16.3	4.8	2,727
WS_soil_temp_20cm_min	2.8	3.4	8	8.4	13.4	15.6	4.6	2,727
WS_soil_temp_20cm_max	2.9	3.7	9.3	9.3	14.9	17.3	5	2,727
WS_rel_hum_med	41.8	65.6	77.8	76.9	88.6	98.5	14.5	2,727
WS_rel_hum_min	22.2	34.7	46.3	54.2	71.6	93.9	22.1	2,727
WS_rel_hum_max	53	95	98.2	95.7	100	100	7.2	2,727
WS_wind_velocity_med	0.5	1.1	1.5	1.6	2	3.8	0.7	2,727
WS_wind_velocity_min	0	0	0	0.2	0.1	1.5	0.4	2,727
WS_wind_velocity_max	1.6	2.7	3.4	3.5	4	7.5	1.2	2,727
WS_rain_med	0	0	0	0	0	0.1	0	2,727
WS_rain_min	0	0	0	0	0	0	0	2,727
WS_rain_max	0	0	0.1	0.4	0.4	12.2	1.5	2,727
WS_global_rad_med	5.6	31.7	160.7	146.6	251.8	299.1	103.8	2,727
WS_global_rad_min	0	0	0	0	0	0	0	2,727
WS_global_rad_max	41	296	801	629.7	909	1087	342.1	2,727
Season	1	1	2	2.3	4	4	1.2	2,727
GSC	2	2.2	2.8	2.6	3	3	0.4	2,727
PT	0	0	0	0.4	1	1	0.5	2,727

Table 51: Statistical summaries of RF3 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1.3	1	6	1	4,221
LMS	1	1	1	1.2	1	3	0.5	4,221
C_LMS	1	1	1	1.3	1	3	0.7	4,221
Lactation_number	0	1	2	2.5	4	9	1.5	4,221
Days_in_milk	0	88	156	156.3	227	378	88	4,147
LKV_milk_yield_in_last_lactation	6,166	8,372	9,864	10,048.3	11,196	15,532	2,082	2,836
LKV_daily_milk_yield	14	27.1	32.2	32.7	38.3	61.1	7.9	3,750
LKV_urea	71	157	192	194.6	230	353	53.7	3,747

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
LKV_somatic_cell_count	10	18	48	136.1	123	3,270	337.1	3,750
LKV_fat	2.1	3.8	4.2	4.3	4.8	7.7	0.8	3,750
LKV_protein	2.6	3.3	3.6	3.6	3.8	4.9	0.3	3,750
LKV_fat_protein_ratio	0.6	1.1	1.2	1.2	1.3	2.3	0.2	3,750
LKV_lactose	4.2	4.8	4.9	4.9	5	5.4	0.2	3,747
Milkings	1	2	2	2.5	3	7	0.7	4,132
Maximum_milking_interval	49.9	512.8	579.3	603.3	669	1,301.2	137.7	3,912
Robot_daily_milk_yield	1.3	24.8	31.1	31.1	37.3	66.1	8.8	4,132
Robot_milk_yield_in_last_lactation	5,980	8,500	9,535	9,836.4	10,981	15,374	2,058.5	2,836
Robot_daily_milk_yield_in_last_lactation	21.4	28	30.5	31.7	35.4	42.9	5.1	2,836
Robot_fat	0.9	3.4	4.2	4.6	5.4	13.1	1.6	4,132
Robot_protein	2.8	3.4	3.5	3.5	3.6	5.6	0.3	4,132
Robot_fat_protein_ratio	0.2	1	1.2	1.3	1.5	3.5	0.4	4,132
Robot_lactose	4.2	4.8	4.9	4.9	4.9	5.1	0.1	4,127
Robot_somatic_cell_count	1	30.5	54	117.4	101	3,920.5	279	3,789
Robot_effect_of_scc	0	0.5	0.9	1.6	1.4	33.8	3	3,789
Milking_temperature	35.9	38.9	39.2	39.2	39.6	41.5	0.5	4,128
Milking_flow	0	2.3	2.9	3	3.6	7.1	1	4,131
Max_milking_flow	0.6	3.4	4.2	4.3	5.2	9.3	1.3	4,132
Conduct_lely_lv	59	66.5	69	69.5	71.5	114	4.6	4,065
Conduct_lely_rv	60	67	69	69.5	71	109	5	4,131
Conduct_lely_lh	60	67	69	69.7	71.5	166	6.1	4,115
Conduct_lely_rh	61	67	69	69.3	71	114	4.1	4,072
Concentrated_feed_intake	0.2	2	3.5	3.4	4.7	7.8	1.6	4,199
Concentrated_feed_remains	0	0.1	0.1	0.2	0.2	2.5	0.3	4,214
Nedap_rum	14.4	403.2	475.2	465.7	547.2	820.8	115.2	3,736
Nedap_feeding	10	195	276	270.7	351	586	110.5	3,728
Nedap_inactive	292	573	680	700.3	807	1,378	178.3	3,736
Nedap_lying	156	633	723	716.9	809	1,131	135.1	2,151
Nedap_get_ups	1	8	10	10.1	12	29	3.8	2,223
Nedap_act	1,284	2,556.8	3,268.5	3,525.8	4,203.2	14,174	1,365.1	2,224
Nedap_act_collar_median	0	4	6	6.6	8	31.5	3.6	3,772
Nedap_act_collar_sum	9	56	77	88.8	110	440	48.5	3,768
Nedap_act_collar_median_day	0.5	4.5	6.5	7.8	9.5	54.5	4.9	3,777

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Nedap_act_collar_sum_day	6	41	58	67.3	83	426	40.3	3,777
Nedap_act_collar_median_day_night	0.1	1	1.1	1.2	1.3	5.5	0.3	3,771
Nedap_act_collar_sum_day_night	0.2	0.7	0.8	0.7	0.8	1	0.1	3,769
Nedap_act_foot_median	72.5	197.5	245	259.2	307	1207	92.5	2,222
Nedap_act_foot_median_day	86	222.5	282.5	308	367.5	1,501.5	131	2,237
Nedap_act_foot_sum_day	774	1,881	2,460	2,710.9	3,289.8	12,174	1,185.1	2,238
Nedap_act_foot_median_day_night	0.4	1	1.1	1.2	1.3	3.5	0.2	2,231
Nedap_act_foot_sum_day_night	0.2	0.7	0.8	0.8	0.8	1	0.1	2,230
SCR_rum	235	532	578.5	569.6	615	732	71	804
SCR_act	26	32.5	35.5	36.4	38.6	79	6.1	748
SCR_act_day	27	33	36	37.5	40	99	7.5	742
SCR_act_day_night	0.8	1	1	1	1	1.5	0.1	748
SCR_heat_probability	-27	-3.5	-2	-1	0	88	6.8	636
SCR_heat_probability_day	-29	-5	-2	-1.1	0	84	8.9	630
Smaxtec_act	0.3	4.5	6.8	6.8	8.8	17.7	2.7	2,937
Smaxtec_act_day	0.4	5.1	7.3	7.4	9.3	20.6	2.8	2,936
Smaxtec_act_day_night	0.7	1	1.1	1.1	1.1	1.9	0.1	2,934
Smaxtec_rum	265.1	505.4	544.8	539.8	581	713.5	62.5	1,529
Smaxtec_temp_median	38.6	39	39.1	39.2	39.3	40.2	0.2	2,935
Smaxtec_temp_min	29.4	33.9	34.7	34.5	35.4	39.3	1.3	2,935
Smaxtec_temp_max	39.3	39.7	39.8	39.9	40	42.4	0.3	2,937
Smaxtec_temp_without_drink_cycles_median	38.7	39.2	39.3	39.3	39.4	40.4	0.2	2,934
Smaxtec_temp_without_drink_cycles_min	38.1	38.6	38.7	38.7	38.8	40	0.2	2,937
Smaxtec_temp_without_drink_cycles_max	39.2	39.6	39.8	39.8	40	42.3	0.3	2,937
Smaxtec_temp_normal_median	39.1	39.3	39.5	39.5	39.6	40	0.2	2,925
Smaxtec_climate_temp_median	2.4	9.3	16.8	14.4	19.8	24.3	6.6	4,169

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Smaxtec_climate_temp_min	-0.3	5.4	12.6	10.7	15.2	19.6	5.6	4,169
Smaxtec_climate_temp_max	4	10.8	20.1	17.8	24.3	29.6	8	4,169
Smaxtec_climate_hum_median	46.5	64.5	72.1	70.6	77.7	85.7	9.7	4,169
Smaxtec_climate_hum_min	29.2	45.4	52	56.2	67.9	83.5	14.8	4,169
Smaxtec_climate_hum_max	62.4	79	81.6	81.2	84.6	89.6	4.9	4,169
Smaxtec_thi_median	38.2	50.1	61.6	57.5	65.4	71.8	10.3	4,169
Smaxtec_thi_min	35.8	45.4	55.4	52.4	58.9	65.3	8.4	4,169
Smaxtec_thi_max	40.6	52	67	63.3	74	83.1	12.9	4,169
WS_thi_med	28	42.1	57.6	52.1	62.7	70.8	13.2	4,221
WS_thi_min	24	35.9	48.7	45.4	54	60.6	10.7	4,221
WS_thi_max	30.7	46.8	66.4	61.8	76.8	88.5	17.4	4,221
WS_temp_2m_med	-2.2	5.3	14.2	11.4	17.7	23.3	7.7	4,221
WS_temp_2m_min	-4.7	0.3	8	6.2	11	16.4	6.2	4,221
WS_temp_2m_max	-0.7	8.2	19.1	16.6	24.9	31.4	9.7	4,221
WS_temp_20cm_med	-2.2	5.6	14.1	11.3	17.3	23.5	7.7	4,221
WS_temp_20cm_min	-6.1	-0.3	6.5	5.2	9.6	16.2	6.1	4,221
WS_temp_20cm_max	-0.4	8	20.8	17.8	26.3	33	10.3	4,221
WS_soil_temp_5cm_med	0.7	8.1	15.4	12.4	18.4	22.6	7.3	4,221
WS_soil_temp_5cm_min	0.5	6.1	13.7	10.8	16.3	19.5	6.4	4,221
WS_soil_temp_5cm_max	1	8.8	16.9	14.3	20.4	27.3	8.3	4,221
WS_soil_temp_20cm_med	1.6	8.4	15.4	12.1	18.1	20.4	6.7	4,221
WS_soil_temp_20cm_min	1.5	7.6	14.9	11.6	17.4	19.7	6.5	4,221
WS_soil_temp_20cm_max	1.7	9	15.9	12.7	18.6	21.8	6.9	4,221
WS_rel_hum_med	47.4	73.8	87	84.4	99.3	100	14.6	4,221
WS_rel_hum_min	18.5	39.8	51.4	60.4	90.8	100	25.8	4,221
WS_rel_hum_max	84.1	100	100	99.3	100	100	2.5	4,221
WS_wind_velocity_med	0.6	1.1	1.7	2.2	2.9	5.7	1.5	4,221
WS_wind_velocity_min	0	0	0.1	0.4	0.4	3.3	0.7	4,221

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
WS_wind_velocity_max	1.6	2.7	3.7	4.8	6.6	12.7	2.7	4,221
WS_rain_med	0	0	0	0	0	0.2	0	4,221
WS_rain_min	0	0	0	0	0	0	0	4,221
WS_rain_max	0	0	0	0.3	0.2	10.9	1.3	4,221
WS_global_rad_med	11.2	51	174.8	162.9	241.7	359.3	105.1	4,221
WS_global_rad_min	0	0	0	0	0	0	0	4,221
WS_global_rad_max	55	358	762	657.1	907	1,064	308.6	4,221
Season	1	2	3	2.6	3	4	1.1	4,221
GSC	1	2	2.5	2.5	3	3	0.4	4,221
PT	0	0	0	0.2	0	1	0.4	4,221

Table 52: Statistical summaries of CDF1 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1	1	1	0	1,299
LMS	1	1	1	1.2	1	3	0.5	1,299
C_LMS	1	1	1	1.3	1	3	0.7	1,299
Lactation_number	1	1	2	2.1	3	5	1	1,299
Days_in_milk	17	79	128	144.7	207	337	82.1	1,299
LKV_daily_milk_yield	13.8	25.9	31.2	31.2	37.2	48.6	8.4	1,260
LKV_urea	65	155	184	184.3	212	297	39.4	1,257
LKV_somatic_cell_count	10	23	62	431.4	171	9,999	1,706.1	1,260
LKV_fat	2.2	3.1	3.6	3.7	4.2	5.7	0.7	1,260
LKV_protein	2.8	3.4	3.6	3.6	3.9	4.7	0.4	1,260
LKV_fat_protein_ratio	0.7	0.9	1	1	1.1	1.8	0.2	1,260
LKV_lactose	4.3	4.8	4.9	4.9	5	5.2	0.1	1,257
Milkings	1	2	2	2.3	3	5	0.7	1,299
Maximum_milking_interval	329.6	522.4	621.8	625	705.1	1,223.2	145.4	1,200
Robot_daily_milk_yield	10.7	24.2	30.9	31.3	37.6	53.6	9	1,299
Robot_milk_yield_in_last_lactation	813	3,278.8	6,434.5	5,955.8	7,767	11,481	2,701.9	840
Robot_daily_milk_yield_in_last_lactation	12	19.4	21.8	22.2	26	30.7	4.7	840
Robot_fat	2.2	3.6	4.1	4.1	4.6	6.2	0.8	1,299
Robot_protein	3	3.5	3.6	3.6	3.7	3.9	0.2	1,299
Robot_fat_protein_ratio	0.6	1	1.2	1.2	1.3	1.7	0.2	1,299
Robot_lactose	4.4	4.8	4.8	4.8	4.9	5	0.1	1,299
Robot_somatic_cell_count	1	25	45	147.8	86.5	2,991	362.3	1,293

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Robot_effect_of_scc	0	0.3	0.6	1.6	1	40.9	3.8	1,293
Milking_temperature	37.6	38.5	38.8	38.7	39	40.6	0.3	1,299
Milking_flow	0.9	2	2.5	2.5	3	5.6	0.8	1,299
Max_milking_flow	1	2.9	3.5	3.6	4.2	8.2	1.1	1,299
Conduct_lely_lv	60.5	66	68.5	69.7	71	128.5	6.9	1,278
Conduct_lely_rv	59	66.5	69	69.5	71.5	119.5	4.7	1,278
Conduct_lely_lh	60.5	67	69	69.4	71	99	3.7	1,257
Conduct_lely_rh	61	67	69	69.5	71	98	4.1	1,257
Concentrated_feed_intake	0.5	2.8	4.7	4.1	5.1	8	1.7	1,299
Concentrated_feed_remains	0	0.1	0.1	0.3	0.4	3	0.4	1,299
SCR_act	26	35.5	38	38.7	41.5	65.5	4.6	1,294
SCR_act_day	26	36.5	39.5	40.2	43.5	75	5.3	1,296
SCR_act_day_night	0.9	1	1	1	1.1	1.4	0.1	1,296
SCR_heat_probability	-35	-3	-1.5	-1	0.5	92	7.1	1,297
SCR_heat_probability_day	-36	-3.5	-1	-0.6	1	100	8.7	1,299
SCR_rum	270	531	571	566.1	607	751	63.1	1,297
Season	1	1	1	1	1	1	0	1,299
GSC	0	3	3	2.9	3	3	0.4	1,299
PT	0	0	0	0.1	0	1	0.3	1,299

Table 53: Statistical summaries of CDF2 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1	1	1	0	1,083
LMS	1	1	1	1.2	1	3	0.5	1,083
C_LMS	1	1	1	1.3	1	3	0.7	1,083
Lactation_number	0	1	2	2.7	4	8	1.9	1,083
Days_in_milk	1	48	113	123.5	175	336	84.1	1,072
LKV_milk_yield_in_last_lactation	5,108	7,625	9,015	8,752.4	10,183	13,675	1,783.4	705
LKV_daily_milk_yield	18.4	24.9	28.9	29.7	34.1	45.7	6.2	950
LKV_urea	65	171	213	208	230	335	49.6	950
LKV_somatic_cell_count	10	31	55	145.3	187	1103	206.4	950
LKV_fat	3.4	3.9	4.3	4.4	4.8	6	0.6	950
LKV_protein	2.9	3.4	3.6	3.5	3.7	4.2	0.3	950
LKV_fat_protein_ratio	0.9	1.1	1.2	1.3	1.3	1.9	0.2	950
LKV_lactose	4.1	4.7	4.8	4.8	4.9	5.1	0.2	950
Milkings	1	2	2	2.3	3	4	0.7	1,054
Maximum_milking_interval	18.8	497.7	585.3	615.3	700.2	1129.7	149.1	1,046

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Robot_daily_milk_yield	7.8	24.6	28.8	29.7	35	50.7	7.1	1,054
Robot_milk_yield_in_last_lactation	5,084.7	7,215.8	8,768	8,589.1	9,906.5	12,598	1,708.3	621
Robot_fat	3.3	4	4.3	4.3	4.6	5.3	0.4	1,054
Robot_protein	3.2	3.4	3.5	3.5	3.6	3.9	0.1	1,054
Robot_fat_protein_ratio	0.9	1.1	1.2	1.2	1.3	1.6	0.1	1,054
Robot_lactose	4.4	4.7	4.8	4.8	4.9	5.1	0.1	1,054
Conduct_lv	4.5	5	5.2	5.3	5.6	6.8	0.4	1,033
Conduct_rv	3.6	5.1	5.3	5.4	5.7	6.8	0.5	1,048
Conduct_lh	3.8	4.8	5.1	5.2	5.4	7.1	0.5	1,054
Conduct_rh	4.6	5	5.3	5.3	5.6	6.3	0.3	991
Concentrated_feed_intake	0	2.2	3.4	3.4	4.5	6.3	1.5	1,062
Lemmer_act	37	83	103	115.1	130	554	56.1	1,051
Lemmer_get_ups	1	6	8	8.5	11	21	3	1,052
Lemmer_lying	12	540	642	630	732	1254	156	1,052
Lemmer_factor_of_restlessness	53	179.2	237.2	427.3	347.9	30501.8	1627.3	1,052
Season	2	2	2	2	2	2	0	1,083
GSC	2.5	3	3	3	3	3	0.1	1,083
PT	0	0	0	0.1	0	1	0.3	1,083

Table 54: Statistical summaries of CDF3 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1.1	1	3	0.5	1,829
LMS	1	1	1	1.3	2	3	0.6	1,829
C_LMS	1	1	1	1.5	2	3	0.8	1,829
Lactation_number	0	2	3	2.9	4	6	1.5	1,829
Days_in_milk	1	60	184	160	230	456	98.8	1,817
LKV_milk_yield_in_last_lactation	6,443	9,089	11,573	11,240.5	12,987	18,396	2,588.4	1,392
LKV_daily_milk_yield	17.5	26.5	32.3	32.7	37.6	51.4	7.3	1,618
LKV_urea	108	175	208	215.8	245	363	54	1,598
LKV_somatic_cell_count	10	20	37	138.5	80	2681	258.2	1,618
LKV_fat	2.4	3.7	4.1	4.2	4.6	7.1	0.8	1,618
LKV_protein	2.7	3.3	3.6	3.6	3.8	4.6	0.4	1,618
LKV_fat_protein_ratio	0.8	1.1	1.2	1.2	1.3	2.3	0.2	1,618
LKV_lactose	4.2	4.8	4.9	4.9	5	5.3	0.2	1,618
Milkings	1	2	2	2.3	3	5	0.7	1,817
Maximum_milking_interval	322.5	517.7	594.1	621.6	710.4	1110.8	144.5	1,628
Robot_daily_milk_yield	0.5	26.2	31.4	32.5	38	72.5	9.7	1,817

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Robot_milk_yield_in_last_lactation	6,482.4	8,895.9	11,179.6	11,170.6	12,792	18,534.5	2,726.4	1,306
Milking_flow	0.5	0.9	1.1	1.1	1.3	1.9	0.3	1,817
Max_milking_flow	0.8	1.3	1.5	1.5	1.8	2.5	0.3	1,817
MDi	1	1	1.1	1.2	1.1	4.2	0.3	1,817
Conduct_lv	2.1	4.3	4.5	4.5	4.7	6.6	0.3	1,776
Conduct_rv	2.1	4.3	4.5	4.5	4.7	6.6	0.3	1,775
Conduct_lh	2.1	4.3	4.5	4.5	4.7	6.7	0.4	1,754
Conduct_rh	0	4.3	4.5	4.4	4.7	7.7	0.8	1,752
Concentrated_feed_intake	0	1.4	3	2.9	4	6.4	1.6	1,822
Delaval_act_avg	10	23	29	30	36	89	10.1	1,515
Delaval_act_rel	44	89	99	100.2	108	293	19.4	1,515
Delaval_act_rel_min	39	80.8	88	88.3	95	191	13.5	1,436
Delaval_act_rel_max	59	100	109	111.2	118	255	21.1	1,436
Season	2	2	3	3	4	4	0.8	1,829
GSC	1	2	2.5	2.6	3	3	0.4	1,829
PT	0	0	0	0.2	0	1	0.4	1,829

Table 55: Statistical summaries of CDF4 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1	1	1	0	4,959
LMS	1	1	1	1.3	1	3	0.6	4,959
C_LMS	1	1	1	1.4	1	3	0.8	4,959
Lactation_number	0	1	3	3.1	4	10	1.9	4,959
Days_in_milk	1	63	137	150.4	216	523	104.9	4,942
LKV_milk_yield_in_last_lactation	3,194	6,730	8,103	8,146.8	9,306	15,263	2,247.2	3,633
LKV_daily_milk_yield	6.5	17.3	22.2	22.7	27.1	43.6	6.7	4,577
LKV_urea	30	96	119.5	123.7	152	254	41.2	4,326
LKV_somatic_cell_count	10	46	100	301.7	230	9,999	738.4	4,433
LKV_fat	2.1	3.5	3.9	3.9	4.3	6.7	0.7	4,577
LKV_protein	2.6	3.2	3.4	3.4	3.6	4.7	0.3	4,577
LKV_fat_protein_ratio	0.7	1	1.1	1.1	1.2	1.7	0.2	4,558
LKV_lactose	3.8	4.7	4.8	4.8	4.9	5.2	0.2	4,427
Milkings	1	2	2	2.3	3	9	0.7	4,927
Maximum_milking_interval	144.7	512.2	578.5	595.5	651.7	1420	130.3	4,377
Robot_daily_milk_yield	0.1	15.2	20.8	21.4	27	60.4	8.7	4,924

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Robot_milk_yield_in_last_lactation	2,644.7	6,533.5	7,871.1	7,861.2	9,067.4	15,033.3	2,293.7	3,582
Robot_fat	2.3	3.8	4.1	4.1	4.4	6.1	0.4	4,905
Robot_protein	2.7	3.2	3.3	3.3	3.4	4.4	0.2	4,904
Robot_fat_protein_ratio	0.6	1.2	1.2	1.3	1.4	2	0.2	4,907
Robot_lactose	2.9	4.3	4.4	4.4	4.6	5	0.2	4,903
Conduct_lv	2.6	4.4	4.8	4.8	5.2	8	0.6	4,719
Conduct_rv	2	4.9	5.2	5.2	5.5	8.9	0.6	4,644
Conduct_lh	3.8	5	5.3	5.3	5.5	8.9	0.5	3,260
Conduct_rh	3	4.3	4.6	4.7	5	7.7	0.6	4,789
Concentrated_feed_intake	0	0.8	1.6	2.1	3.3	5.8	1.5	4,685
Lemmer_act	37	101	132	150.7	171	858	88.3	4,914
Lemmer_get_ups	1	7	9	9.5	12	40	4.1	4,617
Lemmer_lying	24	528	636	630	732	1,212	168	4,620
Lemmer_factor_of_restlessness	53.1	221.2	317.2	420.6	456.6	6,120	449.6	4,618
Smaxtec_act	0.4	3.6	4.3	4.6	5.2	21.4	1.8	4,809
Smaxtec_act_day	0.8	4.5	5.3	5.7	6.4	23.7	2	4,806
Smaxtec_act_day_night	0.4	1.1	1.2	1.2	1.3	2.5	0.2	4,807
Smaxtec_rum	202.9	489.6	532.3	525.2	568.4	735.1	65.6	4,651
Smaxtec_temp_median	38.5	39	39.1	39.1	39.3	40.6	0.2	4,811
Smaxtec_temp_min	27	32.7	33.4	33.4	34.1	37.7	1.2	4,812
Smaxtec_temp_max	39	39.5	39.7	39.7	39.9	42.3	0.3	4,812
Smaxtec_temp_without_drink_cycles_median	38.7	39.1	39.2	39.2	39.4	40.8	0.2	4,811
Smaxtec_temp_without_drink_cycles_min	37.7	38.5	38.6	38.6	38.7	39.8	0.2	4,811
Smaxtec_temp_without_drink_cycles_max	39	39.5	39.7	39.7	39.9	42.2	0.3	4,812
Smaxtec_temp_normal_median	39	39.3	39.4	39.4	39.5	40	0.2	4,812
Smaxtec_climate_temp_median	3.9	8.8	10	10.1	11.9	14.8	2.7	4,848
Smaxtec_climate_temp_min	2.6	7	8.3	7.9	9	12.9	2.4	4,848
Smaxtec_climate_temp_max	5	10.5	12.5	12.8	15.3	20.2	3.2	4,848
Smaxtec_climate_hum_median	59.5	68.2	75	74.5	80.7	83.2	6.7	4,848
Smaxtec_climate_hum_min	43.9	58.5	71.2	67.4	77.1	79	10.4	4,848

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Smaxtec_climate_hum_max	71.4	75.9	80.5	80.4	85	87.3	4.8	4,848
Smaxtec_thi_median	42.3	48.9	51.1	51.3	54.1	58.6	4.1	4,848
Smaxtec_thi_min	41.2	46.8	48.5	48.4	50.5	55.9	3.6	4,848
Smaxtec_thi_max	43	51.5	54.8	55.2	59.3	67.1	5.2	4,848
Season	1	1	1	2	3	3	1	4,959
GSC	2	2.5	2.8	2.7	3	3	0.4	4,959
PT	0	0	0	0.1	0	1	0.3	4,959

Table 56: Statistical summaries of CDF5 (parameters explained in Table 33)

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Breed	1	1	1	1	1	1	0	2,623
LMS	1	1	1	1.2	1	3	0.5	2,623
C_LMS	1	1	1	1.3	1	3	0.7	2,623
Lactation_number	0	1	2	3.2	5	12	2.3	2,623
Days_in_milk	1	81	162	162.7	237	468	98.5	2,600
LKV_milk_yield_in_last_lactation	3,243	7,938	9,068	9,613.1	10,645	18,351	2,374	1,793
LKV_daily_milk_yield	15.7	24.7	31.5	31.4	37.1	51.3	7.4	2,493
LKV_urea	130	185	222	223.9	253	360	47.4	2,493
LKV_somatic_cell_count	10	19	47	213.3	103	5464	613.9	2,493
LKV_fat	2.7	3.9	4.3	4.4	4.7	8	0.7	2,493
LKV_protein	2.4	3.1	3.3	3.3	3.5	4.9	0.3	2,493
LKV_fat_protein_ratio	0.9	1.2	1.3	1.3	1.4	2.4	0.2	2,488
LKV_lactose	4.4	4.9	5	5	5.1	5.4	0.2	2,488
Milkings	1	2	3	2.8	3	6	0.7	2,570
Maximum_milking_interval	52.2	459.6	539.8	558.1	632.5	1,176.7	133.2	2,525
Robot_daily_milk_yield	0.5	23.7	29.5	29.9	35.7	58.7	8	2,570
Robot_milk_yield_in_last_lactation	5,431	7,073	8,193	8,515.2	9,520	14,446	1,865.3	1,772
Robot_daily_milk_yield_in_last_lactation	16.5	23.9	26.5	26.7	28.8	37.6	4.1	1,793
Robot_fat	2	4	4.4	4.5	5	6.5	0.6	2,570
Robot_protein	2.5	3.1	3.2	3.2	3.4	4.9	0.3	2,570
Robot_fat_protein_ratio	0.7	1.3	1.4	1.4	1.5	2	0.2	2,570
Robot_lactose	4.7	4.9	5	4.9	5	5.2	0.1	2,570
Milking_temperature	36.8	37.9	38.1	38.1	38.3	39.8	0.4	2,570
Milking_flow	0.9	2.1	2.7	2.7	3.3	6.1	0.8	2,570

Parameter	Min	Q1	Median	Mean	Q3	Max	SD	N
Max_milking_flow	0.5	3	3.9	3.9	4.7	8	1.1	2,570
Conduct_lely_lv	60	67	69	69.5	71	115.5	5.1	2,528
Conduct_lely_rv	59.5	66	68	69.6	71	138	7.1	2,528
Conduct_lely_lh	60	67	69	69.3	71	94	3.9	2,507
Conduct_lely_rh	61	67	69	69.4	71	97	3.7	2,528
Concentrated_feed_intake	0	4	6	5.6	7.3	10.6	2	2,573
Concentrated_feed_remains	0	0.2	0.5	0.9	1.4	5.9	1	2,570
Body_weight	453.5	562	586	583.6	607	666	35.6	1,419
SCR_act	21.5	35.5	39	39.7	43	81	5.8	2,538
SCR_act_day	26	38	42	42.6	46	93	6.8	2,537
SCR_act_day_night	0.7	1	1.1	1.1	1.1	2	0.1	2,539
SCR_heat_probability	-17	-3.5	-1	-0.3	1	92	8.2	2,539
SCR_heat_probability_day	-19.5	-4	-1	-0.2	2	100	9.1	2,520
SCR_rum	126	537	570	565.8	601	711	56.2	2,539
Season	2	2	2	2	2	2	0	2,623
GSC	2	3	3	2.9	3	3	0.2	2,623
PT	0	0	0	0.1	0	1	0.3	2,602

Table 57: Counts and shares of positive and negative pain tests divided by findings

Findings	Positive pain tests	Percentage of positive pain tests	Negative pain tests	Percentage of negative pain test
SHD	72	13.79%	450	86.21%
SHC	23	15.65%	124	84.35%
CSH	19	13.57%	121	86.43%
DDM1	20	16.95%	98	83.05%
DDM2	43	20.00%	172	80.00%
DDM4	14	11.76%	105	88.24%
DDM4.1	1	6.67%	14	93.33%
WLD	41	13.31%	267	86.69%
HHE	6	13.64%	38	86.36%
HF	6	19.35%	25	80.65%
IH	19	15.70%	102	84.30%
BU	0	0.00%	1	100.00%
WLA	30	38.96%	47	61.04%
DS	18	40.91%	26	59.09%
OLU	5	38.46%	8	61.54%
SU	18	42.86%	24	57.14%
IP	5	55.56%	4	44.44%
TU	2	50.00%	2	50.00%
TN	1	100.00%	0	0.00%

Table 58: Percentage of agreement (PA), quadratic weighted Cohen's kappa (κ_w) and confidence interval (CI) of locomotion and lesion score on each project farm

	RF1	RF2	RF3	CDF1	CDF2	CDF3	CDF4	CDF5
PA	69.9%	48.9%	64.3%	66.1%	78.9%	58.9%	68.9%	69.5%
κ_w	0.49	0.24	0.39	0.33	0.54	0.41	0.54	0.58
CI	0.37-0.61	0.12-0.37	0.25-0.53	0.03-0.63	0.32-0.76	0.23-0.58	0.44-0.65	0.46-0.70

Table 59: Statistical summaries for each parameter grouped by corrected locomotion score (C_LMS) across all farms (parameters explained in Table 33)

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
Animal characteristics									
1	Breed	1.00	1.00	1.00	1.19	1.00	7.00	0.88	19,431
2	Breed	1.00	1.00	1.00	1.17	1.00	7.00	0.94	1,133
3	Breed	1.00	1.00	1.00	1.09	1.00	7.00	0.56	4,019
Milking									
1	Lactation_number	0.00	1.00	2.00	2.64	4.00	12.00	1.76	19,431
2	Lactation_number	0.00	2.00	3.00	3.10	4.00	9.00	1.87	1,133
3	Lactation_number	0.00	2.00	3.00	3.09	4.00	12.00	1.93	4,019
1	Days_in_milk	0.00	76.00	152.00	161.03	228.00	530.00	103.27	19,148

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	Days_in_milk	0.00	68.00	166.00	173.85	276.00	468.00	110.97	1,115
3	Days_in_milk	0.00	58.00	150.00	152.95	227.00	520.00	103.31	3,990
1	LKV_milk_yield_in_last_lactation	3,243.00	8,052.00	9,433.00	9,784.17	11,350.00	21,193.00	2,649.71	12,035
2	LKV_milk_yield_in_last_lactation	6,249.00	8,640.00	10,460.00	10,515.23	12,062.00	15,455.00	2,286.96	795
3	LKV_milk_yield_in_last_lactation	3,194.00	8,342.00	10,378.00	10,444.97	12,444.00	21193.00	2903.97	2,895
1	LKV_daily_milk_yield	7.20	23.10	29.10	29.37	35.40	57.40	8.23	17,784
2	LKV_daily_milk_yield	9.00	22.10	31.10	29.93	37.50	46.00	8.89	1,034
3	LKV_daily_milk_yield	6.50	24.00	29.80	30.24	36.30	61.10	9.03	3,676
1	LKV_urea	30.00	138.00	184.00	184.72	229.00	454.00	64.49	17,188
2	LKV_urea	32.00	151.00	185.00	187.06	218.00	412.00	60.68	1,010
3	LKV_urea	32.00	137.00	184.00	181.71	229.00	369.00	69.35	3,554
1	LKV_somatic_cell_count	10.00	24.00	55.00	205.61	143.00	9,999.00	654.97	17,597
2	LKV_somatic_cell_count	10.00	38.00	65.00	119.05	142.00	2,681.00	184.55	1,034
3	LKV_somatic_cell_count	10.00	20.00	53.00	203.57	152.00	9,999.00	725.67	3,650
1	LKV_fat	2.06	3.65	4.13	4.18	4.62	8.00	0.79	17,772
2	LKV_fat	2.11	3.53	4.04	4.12	4.66	7.08	0.87	1,034
3	LKV_fat	2.32	3.54	4.05	4.12	4.50	7.60	0.83	3,676
1	LKV_protein	2.37	3.28	3.52	3.53	3.78	4.92	0.36	17,784
2	LKV_protein	2.78	3.28	3.58	3.60	3.86	4.58	0.38	1,034
3	LKV_protein	2.49	3.21	3.46	3.46	3.73	4.69	0.38	3,676
1	LKV_fat_protein_ratio	0.59	1.05	1.16	1.19	1.31	2.39	0.22	17,760
2	LKV_fat_protein_ratio	0.69	1.00	1.13	1.15	1.28	2.09	0.24	1,034
3	LKV_fat_protein_ratio	0.60	1.05	1.16	1.20	1.30	2.34	0.25	3,676
1	LKV_lactose	3.61	4.80	4.91	4.89	5.01	5.40	0.19	17,546
2	LKV_lactose	4.27	4.76	4.86	4.85	4.99	5.24	0.19	1,034
3	LKV_lactose	3.83	4.78	4.90	4.88	5.01	5.37	0.19	3,645
1	Milkings	1.00	2.00	2.00	2.53	3.00	9.00	0.74	18,617
2	Milkings	1.00	2.00	2.00	2.38	3.00	5.00	0.75	1,101
3	Milkings	1.00	2.00	2.00	2.40	3.00	6.00	0.73	3,934
1	Maximum_milking_interval	18.77	492.33	563.78	582.43	650.18	1,351.33	131.72	17,652

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	Maximum_milking_interval	174.83	506.00	575.00	605.44	676.69	1266.97	142.38	1,019
3	Maximum_milking_interval	49.87	507.22	579.16	600.13	665.79	1420.00	137.21	3,608
1	Robot_daily_milk_yield	0.06	22.18	28.41	28.71	35.14	72.52	9.34	18,609
2	Robot_daily_milk_yield	0.11	21.81	29.32	29.34	37.65	66.34	10.51	1,101
3	Robot_daily_milk_yield	1.05	22.10	29.61	29.62	36.69	63.23	10.32	3,932
1	Robot_milk_yield_in_current_lactation	2.19	2,404.90	4,894.38	5,273.55	7,569.11	15,874.03	3,454.24	3,870
2	Robot_milk_yield_in_current_lactation	121.12	2,274.49	5,542.73	5,913.95	8,916.91	13,254.48	3,936.55	378
3	Robot_milk_yield_in_current_lactation	27.61	1,909.46	5,653.56	5,302.94	8,034.67	15,527.41	3,537.18	889
1	Robot_milk_yield_in_last_lactation	635.00	7,176.55	8,743.00	8,873.23	10,445.00	20,148.00	2,733.33	9,910
2	Robot_milk_yield_in_last_lactation	2,018.00	7,109.00	10,157.00	9,552.14	11,912.00	14,996.72	3,285.50	564
3	Robot_milk_yield_in_last_lactation	1,734.00	7,314.00	9,017.00	9,346.84	11,197.00	19,333.00	3,128.17	2,188
1	Robot_daily_milk_yield_in_last_lactation	12.00	25.20	28.60	29.18	33.60	43.00	5.84	5,567
2	Robot_daily_milk_yield_in_last_lactation	13.10	23.80	28.40	28.78	33.20	42.70	5.86	370
3	Robot_daily_milk_yield_in_last_lactation	12.60	25.80	29.10	29.69	34.30	43.00	5.92	1,237
1	MDi	1.00	1.00	1.10	1.15	1.15	4.20	0.31	5,157
2	MDi	1.00	1.00	1.10	1.19	1.15	4.25	0.38	493
3	MDi	1.00	1.00	1.10	1.19	1.15	3.85	0.33	1,262
1	Milking_flow	0.00	1.21	2.05	2.16	2.90	6.65	1.09	12,986
2	Milking_flow	0.44	1.00	1.30	1.74	2.40	5.55	1.00	896
3	Milking_flow	0.50	1.18	1.90	2.10	2.90	7.10	1.09	2,768
1	Max_milking_flow	0.50	2.90	4.00	4.11	5.16	10.14	1.67	12,987
2	Max_milking_flow	1.16	2.93	4.10	4.11	5.31	8.40	1.65	896
3	Max_milking_flow	0.60	3.05	4.15	4.21	5.22	11.76	1.79	2,767
1	Robot_conduct_lely	60.00	66.75	68.75	69.01	71.00	96.25	3.40	8,630
2	Robot_conduct_lely	62.00	66.75	69.00	69.39	72.00	80.50	3.52	434

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	Robot_conduct_lely	60.50	67.00	69.00	69.15	71.50	85.25	3.54	1,653
1	Robot_conduct	0.00	4.38	4.70	4.72	5.05	7.46	0.57	9,870
2	Robot_conduct	0.00	4.36	4.55	4.63	4.86	6.48	0.57	661
3	Robot_conduct	0.00	4.42	4.67	4.72	5.03	6.66	0.59	2,274
1	Robot_somatic_cell_count	1.00	30.00	54.00	119.28	101.00	3,920.50	287.54	5,997
2	Robot_somatic_cell_count	1.00	23.75	45.00	122.61	95.00	2,696.50	310.50	351
3	Robot_somatic_cell_count	1.00	27.00	49.00	106.02	93.50	2925.00	216.62	1,143
1	Robot_effect_of_scc	0.00	0.55	1.00	1.78	1.70	43.60	3.20	5,997
2	Robot_effect_of_scc	0.00	0.40	0.80	1.71	1.65	40.85	3.76	351
3	Robot_effect_of_scc	0.00	0.60	1.00	1.92	1.77	33.40	3.33	1,143
1	Robot_fat	0.86	3.79	4.20	4.35	4.74	13.11	1.00	13,410
2	Robot_fat	1.81	3.75	4.33	4.42	4.88	11.64	1.09	604
3	Robot_fat	1.23	3.79	4.24	4.34	4.82	12.15	0.96	2,662
1	Robot_protein	2.51	3.27	3.44	3.44	3.60	5.54	0.27	13,408
2	Robot_protein	2.88	3.40	3.53	3.54	3.67	5.38	0.26	605
3	Robot_protein	2.70	3.22	3.42	3.41	3.57	5.60	0.28	2,662
1	Robot_fat_protein_ratio	0.18	1.11	1.24	1.27	1.39	3.49	0.28	13,411
2	Robot_fat_protein_ratio	0.50	1.09	1.24	1.24	1.41	2.16	0.26	605
3	Robot_fat_protein_ratio	0.40	1.12	1.25	1.27	1.41	3.42	0.26	2,662
1	Robot_lactose	2.90	4.59	4.82	4.75	4.92	5.17	0.24	13,402
2	Robot_lactose	4.02	4.71	4.84	4.78	4.92	5.06	0.20	605
3	Robot_lactose	4.01	4.56	4.82	4.73	4.91	5.19	0.25	2,662
1	Milking_temperature	35.85	38.20	38.60	38.69	39.15	41.30	0.67	8,626
2	Milking_temperature	37.00	38.50	38.90	38.92	39.35	40.60	0.63	434
3	Milking_temperature	36.80	38.25	38.70	38.72	39.10	41.50	0.60	1,653
Constitution									
1	Robot_BCS	2.50	3.70	3.90	3.84	4.10	4.60	0.32	3,679
2	Robot_BCS	3.10	3.70	3.90	3.91	4.10	4.40	0.30	326
3	Robot_BCS	2.70	3.60	3.80	3.79	4.00	4.50	0.33	765
1	Body_weight	453.50	637.00	735.78	733.47	813.88	1,151.60	115.46	5,202
2	Body_weight	459.50	742.32	817.05	806.83	897.97	1,030.10	112.44	420
3	Body_weight	444.40	630.88	763.60	753.77	839.86	999.80	126.44	1,160
Feeding									

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Concentrated_feed_intake	0.00	1.83	3.67	3.73	5.32	10.58	2.17	18,136
2	Concentrated_feed_intake	0.00	1.71	3.72	3.64	5.22	9.20	2.13	1,006
3	Concentrated_feed_intake	0.00	1.99	3.83	3.74	5.25	10.00	2.07	3,646
1	Concentrated_feed_remains	0.00	0.08	0.13	0.36	0.31	5.96	0.61	8,665
2	Concentrated_feed_remains	0.02	0.09	0.14	0.28	0.32	3.05	0.37	443
3	Concentrated_feed_remains	0.00	0.09	0.14	0.44	0.45	5.46	0.67	1,644
1	WT_feed_intake	0.00	34.80	44.02	43.53	53.72	92.16	14.75	4,167
2	WT_feed_intake	4.13	41.50	48.99	49.37	58.07	81.94	11.97	381
3	WT_feed_intake	1.03	37.59	45.56	45.06	52.87	88.84	13.97	889
1	WT_feeding_pace	0.06	0.26	0.33	0.35	0.41	1.37	0.12	4,168
2	WT_feeding_pace	0.17	0.32	0.37	0.39	0.45	0.80	0.11	381
3	WT_feeding_pace	0.17	0.33	0.44	0.44	0.53	2.14	0.15	890
1	WT_feeding_duration	10.00	99.00	133.00	138.55	170.00	792.00	62.08	4,150
2	WT_feeding_duration	10.00	110.00	128.00	133.40	152.00	289.00	40.82	379
3	WT_feeding_duration	12.00	80.00	106.00	112.41	141.00	428.00	47.46	884
1	WT_feeding_duration_day	0.00	72.00	100.00	104.06	128.00	769.00	51.32	4,150
2	WT_feeding_duration_day	10.00	81.50	97.00	100.80	115.00	246.00	32.32	379
3	WT_feeding_duration_day	0.00	59.00	80.00	83.07	103.00	358.00	35.16	884
1	WT_feeding_duration_day_night	0.00	0.67	0.76	0.75	0.85	1.00	0.14	4,150
2	WT_feeding_duration_day_night	0.18	0.68	0.77	0.77	0.85	1.00	0.13	379
3	WT_feeding_duration_day_night	0.00	0.65	0.75	0.75	0.85	1.00	0.15	884
1	WT_trough_visits	1.00	29.00	43.00	46.46	59.00	222.00	25.97	4,174
2	WT_trough_visits	2.00	25.00	33.00	33.00	40.00	77.00	13.29	381
3	WT_trough_visits	2.00	17.00	25.00	28.84	37.00	119.00	16.67	890
1	WT_trough_visits_day	0.00	22.00	33.00	35.72	45.00	178.00	21.10	4,174

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	WT_trough_visits_day	2.00	19.00	25.00	25.66	32.00	71.00	10.87	381
3	WT_trough_visits_day	0.00	13.00	19.00	22.06	28.00	91.00	13.34	890
1	WT_trough_visits_day_night	0.00	0.69	0.78	0.77	0.86	1.00	0.14	4,174
2	WT_trough_visits_day_night	0.27	0.70	0.78	0.78	0.88	1.00	0.13	381
3	WT_trough_visits_day_night	0.00	0.67	0.77	0.77	0.87	1.00	0.15	890
1	WT_feed_intake_per_visit	0.00	0.72	0.97	1.18	1.39	8.71	0.76	4,172
2	WT_feed_intake_per_visit	0.50	1.17	1.51	1.86	2.08	10.94	1.31	381
3	WT_feed_intake_per_visit	0.26	1.10	1.79	2.12	2.64	13.02	1.58	890
1	WT_feeding_duration_per_visit	0.37	2.35	3.13	3.63	4.30	70.30	2.68	4,172
2	WT_feeding_duration_per_visit	1.50	3.17	4.07	4.97	5.47	43.42	3.65	381
3	WT_feeding_duration_per_visit	0.43	3.00	4.42	4.93	5.98	57.17	3.53	890
1	WT_number_of_meals	1.00	7.00	9.00	9.63	12.00	23.00	3.18	3,949
2	WT_number_of_meals	1.00	8.00	9.00	9.38	11.00	17.00	2.67	374
3	WT_number_of_meals	1.00	6.00	8.00	8.37	10.00	19.00	2.87	828
1	WT_number_of_meals_day	0.00	5.00	7.00	7.18	9.00	20.00	2.63	3,949
2	WT_number_of_meals_day	1.00	5.00	7.00	7.06	9.00	15.00	2.32	374
3	WT_number_of_meals_day	0.00	4.00	6.00	6.11	7.00	16.00	2.22	828
1	WT_number_of_meals_day_night	0.00	0.67	0.75	0.75	0.83	1.00	0.14	3,949
2	WT_number_of_meals_day_night	0.25	0.67	0.75	0.76	0.86	1.00	0.14	374
3	WT_number_of_meals_day_night	0.00	0.64	0.75	0.74	0.83	1.00	0.15	828
1	WT_feed_intake_per_meal	0.83	3.53	4.67	5.11	6.17	23.91	2.29	3,949
2	WT_feed_intake_per_meal	2.14	4.26	5.46	5.72	6.85	13.55	2.07	374
3	WT_feed_intake_per_meal	1.51	4.41	5.58	6.15	7.39	16.56	2.49	828
1	WT_feeding_duration_per_meal	6.00	10.83	14.48	16.29	19.22	234.33	10.56	3,949
2	WT_feeding_duration_per_meal	6.23	11.10	14.25	16.14	18.76	175.55	11.58	374

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	WT_feeding_duration_per_meal	6.03	10.28	13.62	15.41	18.24	148.63	9.32	828
1	ENGS_feeding	1.00	45.00	79.00	89.56	127.00	288.00	57.23	934
2	ENGS_feeding	1.00	63.75	107.00	103.26	137.00	230.00	51.29	144
3	ENGS_feeding	6.00	45.50	83.50	80.38	112.25	213.00	42.28	188
1	ENGS_feeding_day	0.00	32.00	60.00	67.30	94.75	220.00	44.97	934
2	ENGS_feeding_day	0.00	51.00	79.50	78.55	108.00	171.00	37.73	144
3	ENGS_feeding_day	0.00	35.75	60.00	58.90	81.00	169.00	31.17	188
1	ENGS_feeding_day_night	0.00	0.65	0.77	0.75	0.86	1.00	0.18	934
2	ENGS_feeding_day_night	0.00	0.69	0.79	0.78	0.88	1.00	0.15	144
3	ENGS_feeding_day_night	0.00	0.65	0.75	0.74	0.85	1.00	0.18	188
1	ENGS_number_of_meals	0.00	6.00	9.00	8.63	11.00	21.00	3.55	934
2	ENGS_number_of_meals	0.00	7.00	9.00	8.98	11.00	18.00	3.11	144
3	ENGS_number_of_meals	0.00	6.00	8.00	8.70	11.00	25.00	3.87	188
1	ENGS_number_of_meals_day	0.00	5.00	6.00	6.49	8.00	18.00	2.82	934
2	ENGS_number_of_meals_day	0.00	5.00	7.00	6.71	8.00	13.00	2.43	144
3	ENGS_number_of_meals_day	0.00	5.00	6.00	6.35	8.00	17.00	2.79	188
1	ENGS_number_of_meals_day_night	0.00	0.67	0.75	0.76	0.86	1.00	0.16	911
2	ENGS_number_of_meals_day_night	0.46	0.67	0.75	0.76	0.83	1.00	0.13	141
3	ENGS_number_of_meals_day_night	0.00	0.67	0.75	0.74	0.84	1.00	0.17	186
1	ENGS_feeding_duration_per_meal	1.00	5.70	9.12	10.84	14.67	63.00	7.11	911
2	ENGS_feeding_duration_per_meal	1.50	6.88	11.42	12.14	15.80	34.00	6.91	141
3	ENGS_feeding_duration_per_meal	1.12	6.02	9.33	9.79	13.21	26.29	4.96	186
1	Nedap_feeding	10.00	262.00	377.00	377.46	504.00	806.40	154.74	5,128

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	Nedap_feeding	61.00	196.00	271.00	294.94	382.50	676.80	129.86	291
3	Nedap_feeding	10.00	226.25	374.40	366.46	504.00	806.40	173.87	1,014
Rumination									
1	Smaxtec_rum	188.00	490.00	531.72	525.48	568.71	735.13	65.65	5,539
2	Smaxtec_rum	338.73	504.10	539.20	535.62	576.90	666.90	60.52	245
3	Smaxtec_rum	237.20	490.12	531.84	527.36	571.28	714.02	64.29	1,108
1	SCR_rum	11.00	520.00	562.00	553.23	599.00	748.00	71.69	6,790
2	SCR_rum	206.00	509.00	561.00	549.89	605.00	751.00	79.56	541
3	SCR_rum	61.00	504.00	557.00	545.81	599.00	732.00	81.05	1,533
1	SCR_rum_day	2.00	306.00	343.00	337.58	377.00	533.00	61.76	3,032
2	SCR_rum_day	109.00	310.50	356.00	345.51	389.00	496.00	62.34	359
3	SCR_rum_day	61.00	302.00	340.00	336.09	380.00	545.00	68.11	833
1	SCR_rum_day_night	0.01	0.59	0.63	0.63	0.66	1.00	0.06	3,032
2	SCR_rum_day_night	0.42	0.60	0.65	0.64	0.68	0.85	0.06	359
3	SCR_rum_day_night	0.29	0.61	0.64	0.64	0.68	1.00	0.06	833
1	Nedap_rum	14.40	291.00	395.00	393.24	504.00	763.20	138.14	5,153
2	Nedap_rum	97.00	345.60	432.00	406.98	489.60	691.20	113.47	290
3	Nedap_rum	10.00	188.75	291.50	329.72	477.40	820.80	173.54	1,020
Heat detection									
1	SCR_heat_probability	-27.00	-3.50	-1.00	-0.50	0.50	92.00	7.78	3,621
2	SCR_heat_probability	-35.00	-3.50	-2.00	-1.05	0.00	88.00	9.07	177
3	SCR_heat_probability	-22.00	-4.00	-1.50	-1.01	0.50	74.00	7.04	674
1	SCR_heat_probability_day	-29.00	-4.00	-1.00	-0.34	1.00	100.00	9.02	3,607
2	SCR_heat_probability_day	-36.00	-3.50	-1.50	-0.44	0.00	84.00	10.64	177

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	SCR_heat_probability_day	-25.00	-4.00	-1.50	-0.98	1.00	84.00	7.95	665
1	Lemmer_factor_of_restlessness	53.23	226.00	320.00	452.24	457.71	30,501.82	890.26	4,532
2	Lemmer_factor_of_restlessness	84.60	160.62	215.64	296.17	305.06	1,737.42	253.20	152
3	Lemmer_factor_of_restlessness	52.96	155.66	231.78	301.39	345.81	5,668.09	310.06	986
Lying									
1	Nedap_lying	248.00	639.00	727.00	719.49	804.00	1,075.00	119.47	1,634
2	Nedap_lying	340.00	630.00	710.00	740.17	854.50	1,081.00	155.98	135
3	Nedap_lying	156.00	583.00	709.50	697.47	815.00	1,131.00	180.71	382
1	Nedap_get_ups	1.00	8.00	10.00	10.43	12.00	29.00	3.52	1,687
2	Nedap_get_ups	1.00	6.00	9.00	9.83	13.00	22.00	4.48	135
3	Nedap_get_ups	1.00	6.00	8.00	8.83	11.00	28.00	4.42	401
1	ENGS_lying	4.00	587.75	688.00	677.59	780.25	1,159.00	152.74	3,872
2	ENGS_lying	4.00	558.00	680.00	641.08	789.00	1,080.00	227.19	337
3	ENGS_lying	34.00	513.50	687.50	688.92	843.50	1,258.00	232.00	882
1	ENGS_lying_day	0.00	313.00	387.00	380.71	455.00	716.00	109.69	3,872
2	ENGS_lying_day	0.00	313.00	395.00	374.36	463.00	699.00	145.39	337
3	ENGS_lying_day	0.00	293.00	411.00	410.50	526.75	835.00	165.08	882
1	ENGS_lying_day_night	0.00	0.51	0.56	0.56	0.61	1.00	0.10	3,872
2	ENGS_lying_day_night	0.00	0.52	0.58	0.58	0.64	1.00	0.14	337
3	ENGS_lying_day_night	0.00	0.54	0.60	0.59	0.66	1.00	0.13	882
1	ENGS_lying_bouts	1.00	12.00	15.00	17.47	20.00	109.00	9.93	3,872
2	ENGS_lying_bouts	1.00	8.00	13.00	14.09	18.00	61.00	8.53	339
3	ENGS_lying_bouts	1.00	9.00	13.00	16.92	19.75	81.00	13.47	882
1	ENGS_lying_bouts_day	0.00	7.00	10.00	11.18	13.00	60.00	6.49	3,872
2	ENGS_lying_bouts_day	0.00	5.00	8.00	9.11	11.00	45.00	5.87	337
3	ENGS_lying_bouts_day	0.00	6.00	8.00	10.89	13.00	60.00	8.75	882

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	ENGS_lying_bouts_day_night	0.00	0.57	0.65	0.64	0.73	1.00	0.12	3,872
2	ENGS_lying_bouts_day_night	0.00	0.56	0.67	0.66	0.76	1.00	0.18	339
3	ENGS_lying_bouts_day_night	0.00	0.57	0.67	0.66	0.75	1.00	0.15	882
1	ENGS_lying_duration_per_bout	2.00	32.32	44.50	48.18	58.42	510.00	27.38	3,872
2	ENGS_lying_duration_per_bout	1.60	33.13	47.75	64.58	69.45	719.00	68.55	337
3	ENGS_lying_duration_per_bout	5.00	31.54	52.88	67.15	80.83	713.00	68.02	882
1	Lemmer_lying	10.80	529.80	628.20	616.20	715.80	1,252.20	152.57	4,534
2	Lemmer_lying	229.80	530.85	657.60	653.29	771.15	1,006.20	157.03	152
3	Lemmer_lying	46.80	544.35	693.00	676.13	825.00	1,212.00	213.52	986
1	Lemmer_get_ups	1.00	6.00	9.00	9.17	11.00	40.00	3.93	4,534
2	Lemmer_get_ups	4.00	8.00	10.00	10.33	12.00	23.00	3.45	152
3	Lemmer_get_ups	1.00	7.00	9.00	9.90	12.00	27.00	3.94	983
Activity									
1	Delaval_act_avg	12.00	24.00	30.00	31.67	38.00	89.00	10.15	1,055
2	Delaval_act_avg	11.00	19.00	28.00	27.95	34.00	60.00	9.68	116
3	Delaval_act_avg	10.00	20.00	25.00	25.70	31.00	75.00	8.57	344
1	Delaval_act_rel	59.00	91.00	100.00	100.87	108.00	287.00	17.24	1,055
2	Delaval_act_rel	55.00	89.00	99.50	100.84	109.00	229.00	21.90	116
3	Delaval_act_rel	44.00	84.00	95.00	97.81	105.00	293.00	24.09	344
1	Delaval_act_rel_min	50.00	82.00	89.00	89.23	96.00	137.00	11.76	1,008
2	Delaval_act_rel_min	46.00	79.00	88.00	86.41	95.00	162.00	15.48	112
3	Delaval_act_rel_min	39.00	77.00	84.00	86.16	93.00	191.00	17.33	316
1	Delaval_act_rel_max	59.00	101.00	110.00	111.24	118.00	255.00	18.46	1,008
2	Delaval_act_rel_max	62.00	103.75	111.00	114.04	121.25	255.00	25.67	112
3	Delaval_act_rel_max	65.00	96.00	106.00	110.05	115.00	255.00	26.67	316
1	ENGS_act	31.00	1,803.00	2,223.00	2,299.33	2,707.00	8,735.00	869.84	3,870

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	ENGS_act	30.00	1,484.50	1,891.50	1,869.15	2,305.50	6,803.00	841.96	336
3	ENGS_act	59.00	1,379.25	1,831.00	1,965.86	2,443.00	7,532.00	891.58	882
1	ENGS_act_day	0.00	1,393.00	1,740.00	1,802.66	2,125.75	7,471.00	707.68	3,870
2	ENGS_act_day	0.00	1,115.75	1,458.00	1,441.34	1,807.75	5,840.00	676.50	336
3	ENGS_act_day	0.00	1,051.25	1,401.50	1,491.74	1,816.25	6,416.00	695.36	882
1	ENGS_act_day_night	0.00	0.74	0.79	0.78	0.84	1.00	0.08	3,870
2	ENGS_act_day_night	0.00	0.72	0.78	0.76	0.83	1.00	0.12	336
3	ENGS_act_day_night	0.00	0.71	0.76	0.76	0.82	0.99	0.10	882
1	Smaxtec_act	0.31	3.96	4.86	5.65	6.98	21.36	2.43	7,183
2	Smaxtec_act	0.31	4.26	5.32	5.78	7.92	16.89	2.40	365
3	Smaxtec_act	0.42	3.71	4.69	5.41	6.92	15.09	2.34	1,491
1	Smaxtec_act_day	0.40	4.80	5.88	6.49	7.76	23.69	2.46	7,180
2	Smaxtec_act_day	0.40	4.90	6.35	6.41	8.01	17.67	2.30	364
3	Smaxtec_act_day	0.39	4.53	5.64	6.21	7.75	20.65	2.41	1,491
1	Smaxtec_act_day_night	0.43	1.06	1.15	1.18	1.27	2.32	0.18	7,181
2	Smaxtec_act_day_night	0.68	1.04	1.11	1.14	1.22	1.94	0.16	365
3	Smaxtec_act_day_night	0.72	1.05	1.14	1.18	1.26	2.53	0.20	1,488
1	SCR_act	21.50	36.50	40.00	41.16	44.50	141.00	7.77	6,740
2	SCR_act	26.00	34.50	38.00	38.81	42.50	84.50	6.47	543
3	SCR_act	25.00	34.00	37.00	38.53	40.50	150.00	10.18	1,521
1	SCR_act_day	20.50	38.50	43.00	44.39	48.50	146.50	9.21	6,737
2	SCR_act_day	26.00	36.00	40.50	41.42	45.50	100.50	8.56	543
3	SCR_act_day	25.00	35.00	39.00	40.95	44.00	151.00	11.07	1,519
1	SCR_act_day_night	0.60	1.02	1.06	1.08	1.12	2.15	0.09	6,743
2	SCR_act_day_night	0.74	1.01	1.04	1.06	1.10	2.01	0.09	543
3	SCR_act_day_night	0.55	1.01	1.04	1.06	1.10	1.99	0.10	1,521

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Lemmer_act	37.00	102.00	132.00	151.52	172.00	858.00	86.69	4,776
2	Lemmer_act	47.00	73.00	94.00	118.44	127.00	590.00	87.01	173
3	Lemmer_act	37.00	79.00	103.00	115.45	133.00	774.00	65.02	1,016
1	Nedap_inactive	225.00	548.00	639.00	661.20	752.00	1,378.00	162.54	5,132
2	Nedap_inactive	363.00	639.00	725.50	732.20	829.75	1,147.00	127.35	290
3	Nedap_inactive	251.00	627.00	719.00	737.74	812.00	1,357.00	168.60	1,019
1	Nedap_act_collar_median	1.00	4.50	7.00	8.24	10.50	71.00	5.05	5,168
2	Nedap_act_collar_median	0.00	4.50	6.00	6.88	9.00	21.50	3.46	291
3	Nedap_act_collar_median	0.00	4.00	6.00	7.02	9.50	53.00	4.25	1,017
1	Nedap_act_collar_sum	14.00	63.00	95.00	110.23	140.00	859.00	65.69	5,166
2	Nedap_act_collar_sum	9.00	62.00	81.00	93.54	119.00	330.00	48.20	290
3	Nedap_act_collar_sum	11.00	58.00	83.00	95.10	125.00	635.00	57.80	1,016
1	Nedap_act_collar_median_day	0.50	5.00	8.00	9.70	12.50	89.50	6.56	5,172
2	Nedap_act_collar_median_day	0.50	5.00	7.00	7.93	10.50	30.00	4.45	292
3	Nedap_act_collar_median_day	0.00	4.50	7.00	7.94	10.00	85.50	5.80	1,017
1	Nedap_act_collar_sum_day	6.00	46.00	71.00	82.89	105.00	737.00	52.62	5,172
2	Nedap_act_collar_sum_day	6.00	43.75	60.50	69.69	93.00	308.00	38.89	292
3	Nedap_act_collar_sum_day	6.00	41.00	61.00	69.09	91.00	534.00	46.01	1,017
1	Nedap_act_collar_median_day_night	0.13	1.00	1.12	1.17	1.28	5.47	0.27	5,168
2	Nedap_act_collar_median_day_night	0.70	1.00	1.11	1.15	1.25	2.86	0.23	290
3	Nedap_act_collar_median_day_night	0.20	1.00	1.07	1.12	1.22	4.21	0.28	1,016
1	Nedap_act_collar_sum_day_night	0.16	0.70	0.75	0.75	0.80	0.98	0.09	5,167
2	Nedap_act_collar_sum_day_night	0.44	0.69	0.74	0.74	0.79	0.93	0.08	290

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	Nedap_act_collar_sum_day_night	0.26	0.67	0.73	0.72	0.78	0.95	0.09	1,016
1	Nedap_act	1,304.00	2,661.50	3,405.50	3,641.51	4,331.75	14,174.00	1,371.97	1,686
2	Nedap_act	1,789.00	2,596.50	2,979.00	3,256.28	3,702.50	9,391.00	966.14	135
3	Nedap_act	1,284.00	2,324.00	2,849.00	3,132.03	3,718.00	13,726.00	13,66.53	403
1	Nedap_act_foot_median	72.50	202.50	252.00	266.24	315.00	1207.00	92.27	1,684
2	Nedap_act_foot_median	135.50	196.00	230.50	239.59	273.00	427.00	59.48	135
3	Nedap_act_foot_median	73.00	175.25	222.50	236.61	280.75	1,049.50	97.93	403
1	Nedap_act_foot_median_day	89.00	231.50	290.75	320.30	385.00	1,476.50	132.45	1,698
2	Nedap_act_foot_median_day	109.00	219.50	255.00	264.77	306.00	502.50	72.87	135
3	Nedap_act_foot_median_day	86.00	191.00	255.50	270.54	322.38	1,501.50	130.29	404
1	Nedap_act_foot_sum_day	893.00	1,952.25	2,584.00	2,815.98	3,409.50	11,056.00	1189.97	1,698
2	Nedap_act_foot_sum_day	1,206.00	1,886.00	2,244.00	2,485.52	3,025.00	8,972.00	924.82	135
3	Nedap_act_foot_sum_day	774.00	1,667.00	2,074.00	2,345.25	2,817.00	12,174.00	1,161.11	405
1	Nedap_act_foot_median_day_night	0.37	1.03	1.15	1.20	1.29	3.49	0.25	1,693
2	Nedap_act_foot_median_day_night	0.55	1.00	1.09	1.11	1.20	1.67	0.16	135
3	Nedap_act_foot_median_day_night	0.61	1.00	1.10	1.15	1.25	3.40	0.24	403
1	Nedap_act_foot_sum_day_night	0.22	0.72	0.78	0.77	0.82	0.95	0.08	1,692
2	Nedap_act_foot_sum_day_night	0.57	0.70	0.75	0.75	0.80	0.96	0.07	135
3	Nedap_act_foot_sum_day_night	0.48	0.70	0.75	0.74	0.79	0.91	0.07	403
Body temperature									
1	Smaxtec_temp_normal_median	39.00	39.28	39.39	39.41	39.53	40.00	0.19	7,190
2	Smaxtec_temp_normal_median	39.11	39.44	39.52	39.53	39.64	39.96	0.17	385
3	Smaxtec_temp_normal_median	39.00	39.34	39.46	39.48	39.61	40.00	0.20	1,471

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Smaxtec_temp_median	38.45	39.00	39.12	39.14	39.25	40.64	0.20	7,226
2	Smaxtec_temp_median	38.78	39.10	39.24	39.22	39.34	39.84	0.18	386
3	Smaxtec_temp_median	38.56	39.06	39.19	39.21	39.34	40.16	0.23	1,490
1	Smaxtec_temp_min	26.99	32.98	33.87	33.83	34.75	39.27	1.35	7,228
2	Smaxtec_temp_min	30.29	33.26	34.26	34.15	35.08	37.01	1.25	385
3	Smaxtec_temp_min	28.69	32.73	33.48	33.47	34.30	37.33	1.24	1,491
1	Smaxtec_temp_max	39.00	39.58	39.73	39.77	39.91	42.35	0.31	7,228
2	Smaxtec_temp_max	39.24	39.76	39.91	39.92	40.08	41.08	0.25	386
3	Smaxtec_temp_max	39.15	39.65	39.82	39.86	40.00	42.35	0.34	1,491
1	Smaxtec_temp_without_drink_cycles_median	38.69	39.13	39.24	39.26	39.37	40.78	0.20	7,183
2	Smaxtec_temp_without_drink_cycles_median	38.90	39.27	39.37	39.38	39.48	39.96	0.18	386
3	Smaxtec_temp_without_drink_cycles_median	38.74	39.19	39.30	39.33	39.47	40.36	0.22	1,490
1	Smaxtec_temp_without_drink_cycles_min	37.74	38.50	38.63	38.64	38.76	39.97	0.21	7,185
2	Smaxtec_temp_without_drink_cycles_min	38.30	38.59	38.75	38.72	38.85	39.51	0.18	386
3	Smaxtec_temp_without_drink_cycles_min	37.99	38.54	38.67	38.68	38.81	39.62	0.22	1,492
1	Smaxtec_temp_without_drink_cycles_max	38.99	39.55	39.70	39.75	39.88	42.32	0.31	7,182
2	Smaxtec_temp_without_drink_cycles_max	39.24	39.73	39.87	39.89	40.03	41.07	0.26	386
3	Smaxtec_temp_without_drink_cycles_max	39.16	39.63	39.79	39.84	39.98	42.28	0.34	1,488
Climate									
1	Smaxtec_climate_temp_median	2.37	8.91	10.95	11.84	14.48	24.34	5.04	9,100
2	Smaxtec_climate_temp_median	2.37	9.76	13.94	13.44	17.71	24.34	5.46	436
3	Smaxtec_climate_temp_median	2.37	8.91	10.46	11.32	14.12	24.34	4.60	1,804

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Smaxtec_climate_temp_min	-0.34	5.26	8.36	8.71	11.73	19.63	4.36	9,100
2	Smaxtec_climate_temp_min	-0.34	6.67	9.36	9.94	13.27	19.63	4.63	436
3	Smaxtec_climate_temp_min	-0.34	5.43	8.35	8.41	10.50	19.63	3.94	1,804
1	Smaxtec_climate_temp_max	3.98	11.10	14.09	15.08	18.33	29.55	6.01	9,100
2	Smaxtec_climate_temp_max	3.98	11.84	16.85	16.84	22.06	29.55	6.50	436
3	Smaxtec_climate_temp_max	3.98	10.50	13.17	14.31	17.11	29.55	5.51	1,804
1	Smaxtec_climate_hum_median	46.54	67.44	73.50	73.84	81.30	100.00	11.17	8,793
2	Smaxtec_climate_hum_median	46.54	65.21	72.74	73.40	80.90	100.00	12.34	408
3	Smaxtec_climate_hum_median	46.54	68.07	74.92	74.68	81.31	100.00	11.12	1,735
1	Smaxtec_climate_hum_min	1.21	50.02	62.47	61.98	76.28	98.77	16.12	8,793
2	Smaxtec_climate_hum_min	1.21	46.35	58.50	59.10	75.65	98.77	17.68	408
3	Smaxtec_climate_hum_min	1.21	52.03	64.68	63.39	77.07	98.77	16.39	1,735
1	Smaxtec_climate_hum_max	62.39	77.22	82.13	82.63	85.64	100.00	7.46	8,793
2	Smaxtec_climate_hum_max	62.39	78.70	81.86	83.20	85.90	100.00	7.87	408
3	Smaxtec_climate_hum_max	62.39	77.43	82.92	82.82	85.65	100.00	7.58	1,735
1	Smaxtec_thi_median	28.11	45.35	51.61	51.99	58.05	71.76	9.84	8,793
2	Smaxtec_thi_median	28.11	49.12	56.38	54.88	63.05	71.76	10.22	408
3	Smaxtec_thi_median	28.11	46.61	51.13	51.45	57.29	71.76	8.79	1,735
1	Smaxtec_thi_min	35.45	44.81	48.84	49.59	54.54	65.33	6.44	8,793
2	Smaxtec_thi_min	35.45	46.59	51.26	51.43	57.46	65.33	7.02	408
3	Smaxtec_thi_min	35.45	45.19	48.54	49.10	52.44	65.33	5.88	1,735
1	Smaxtec_thi_max	39.45	52.05	57.31	58.86	64.99	83.07	9.91	8,793
2	Smaxtec_thi_max	39.45	52.86	62.05	61.87	71.54	83.07	10.92	408
3	Smaxtec_thi_max	39.45	51.50	55.79	57.56	62.37	83.07	9.09	1,735
1	WS_thi_med	27.20	39.07	48.76	49.24	60.43	70.76	11.71	10,024
2	WS_thi_med	28.03	39.08	48.76	49.15	60.47	70.76	11.67	699

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	WS_thi_med	27.20	36.79	46.80	47.11	56.20	70.76	11.18	2,067
1	WS_thi_min	22.57	36.12	42.93	43.31	51.76	61.12	9.49	10,024
2	WS_thi_min	23.54	35.60	42.98	43.06	52.19	61.12	9.74	699
3	WS_thi_min	22.57	34.83	41.05	41.61	48.04	61.12	8.96	2,067
1	WS_thi_max	30.74	44.29	59.18	58.03	70.81	91.66	15.33	10,024
2	WS_thi_max	30.74	44.42	58.82	58.10	69.80	91.66	15.03	699
3	WS_thi_max	30.74	42.26	55.75	55.39	66.38	91.66	14.82	2,067
1	WS_temp_2m_med	-3.36	3.42	8.59	9.39	16.00	23.28	6.89	10,024
2	WS_temp_2m_med	-2.22	3.52	8.75	9.44	15.96	23.28	6.83	699
3	WS_temp_2m_med	-3.36	2.17	7.43	8.11	13.25	23.28	6.54	2,067
1	WS_temp_2m_min	-7.90	-0.60	2.70	4.37	9.40	16.40	5.95	10,024
2	WS_temp_2m_min	-6.70	-0.60	3.30	4.50	9.50	16.40	5.93	699
3	WS_temp_2m_min	-7.90	-1.05	1.60	3.25	7.90	16.40	5.57	2,067
1	WS_temp_2m_max	-0.70	6.80	15.10	14.49	21.80	33.40	8.56	10,024
2	WS_temp_2m_max	-0.70	6.90	14.90	14.53	21.00	33.40	8.39	699
3	WS_temp_2m_max	-0.70	5.60	13.10	13.01	19.20	33.40	8.28	2,067
1	WS_temp_20cm_med	-3.93	2.86	7.80	9.06	15.61	23.52	6.94	10,024
2	WS_temp_20cm_med	-2.20	2.66	7.78	9.06	15.68	23.52	6.96	699
3	WS_temp_20cm_med	-3.93	2.08	6.34	7.75	12.78	23.52	6.52	2,067
1	WS_temp_20cm_min	-9.60	-1.80	1.50	2.77	7.60	16.20	6.21	10,024
2	WS_temp_20cm_min	-8.60	-2.30	2.20	2.85	7.80	16.20	6.26	699
3	WS_temp_20cm_min	-9.60	-2.30	0.40	1.65	6.30	16.20	5.78	2,067
1	WS_temp_20cm_max	-0.40	8.00	17.00	15.85	23.60	33.00	9.06	10,024
2	WS_temp_20cm_max	-0.40	8.10	16.90	15.88	23.50	33.00	8.90	699
3	WS_temp_20cm_max	-0.40	6.30	14.90	14.30	21.25	33.00	8.75	2,067
1	WS_soil_temp_5cm_med	0.70	4.40	9.63	10.42	16.40	22.61	6.65	10,024

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	WS_soil_temp_5cm_med	0.70	4.44	9.70	10.55	16.55	22.61	6.55	699
3	WS_soil_temp_5cm_med	0.70	3.55	8.31	9.19	14.35	22.61	6.20	2,067
1	WS_soil_temp_5cm_min	0.50	2.60	7.40	8.74	14.50	19.50	6.20	10,024
2	WS_soil_temp_5cm_min	0.50	2.80	8.00	8.89	14.95	19.50	6.13	699
3	WS_soil_temp_5cm_min	0.50	2.10	6.20	7.58	12.80	19.50	5.75	2,067
1	WS_soil_temp_5cm_max	1.00	6.30	12.40	12.41	18.50	28.50	7.35	10,024
2	WS_soil_temp_5cm_max	1.00	6.30	12.30	12.53	18.40	28.50	7.18	699
3	WS_soil_temp_5cm_max	1.00	5.60	10.40	11.12	16.80	28.50	6.87	2,067
1	WS_soil_temp_20cm_med	1.64	4.57	9.18	10.37	15.81	20.44	6.09	10,024
2	WS_soil_temp_20cm_med	1.64	5.00	9.39	10.59	16.20	20.44	5.99	699
3	WS_soil_temp_20cm_med	1.64	3.89	8.41	9.26	14.33	20.44	5.67	2,067
1	WS_soil_temp_20cm_min	1.50	4.10	8.70	9.95	15.30	19.70	5.96	10,024
2	WS_soil_temp_20cm_min	1.50	4.70	8.80	10.18	15.70	19.70	5.85	699
3	WS_soil_temp_20cm_min	1.50	3.50	7.60	8.87	13.70	19.70	5.55	2,067
1	WS_soil_temp_20cm_max	1.70	5.00	9.80	10.87	16.30	21.80	6.26	10,024
2	WS_soil_temp_20cm_max	1.70	5.20	10.00	11.09	16.70	21.80	6.16	699
3	WS_soil_temp_20cm_max	1.70	4.40	9.00	9.74	14.90	21.80	5.82	2,067
1	WS_rel_hum_med	41.79	73.20	87.31	84.05	98.17	100.00	14.99	10,024
2	WS_rel_hum_med	41.79	77.42	90.17	86.23	99.58	100.00	14.23	699
3	WS_rel_hum_med	41.79	74.96	88.49	85.18	98.54	100.00	14.38	2,067
1	WS_rel_hum_min	17.80	39.80	57.80	62.32	90.20	100.00	25.85	10,024
2	WS_rel_hum_min	17.80	42.00	60.90	65.56	97.20	100.00	26.44	699
3	WS_rel_hum_min	17.80	40.90	62.30	64.27	91.10	100.00	25.66	2,067
1	WS_rel_hum_max	53.00	99.30	100.00	98.39	100.00	100.00	4.66	10,024
2	WS_rel_hum_max	53.00	99.80	100.00	99.00	100.00	100.00	3.47	699
3	WS_rel_hum_max	53.00	99.20	100.00	98.49	100.00	100.00	4.30	2,067

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	WS_wind_velocity_med	0.50	1.09	1.50	1.76	2.03	5.68	1.03	10,024
2	WS_wind_velocity_med	0.50	1.08	1.41	1.68	1.95	5.68	0.95	699
3	WS_wind_velocity_med	0.50	1.12	1.51	1.79	2.09	5.68	1.05	2,067
1	WS_wind_velocity_min	0.00	0.00	0.00	0.19	0.10	3.30	0.48	10,024
2	WS_wind_velocity_min	0.00	0.00	0.00	0.16	0.10	3.30	0.39	699
3	WS_wind_velocity_min	0.00	0.00	0.00	0.21	0.20	3.30	0.47	2,067
1	WS_wind_velocity_max	1.60	2.70	3.50	4.03	4.70	12.70	1.99	10,024
2	WS_wind_velocity_max	1.60	2.60	3.40	3.90	4.45	12.70	1.95	699
3	WS_wind_velocity_max	1.60	2.70	3.50	4.05	4.60	12.70	2.07	2,067
1	WS_rain_med	0.00	0.00	0.00	0.01	0.01	0.22	0.03	10,024
2	WS_rain_med	0.00	0.00	0.00	0.01	0.01	0.22	0.03	699
3	WS_rain_med	0.00	0.00	0.00	0.01	0.01	0.22	0.03	2,067
1	WS_rain_min	0.00	0.00	0.00	0.00	0.00	0.01	0.00	10,024
2	WS_rain_min	0.00	0.00	0.00	0.00	0.00	0.01	0.00	699
3	WS_rain_min	0.00	0.00	0.00	0.00	0.00	0.01	0.00	2,067
1	WS_rain_max	0.00	0.00	0.02	0.35	0.26	12.20	1.18	10,024
2	WS_rain_max	0.00	0.00	0.01	0.30	0.22	12.20	1.10	699
3	WS_rain_max	0.00	0.00	0.03	0.30	0.28	12.20	0.98	2,067
1	WS_global_rad_med	5.61	55.38	145.26	149.76	223.91	359.26	98.90	10,024
2	WS_global_rad_med	5.61	55.38	134.28	142.66	213.23	359.26	96.26	699
3	WS_global_rad_med	5.61	49.39	130.38	135.55	208.60	359.26	94.99	2,067
1	WS_global_rad_min	0.00	0.00	0.00	0.06	0.00	2.00	0.27	10,024
2	WS_global_rad_min	0.00	0.00	0.00	0.11	0.00	2.00	0.37	699
3	WS_global_rad_min	0.00	0.00	0.00	0.06	0.00	2.00	0.27	2,067
1	WS_global_rad_max	41.00	346.00	694.00	619.57	871.00	1164.00	303.34	10,024
2	WS_global_rad_max	41.00	351.00	632.00	598.70	843.00	1164.00	297.49	699
3	WS_global_rad_max	41.00	303.50	631.00	581.60	843.00	1164.00	303.13	2,067
1	Season	1.00	1.00	2.00	2.14	3.00	4.00	0.98	19,431
2	Season	1.00	1.00	2.00	2.21	3.00	4.00	0.99	1,133
3	Season	1.00	1.00	2.00	2.20	3.00	4.00	1.03	4,019
Claw health									

C_LMS	variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	GSC	1.00	2.50	3.00	2.67	3.00	3.00	0.40	19,316
2	GSC	1.00	2.00	2.50	2.54	3.00	3.00	0.47	1,107
3	GSC	1.00	2.25	2.75	2.63	3.00	3.00	0.42	3,971
1	PT	0.00	0.00	0.00	0.15	0.00	1.00	0.36	19,316
2	PT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1,107
3	PT	0.00	0.00	0.00	0.41	1.00	1.00	0.49	3,950

Table 60: Statistical summaries for each parameter grouped by locomotion score (LMS) across all farms (parameters explained in Table 33)

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
Animal characteristics									
1	Breed	1	1	1	1.1	1	6	0.7	1,9431
2	Breed	1	1	1	1	1	4	0.3	3,736
3	Breed	1	1	1	1.1	1	3	0.4	1,416
Milking									
1	Days_in_milk	0	76	152	161	228	530	103.3	19,148
2	Days_in_milk	0	64	153	160.4	239	520	107.3	3,704
3	Days_in_milk	0	53	150	149.9	226	517	99.6	1,401
1	Lactation_number	0	1	2	2.6	4	12	1.8	19,431
2	Lactation_number	0	2	3	3	4	12	1.8	3,736
3	Lactation_number	0	1	3	3.3	5	12	2.1	1,416
1	LKV_daily_milk_yield	7.2	23.1	29.1	29.4	35.4	57.4	8.2	17,784
2	LKV_daily_milk_yield	6.5	23.6	30.6	30.6	37	61.1	9.1	3,418
3	LKV_daily_milk_yield	8.8	23.8	29.1	29.1	35.1	51.4	8.7	1,292
1	LKV_fat	2.1	3.6	4.1	4.2	4.6	8	0.8	17,772
2	LKV_fat	2.1	3.6	4.1	4.1	4.6	7.1	0.8	3,418
3	LKV_fat	2.4	3.5	4	4.1	4.4	7.6	1	1,292
1	LKV_fat_protein_ratio	0.6	1	1.2	1.2	1.3	2.4	0.2	17,760
2	LKV_fat_protein_ratio	0.6	1	1.2	1.2	1.3	2.3	0.2	3,418
3	LKV_fat_protein_ratio	0.7	1	1.1	1.2	1.3	2.3	0.3	1,292
1	LKV_lactose	3.6	4.8	4.9	4.9	5	5.4	0.2	17,546
2	LKV_lactose	4	4.8	4.9	4.9	5	5.4	0.2	3,390
3	LKV_lactose	3.8	4.7	4.9	4.9	5	5.3	0.2	1,289
1	LKV_milk_yield_in_last_lactation	3,243	8,052	9,433	9,784.2	11,350	21,193	2,649.7	12,035
2	LKV_milk_yield_in_last_lactation	3,194	8,342	10,183	10,440.4	12,444	21,193	2,757.8	2,726
3	LKV_milk_yield_in_last_lactation	3,194	8,720	10,734	10,515.9	12,108	21,193	2,851.8	964
1	LKV_protein	2.4	3.3	3.5	3.5	3.8	4.9	0.4	17,784
2	LKV_protein	2.5	3.2	3.5	3.5	3.8	4.7	0.4	3,418

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	LKV_protein	2.6	3.1	3.5	3.4	3.7	4.7	0.4	1,292
1	LKV_somatic_cell_count	10	24	55	205.6	143	9,999	655	17,597
2	LKV_somatic_cell_count	10	21	55	135	121	9,999	307.7	3,395
3	LKV_somatic_cell_count	10	26	58	316.3	187	9,999	1,118.2	1,289
1	LKV_urea	30	138	184	184.7	229	454	64.5	17,188
2	LKV_urea	32	148	187	184.9	225	412	63.8	3,337
3	LKV_urea	32	124	178	177.4	233	369	76.6	1,227
1	Max_milking_flow	0.5	2.9	4	4.1	5.2	10.1	1.7	12,987
2	Max_milking_flow	0.6	2.8	4	4.1	5.1	10	1.7	2,713
3	Max_milking_flow	0.8	3.3	4.4	4.6	5.6	11.8	1.9	950
1	Maximum_milking_interval	18.8	492.3	563.8	582.4	650.2	1,351.3	131.7	17,652
2	Maximum_milking_interval	49.9	503	572.8	594.6	660.2	1,272.8	134.8	3,393
3	Maximum_milking_interval	324.2	521	596.7	619.7	694.9	1,420	146.1	1,234
1	MDI	1	1	1.1	1.2	1.1	4.2	0.3	5,157
2	MDI	1	1	1.1	1.2	1.1	4.2	0.3	1,282
3	MDI	1	1	1.1	1.2	1.2	3.5	0.4	473
1	Milking_flow	0	1.2	2	2.2	2.9	6.7	1.1	12,986
2	Milking_flow	0.4	1.1	1.8	2	2.7	7	1.1	2,713
3	Milking_flow	0.5	1.2	1.9	2.1	2.8	7.1	1.1	951
1	Milking_temperature	35.8	38.2	38.6	38.7	39.2	41.3	0.7	8,626
2	Milking_temperature	36.8	38.3	38.8	38.8	39.2	41.5	0.6	1,568
3	Milking_temperature	37.1	38.3	38.8	38.7	39.1	40.6	0.6	519
1	Milkings	1	2	2	2.5	3	9	0.7	18,617
2	Milkings	1	2	2	2.4	3	5	0.7	3,667
3	Milkings	1	2	2	2.3	3	6	0.7	1,368
1	Robot_conduct	0	4.4	4.7	4.7	5	7.5	0.6	9,870
2	Robot_conduct	0	4.4	4.7	4.7	5	6.7	0.6	2,089
3	Robot_conduct	0	4.4	4.6	4.7	5	6.3	0.6	846
1	Robot_conduct_lely	60	66.8	68.8	69	71	96.2	3.4	8,630
2	Robot_conduct_lely	60.5	67	69	69.2	71.5	84	3.4	1,568
3	Robot_conduct_lely	60.5	66.8	68.5	69.1	71	85.2	4	519
1	Robot_daily_milk_yield	0.1	22.2	28.4	28.7	35.1	72.5	9.3	18,609
2	Robot_daily_milk_yield	0.1	22.4	30.1	30.1	37.4	66.3	10.4	3,666
3	Robot_daily_milk_yield	1	20.7	28.2	28.1	34.9	62.7	10.2	1,367
1	Robot_daily_milk_yield_in_last_lactation	12	25.2	28.6	29.2	33.6	43	5.8	5,567

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	Robot_daily_milk_yield_in_last_lactation	12.6	25.3	29.1	29.4	34.3	43	5.6	1,222
3	Robot_daily_milk_yield_in_last_lactation	12.6	27.1	28.7	29.7	33.7	43	6.7	385
1	Robot_effect_of_scc	0	0.6	1	1.8	1.7	43.6	3.2	5,997
2	Robot_effect_of_scc	0	0.5	0.9	1.9	1.8	40.9	3.5	1,157
3	Robot_effect_of_scc	0	0.6	1	1.7	1.6	33.4	3.1	337
1	Robot_fat	0.9	3.8	4.2	4.4	4.7	13.1	1	13,410
2	Robot_fat	1.2	3.7	4.2	4.3	4.9	11.6	1	2,376
3	Robot_fat	2	3.9	4.3	4.5	4.8	12.2	1	890
1	Robot_fat_protein_ratio	0.2	1.1	1.2	1.3	1.4	3.5	0.3	13,411
2	Robot_fat_protein_ratio	0.4	1.1	1.2	1.2	1.4	2.5	0.3	2,377
3	Robot_fat_protein_ratio	0.7	1.2	1.3	1.3	1.4	3.4	0.3	890
1	Robot_lactose	2.9	4.6	4.8	4.7	4.9	5.2	0.2	13,402
2	Robot_lactose	4	4.6	4.8	4.8	4.9	5.2	0.2	2,377
3	Robot_lactose	4	4.6	4.8	4.7	4.9	5.2	0.2	890
1	Robot_milk_yield_in_current_lactation	2.2	2,404.9	4,894.4	5,273.6	7,569.1	1,5874	3,454.2	3,870
2	Robot_milk_yield_in_current_lactation	27.6	2,264.7	5,584.7	5,843.9	8,463.3	15,469	3,716.1	906
3	Robot_milk_yield_in_current_lactation	71.9	1,126.6	5,628.2	4,585.1	7,125.9	15,527.4	3,393.3	361
1	Robot_milk_yield_in_last_lactation	635	7,176.6	8,743	8,873.2	10,445	20,148	2,733.3	9,910
2	Robot_milk_yield_in_last_lactation	1,734	7,261.7	9,085	9,456.8	11,631.9	19,333	3,112.9	2,054
3	Robot_milk_yield_in_last_lactation	1,734	7,314	9,017	9,189.2	11,197	19,333	3,294.8	698
1	Robot_protein	2.5	3.3	3.4	3.4	3.6	5.5	0.3	13,408
2	Robot_protein	2.7	3.3	3.5	3.5	3.6	5.4	0.3	2,377
3	Robot_protein	2.7	3.2	3.4	3.4	3.5	5.6	0.3	890
1	Robot_somatic_cell_count	1	30	54	119.3	101	3920.5	287.5	5,997
2	Robot_somatic_cell_count	1	25	46	111.7	92.5	2696.5	242	1,157
3	Robot_somatic_cell_count	1	31	63	103.8	94	2925	242.1	337
Constitution									
1	Robot_BCS	2.5	3.7	3.9	3.8	4.1	4.6	0.3	3,679
2	Robot_BCS	2.7	3.6	3.8	3.8	4.1	4.5	0.3	772
3	Robot_BCS	2.8	3.5	3.8	3.8	4	4.4	0.3	319

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Body_weight	453.5	637	735.8	733.5	813.9	1151.6	115.5	5,202
2	Body_weight	459.5	699.6	780.9	773.9	876.2	1030.1	121.2	1,130
3	Body_weight	444.4	630.1	783.4	752.7	840.9	999.8	133.3	450
Feeding									
1	Concentrated_feed_intake	0	1.8	3.7	3.7	5.3	10.6	2.2	18,136
2	Concentrated_feed_intake	0	1.9	3.9	3.8	5.3	9.7	2.1	3,417
3	Concentrated_feed_intake	0	2	3.6	3.6	4.9	10	2	1,235
1	Concentrated_feed_remains	0	0.1	0.1	0.4	0.3	6	0.6	8,665
2	Concentrated_feed_remains	0	0.1	0.1	0.4	0.4	5.5	0.6	1,570
3	Concentrated_feed_remains	0	0.1	0.2	0.5	0.6	5.2	0.8	517
1	WT_feed_intake	0	34.8	44	43.5	53.7	92.2	14.7	4,167
2	WT_feed_intake	1	39.5	48	47.6	56.5	86.4	13.5	927
3	WT_feed_intake	6.9	36.8	44	43	49.6	88.8	13.1	343
1	WT_feed_intake_per_meal	0.8	3.5	4.7	5.1	6.2	23.9	2.3	3,949
2	WT_feed_intake_per_meal	1.5	4.3	5.5	6	7.2	15.5	2.4	880
3	WT_feed_intake_per_meal	1.9	4.5	5.6	6.1	7.2	16.6	2.4	322
1	WT_feed_intake_per_visit	0	0.7	1	1.2	1.4	8.7	0.8	4,172
2	WT_feed_intake_per_visit	0.4	1.1	1.6	1.9	2.3	10.9	1.2	928
3	WT_feed_intake_per_visit	0.3	1.2	1.9	2.4	2.7	13	2	343
1	WT_feeding_duration	10	99	133	138.5	170	792	62.1	4,150
2	WT_feeding_duration	10	97	122	126.4	153	428	47.2	922
3	WT_feeding_duration	19	73	95	97.8	118	253	37.5	341
1	WT_feeding_duration_day	0	72	100	104.1	128	769	51.3	4,150
2	WT_feeding_duration_day	0	69	92	93.6	112	358	35.9	922
3	WT_feeding_duration_day	10	54	71	74.4	92	179	29.2	341
1	WT_feeding_duration_day_night	0	0.7	0.8	0.8	0.8	1	0.1	4,150
2	WT_feeding_duration_day_night	0	0.7	0.8	0.8	0.8	1	0.1	922
3	WT_feeding_duration_day_night	0.3	0.7	0.8	0.8	0.9	1	0.1	341

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	WT_feeding_duration_per_meal	6	10.8	14.5	16.3	19.2	234.3	10.6	3,949
2	WT_feeding_duration_per_meal	6	11	14.4	16	19	175.6	9.3	880
3	WT_feeding_duration_per_meal	6	10	12.8	14.6	16.7	148.6	11.9	322
1	WT_feeding_duration_per_visit	0.4	2.4	3.1	3.6	4.3	70.3	2.7	4,172
2	WT_feeding_duration_per_visit	0.4	3.1	4.3	4.8	5.7	43.4	2.9	928
3	WT_feeding_duration_per_visit	0.7	3.1	4.4	5.4	6.1	57.2	4.8	343
1	WT_feeding_pace	0.06	0.26	0.33	0.35	0.41	1.37	0.12	4,168
2	WT_feeding_pace	0.17	0.32	0.40	0.41	0.50	2.14	0.14	928
3	WT_feeding_pace	0.18	0.37	0.46	0.47	0.55	0.99	0.13	343
1	WT_number_of_meals	1	7	9	9.6	12	23	3.2	3,949
2	WT_number_of_meals	1	7	9	9	11	19	2.9	880
3	WT_number_of_meals	2	6	8	7.9	10	17	2.6	322
1	WT_number_of_meals_day	0	5	7	7.2	9	20	2.6	3,949
2	WT_number_of_meals_day	0	5	6	6.6	8	16	2.3	880
3	WT_number_of_meals_day	1	4	6	5.9	7	12	2.1	322
1	WT_number_of_meals_day_night	0	0.7	0.8	0.7	0.8	1	0.1	3,949
2	WT_number_of_meals_day_night	0	0.6	0.8	0.7	0.8	1	0.1	880
3	WT_number_of_meals_day_night	0.2	0.7	0.8	0.8	0.9	1	0.2	322
1	WT_trough_visits	1	29	43	46.5	59	222	26	4,174
2	WT_trough_visits	2	21	30	32.1	40	119	16.1	928
3	WT_trough_visits	4	15	22	24.6	32	78	13.7	343
1	WT_trough_visits_day	0	22	33	35.7	45	178	21.1	4,174
2	WT_trough_visits_day	0	15	23	24.6	31	91	13.1	928
3	WT_trough_visits_day	2	11	18	19.3	25	69	11	343
1	WT_trough_visits_day_night	0	0.7	0.8	0.8	0.9	1	0.1	4,174
2	WT_trough_visits_day_night	0	0.7	0.8	0.8	0.9	1	0.1	928
3	WT_trough_visits_day_night	0.3	0.7	0.8	0.8	0.9	1	0.2	343
1	ENGS_feeding	1	45	79	89.6	127	288	57.2	934

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	ENGS_feeding	1	59.2	94	94.3	125.8	230	48.5	242
3	ENGS_feeding	7	44	77.5	79.6	113	213	43.9	90
1	ENGS_feeding_day	0	32	60	67.3	94.8	220	45	934
2	ENGS_feeding_day	0	45.2	70	70.8	98.8	171	36.2	242
3	ENGS_feeding_day	0	34.5	57	58.3	77	169	32	90
1	ENGS_feeding_day_night	0	0.7	0.8	0.8	0.9	1	0.2	934
2	ENGS_feeding_day_night	0	0.7	0.8	0.8	0.9	1	0.2	242
3	ENGS_feeding_day_night	0	0.6	0.8	0.7	0.9	1	0.2	90
1	ENGS_feeding_duration_per_meal	1	5.7	9.1	10.8	14.7	63	7.1	911
2	ENGS_feeding_duration_per_meal	1.5	6.9	10.6	11.2	14.1	34	6.2	238
3	ENGS_feeding_duration_per_meal	1.1	5.4	8.8	9.6	13.7	26.3	5.3	89
1	ENGS_number_of_meals	0	6	9	8.6	11	21	3.6	934
2	ENGS_number_of_meals	0	7	9	8.8	11	18	3.2	242
3	ENGS_number_of_meals	0	6	8	9	10	25	4.4	90
1	ENGS_number_of_meals_day	0	5	6	6.5	8	18	2.8	934
2	ENGS_number_of_meals_day	0	5	6.5	6.5	8	13	2.5	242
3	ENGS_number_of_meals_day	0	5	6	6.6	8	17	3.1	90
1	ENGS_number_of_meals_day_night	0	0.7	0.8	0.8	0.9	1	0.2	911
2	ENGS_number_of_meals_day_night	0	0.7	0.8	0.7	0.8	1	0.2	238
3	ENGS_number_of_meals_day_night	0.4	0.7	0.8	0.8	0.9	1	0.2	89
1	Nedap_feeding	10	262	377	377.5	504	806.4	154.7	5,128
2	Nedap_feeding	10	222	350	354	475.2	777.6	159.5	1,046
3	Nedap_feeding	10	190	292	336.4	504	806.4	197.1	259
Rumination									
1	Nedap_rum	14.4	291	395	393.2	504	763.2	138.1	5,153
2	Nedap_rum	29	227.8	378.5	363.9	489.6	820.8	161.2	1,048

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	Nedap_rum	10	151	234.7	278.5	417.6	648	164.1	262
1	SCR_rum	11	520	562	553.2	599	748	71.7	6,790
2	SCR_rum	61	509	561	551.7	603	751	77.8	1,436
3	SCR_rum	100	499.2	550.5	536	593	713	85.8	638
1	SCR_rum_day	2	306	343	337.6	377	533	61.8	3,032
2	SCR_rum_day	61	307.8	345	341.5	384	545	65.2	860
3	SCR_rum_day	71	295	338	332.4	380.2	498	69.6	332
1	SCR_rum_day_night	0	0.6	0.6	0.6	0.7	1	0.1	3,032
2	SCR_rum_day_night	0.4	0.6	0.6	0.6	0.7	1	0.1	860
3	SCR_rum_day_night	0.3	0.6	0.6	0.6	0.7	0.8	0.1	332
1	Smaxtec_rum	188	490	531.7	525.5	568.7	735.1	65.6	5,539
2	Smaxtec_rum	256.9	495.1	533	528.9	568.2	689.5	59.3	915
3	Smaxtec_rum	237.2	488.2	534.7	528.8	582.8	714	72	438
Heat detection									
1	SCR_heat_probability	-27	-3.5	-1	-0.5	0.5	92	7.8	3,621
2	SCR_heat_probability	-35	-3.5	-1.5	-0.9	0.5	88	7.2	558
3	SCR_heat_probability	-22	-4	-2	-1.2	0	74	8.1	293
1	SCR_heat_probability_day	-29	-4	-1	-0.3	1	100	9	3,607
2	SCR_heat_probability_day	-36	-4	-1	-0.7	1	84	8.4	552
3	SCR_heat_probability_day	-25	-4	-2	-1.2	0.5	84	8.9	290
1	Lemmer_factor_of_restlessness	53.2	226	320	452.2	457.7	30,501.8	890.3	4,532
2	Lemmer_factor_of_restlessness	63.1	178.3	245.4	318.4	365.7	3,096.4	269.1	765
3	Lemmer_factor_of_restlessness	53	125.6	179.8	264.4	293.9	5,668.1	360.4	373
Lying									
1	ENGS_lying	4	587.8	688	677.6	780.2	1,159	152.7	3,872
2	ENGS_lying	4	499	649	640	788.2	1,252	221	868
3	ENGS_lying	34	624.5	787	764	916.5	1,258	233.8	351
1	ENGS_lying_bouts	1	12	15	17.5	20	109	9.9	3,872

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	ENGS_lying_bouts	1	9	14	16.5	20	73	11.6	870
3	ENGS_lying_bouts	1	7	11	15.1	16	81	14	351
1	ENGS_lying_bouts_day	0	7	10	11.2	13	60	6.5	3,872
2	ENGS_lying_bouts_day	0	6	9	10.6	13	48	7.7	868
3	ENGS_lying_bouts_day	0	5	7	9.8	11	60	8.9	351
1	ENGS_lying_bouts_day_night	0	0.6	0.6	0.6	0.7	1	0.1	3,872
2	ENGS_lying_bouts_day_night	0	0.6	0.7	0.7	0.8	1	0.2	870
3	ENGS_lying_bouts_day_night	0	0.6	0.7	0.7	0.8	1	0.2	351
1	ENGS_lying_day	0	313	387	380.7	455	716	109.7	3,872
2	ENGS_lying_day	0	283.8	375.5	374.8	472	833	152.9	868
3	ENGS_lying_day	4	365	475	464.2	579.5	835	161.7	351
1	ENGS_lying_day_night	0	0.5	0.6	0.6	0.6	1	0.1	3,872
2	ENGS_lying_day_night	0	0.5	0.6	0.6	0.7	1	0.1	868
3	ENGS_lying_day_night	0	0.6	0.6	0.6	0.7	1	0.1	351
1	ENGS_lying_duration_per_bout	2	32.3	44.5	48.2	58.4	510	27.4	3,872
2	ENGS_lying_duration_per_bout	1.6	29.8	46.6	60	68	719	64.1	868
3	ENGS_lying_duration_per_bout	5.7	40.8	70.8	82.3	96.7	548.5	75	351
1	Lemmer_get_ups	1	6	9	9.2	11	40	3.9	4,534
2	Lemmer_get_ups	1	7	9	9.4	12	24	3.7	763
3	Lemmer_get_ups	2	8	11	11.1	13	27	4	372
1	Lemmer_lying	0.2	8.8	10.5	10.3	11.9	20.9	2.5	4,534
2	Lemmer_lying	0.9	8.9	10.8	10.7	12.7	18.3	2.8	765
3	Lemmer_lying	0.8	9.7	13.2	12.3	15.3	20.2	4.3	373
1	Nedap_lying	248	639	727	719.5	804	1,075	119.5	1,634
2	Nedap_lying	156	590.5	694.5	686.3	784	1,081	161.4	404
3	Nedap_lying	229	674	815	788.4	944	1,131	199.6	113
1	Nedap_get_ups	1	8	10	10.4	12	29	3.5	1,687
2	Nedap_get_ups	1	6	9	9.2	11	28	4.4	404
3	Nedap_get_ups	1	6	8	8.7	11	26	4.7	132
Activity									
1	Delaval_act_avg	12	24	30	31.7	38	89	10.2	1,055
2	Delaval_act_avg	10	22	28	27.6	32.8	75	8.7	358

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
3	Delaval_act_avg	11	16	19.5	21.5	24	51	8.1	102
1	Delaval_act_rel	59	91	100	100.9	108	287	17.2	1,055
2	Delaval_act_rel	55	87	97	98.3	107	229	19.7	358
3	Delaval_act_rel	44	82	91.5	99.6	105.8	293	34	102
1	Delaval_act_rel_max	59	101	110	111.2	118	255	18.5	1,008
2	Delaval_act_rel_max	62	99.2	108	109.3	116	255	20.6	330
3	Delaval_act_rel_max	65	93	103	117.1	125.8	255	39.8	98
1	Delaval_act_rel_min	50	82	89	89.2	96	137	11.8	1,008
2	Delaval_act_rel_min	46	79	86	86.8	94	191	15.6	330
3	Delaval_act_rel_min	39	72.2	82	84.2	93.8	178	20.5	98
1	ENGS_act	31	1,803	2,223	2,299.3	2,707	8,735	869.8	3,870
2	ENGS_act	30	1,494	1,968	2,028	2,454.5	7,532	893.8	867
3	ENGS_act	94	1,226.5	1,566	1,719.8	2,157.5	6,399	801	351
1	ENGS_act_day	0	1,393	1,740	1,802.7	2,125.8	7,471	707.7	3,870
2	ENGS_act_day	0	1,125	1,490	1,549.8	1,865.5	6,416	711.3	867
3	ENGS_act_day	0	954	1,209	1,300.2	1,631	5,652	600.4	351
1	ENGS_act_day_night	0	0.7	0.8	0.8	0.8	1	0.1	3,870
2	ENGS_act_day_night	0	0.7	0.8	0.8	0.8	1	0.1	867
3	ENGS_act_day_night	0	0.7	0.8	0.8	0.8	1	0.1	351
1	Lemmer_act	37	102	132	151.5	172	858	86.7	4,776
2	Lemmer_act	41	83	108	122.4	138.8	774	71.9	814
3	Lemmer_act	37	66	88	101.8	119.5	487	58.6	375
1	Nedap_inactive	225	548	639	661.2	752	1378	162.5	5,132
2	Nedap_inactive	251	620	710	714.9	801	1,306	137.5	1,047
3	Nedap_inactive	456	686.5	767.5	822.9	963	1,357	209	262
1	Nedap_act	1,304	2,661.5	3,405.5	3,641.5	4,331.8	14,174	1,372	1,686
2	Nedap_act	1,287	2,517	3,133	3,289	3,936	11,030	1,188.3	405
3	Nedap_act	1,284	2,214	2,480	2,780.2	2,924	13,726	1,458.9	133

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Nedap_act_collar_median	1	4.5	7	8.2	10.5	71	5.1	5,168
2	Nedap_act_collar_median	0	4.5	6.5	7.1	9.5	53	4.1	1,046
3	Nedap_act_collar_median	0	4	6	6.6	9	30.5	3.8	262
1	Nedap_act_collar_median_day	0.5	5	8	9.7	12.5	89.5	6.6	5,172
2	Nedap_act_collar_median_day	0.5	4.5	7	8.1	10.5	85.5	5.7	1,047
3	Nedap_act_collar_median_day	0	4	6	7.3	9.5	46	4.9	262
1	Nedap_act_collar_median_day_night	0.1	1	1.1	1.2	1.3	5.5	0.3	5,168
2	Nedap_act_collar_median_day_night	0.2	1	1.1	1.1	1.2	4.2	0.3	1,045
3	Nedap_act_collar_median_day_night	0.3	1	1.1	1.1	1.2	3	0.3	261
1	Nedap_act_collar_sum	14	63	95	110.2	140	859	65.7	5,166
2	Nedap_act_collar_sum	9	60	83	96.3	127	635	56.7	1,045
3	Nedap_act_collar_sum	11	54	78	88.8	116	439	51.6	261
1	Nedap_act_collar_sum_day	6	46	71	82.9	105	737	52.6	5,172
2	Nedap_act_collar_sum_day	6	42	61	70.5	93	534	45	1,047
3	Nedap_act_collar_sum_day	6	35.2	56.5	64	83	410	42.3	262
1	Nedap_act_collar_sum_day_night	0.2	0.7	0.8	0.7	0.8	1	0.1	5,167
2	Nedap_act_collar_sum_day_night	0.3	0.7	0.7	0.7	0.8	0.9	0.1	1,045
3	Nedap_act_collar_sum_day_night	0.4	0.7	0.7	0.7	0.8	0.9	0.1	261
1	Nedap_act_foot_median	72.5	202.5	252	266.2	315	1,207	92.3	1,684
2	Nedap_act_foot_median	73	187.5	238.5	245.8	289.5	783.5	80.1	405
3	Nedap_act_foot_median	88.5	167.5	190.5	211.5	224	1,049.5	110.8	133
1	Nedap_act_foot_median_day	89	231.5	290.8	320.3	385	1,476.5	132.5	1,698
2	Nedap_act_foot_median_day	87.5	212.2	270	281.7	336.5	1,501.5	112.8	407
3	Nedap_act_foot_median_day	86	174.5	211.8	230.4	258	1,360.5	127.3	132

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Nedap_act_foot_median_day_night	0.4	1	1.2	1.2	1.3	3.5	0.3	1,693
2	Nedap_act_foot_median_day_night	0.6	1	1.1	1.1	1.2	3.4	0.2	405
3	Nedap_act_foot_median_day_night	0.6	1	1	1.1	1.2	2.2	0.2	133
1	Nedap_act_foot_sum_day	893	1,952.2	2,584	2,816	3,409.5	11,056	1,190	1,698
2	Nedap_act_foot_sum_day	774	1,799	2,300	2,486.9	3,019	9,600	1,002	407
3	Nedap_act_foot_sum_day	839	1,555	1,829	2,054.1	2,074	12,174	1,334	133
1	Nedap_act_foot_sum_day_night	0.2	0.7	0.8	0.8	0.8	1	0.1	1,692
2	Nedap_act_foot_sum_day_night	0.5	0.7	0.8	0.7	0.8	1	0.1	405
3	Nedap_act_foot_sum_day_night	0.5	0.7	0.7	0.7	0.8	0.9	0.1	133
1	Smaxtec_act	0.3	4	4.9	5.6	7	21.4	2.4	7,183
2	Smaxtec_act	0.3	4.1	5	5.6	6.8	16.9	2.3	1,225
3	Smaxtec_act	0.4	3.1	4.4	5.2	7.4	13.2	2.5	631
1	Smaxtec_act_day	0.4	4.8	5.9	6.5	7.8	23.7	2.5	7,180
2	Smaxtec_act_day	0.4	4.9	6	6.4	7.7	20.6	2.2	1,224
3	Smaxtec_act_day	0.4	3.9	5.4	6	8	19.7	2.6	631
1	Smaxtec_act_day_night	0.4	1.1	1.1	1.2	1.3	2.3	0.2	7,181
2	Smaxtec_act_day_night	0.7	1.1	1.1	1.2	1.2	2.5	0.2	1,224
3	Smaxtec_act_day_night	0.7	1	1.1	1.2	1.3	2.4	0.2	629
Body temperature									
1	Smaxtec_temp_max	39	39.6	39.7	39.8	39.9	42.4	0.3	7,228
2	Smaxtec_temp_max	39.1	39.7	39.8	39.9	40	42.4	0.4	1,246
3	Smaxtec_temp_max	39.3	39.7	39.8	39.9	40	41.6	0.3	631
1	Smaxtec_temp_median	38.5	39	39.1	39.1	39.3	40.6	0.2	7,226
2	Smaxtec_temp_median	38.6	39	39.2	39.2	39.3	40.2	0.2	1,245
3	Smaxtec_temp_median	38.8	39.1	39.2	39.3	39.4	40	0.2	631
1	Smaxtec_temp_min	27	33	33.9	33.8	34.8	39.3	1.4	7,228
2	Smaxtec_temp_min	28.7	32.9	33.8	33.7	34.6	37.3	1.3	1,244
3	Smaxtec_temp_min	28.7	32.6	33.4	33.4	34.2	36.7	1.2	632

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Smaxtec_temp_normal_median	39	39.3	39.4	39.4	39.5	40	0.2	7,190
2	Smaxtec_temp_normal_median	39	39.4	39.5	39.5	39.6	40	0.2	1,224
3	Smaxtec_temp_normal_median	39.1	39.4	39.5	39.5	39.6	40	0.2	632
1	Smaxtec_temp_without_drink_cycles_max	39	39.5	39.7	39.7	39.9	42.3	0.3	7,182
2	Smaxtec_temp_without_drink_cycles_max	39.2	39.7	39.8	39.9	40	42.3	0.4	1,245
3	Smaxtec_temp_without_drink_cycles_max	39.3	39.6	39.8	39.8	40	41.6	0.3	629
1	Smaxtec_temp_without_drink_cycles_median	38.7	39.1	39.2	39.3	39.4	40.8	0.2	7,183
2	Smaxtec_temp_without_drink_cycles_median	38.7	39.2	39.3	39.3	39.5	40.4	0.2	1,245
3	Smaxtec_temp_without_drink_cycles_median	38.9	39.2	39.3	39.4	39.5	40.2	0.2	631
1	Smaxtec_temp_without_drink_cycles_min	37.7	38.5	38.6	38.6	38.8	40	0.2	7,185
2	Smaxtec_temp_without_drink_cycles_min	38	38.5	38.7	38.7	38.8	39.6	0.2	1,246
3	Smaxtec_temp_without_drink_cycles_min	38.1	38.6	38.7	38.7	38.8	39.5	0.2	632
Climate									
1	Smaxtec_climate_hum_max	62.4	77.2	82.1	82.6	85.6	100	7.5	8,793
2	Smaxtec_climate_hum_max	62.4	77.1	81.6	82.8	85.7	100	8	1,556
3	Smaxtec_climate_hum_max	62.4	79.8	84.4	83.3	85.7	100	6.5	587
1	Smaxtec_climate_hum_median	46.5	67.4	73.5	73.8	81.3	100	11.2	8,793
2	Smaxtec_climate_hum_median	46.5	67.4	73.2	74	81.1	100	11.8	1,556
3	Smaxtec_climate_hum_median	46.5	71	79.6	75.7	81.4	100	10.1	587
1	Smaxtec_climate_hum_min	1.2	50	62.5	62	76.3	98.8	16.1	8,793
2	Smaxtec_climate_hum_min	1.2	50	60.8	61.3	75.8	98.8	16.7	1,556
3	Smaxtec_climate_hum_min	1.2	54.5	74.9	66	77.7	98.8	16.2	587

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
1	Smaxtec_climate_temp_max	4	11.1	14.1	15.1	18.3	29.6	6	9,100
2	Smaxtec_climate_temp_max	4	11.2	15.3	15.3	19.1	29.6	5.9	1,641
3	Smaxtec_climate_temp_max	4	10.4	12.1	13.3	16	29.6	5.2	599
1	Smaxtec_climate_temp_median	2.4	8.9	10.9	11.8	14.5	24.3	5	9,100
2	Smaxtec_climate_temp_median	2.4	9.2	11.6	12.2	14.8	24.3	5	1,641
3	Smaxtec_climate_temp_median	2.4	8.1	9.8	10.6	12.1	24.3	4.2	599
1	Smaxtec_climate_temp_min	-0.3	5.3	8.4	8.7	11.7	19.6	4.4	9,100
2	Smaxtec_climate_temp_min	-0.3	5.6	8.6	9	12.4	19.6	4.3	1,641
3	Smaxtec_climate_temp_min	-0.3	5.1	8.3	8	9.7	18.5	3.5	599
1	Smaxtec_thi_max	39.4	52	57.3	58.9	65	83.1	9.9	8,793
2	Smaxtec_thi_max	39.4	52.2	58.3	59.3	66.1	83.1	9.9	1,556
3	Smaxtec_thi_max	39.4	51.3	54.1	56	60.5	83.1	8.4	587
1	Smaxtec_thi_median	28.1	45.3	51.6	52	58	71.8	9.8	8,793
2	Smaxtec_thi_median	28.1	47.6	52.3	52.7	58.6	71.8	9.6	1,556
3	Smaxtec_thi_median	28.1	46.4	50.4	50.6	53.7	71.8	7.8	587
1	Smaxtec_thi_min	35.5	44.8	48.8	49.6	54.5	65.3	6.4	8,793
2	Smaxtec_thi_min	35.5	45.4	49.1	50	55	65.3	6.4	1,556
3	Smaxtec_thi_min	35.5	44.8	48.5	48.4	50.5	64	5.2	587
1	WS_global_rad_max	41	346	694	619.6	871	1164	303.3	10,024
2	WS_global_rad_max	41	323	656	592.7	845	1164	299.8	2,060
3	WS_global_rad_max	41	296	561	566.1	826	1164	306.7	706
1	WS_global_rad_med	5.6	55.4	145.3	149.8	223.9	359.3	98.9	10,024
2	WS_global_rad_med	5.6	51	131.6	139.5	213.1	359.3	95.3	2,060
3	WS_global_rad_med	5.6	42.4	121.9	131.1	197.3	359.3	95.2	706
1	WS_global_rad_min	0	0	0	0.1	0	2	0.3	10,024
2	WS_global_rad_min	0	0	0	0.1	0	2	0.3	2,060
3	WS_global_rad_min	0	0	0	0.1	0	2	0.3	706
1	WS_rain_max	0	0	0	0.3	0.3	12.2	1.2	10,024
2	WS_rain_max	0	0	0	0.3	0.3	12.2	1.1	2,060
3	WS_rain_max	0	0	0.1	0.3	0.3	12.2	0.9	706
1	WS_rain_med	0	0	0	0	0	0.2	0	10,024

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	WS_rain_med	0	0	0	0	0	0.2	0	2,060
3	WS_rain_med	0	0	0	0	0	0.2	0	706
1	WS_rain_min	0	0	0	0	0	0	0	10,024
2	WS_rain_min	0	0	0	0	0	0	0	2,060
3	WS_rain_min	0	0	0	0	0	0	0	706
1	WS_rel_hum_max	53	99.3	100	98.4	100	100	4.7	10,024
2	WS_rel_hum_max	53	99.3	100	98.4	100	100	4.5	2,060
3	WS_rel_hum_max	67.1	99.5	100	99.1	100	100	2.6	706
1	WS_rel_hum_med	41.8	73.2	87.3	84.1	98.2	100	15	10,024
2	WS_rel_hum_med	41.8	73.9	88.3	84.9	98.9	100	14.8	2,060
3	WS_rel_hum_med	46.2	79.3	90.2	87.1	99.2	100	12.8	706
1	WS_rel_hum_min	17.8	39.8	57.8	62.3	90.2	100	25.8	10,024
2	WS_rel_hum_min	17.8	40.7	60.9	64	91.4	100	26.1	2,060
3	WS_rel_hum_min	17.8	42.9	64.6	66.3	94.7	100	25.2	706
1	WS_soil_temp_20cm_max	1.7	5	9.8	10.9	16.3	21.8	6.3	10,024
2	WS_soil_temp_20cm_max	1.7	4.9	9.6	10.4	15.8	21.8	5.9	2,060
3	WS_soil_temp_20cm_max	1.7	4.3	6.9	9.2	13.1	21.8	5.8	706
1	WS_soil_temp_20cm_med	1.6	4.6	9.2	10.4	15.8	20.4	6.1	10,024
2	WS_soil_temp_20cm_med	1.6	4.4	9	9.9	15	20.4	5.8	2,060
3	WS_soil_temp_20cm_med	1.6	3.8	6.7	8.7	12.8	20.4	5.7	706
1	WS_soil_temp_20cm_min	1.5	4.1	8.7	10	15.3	19.7	6	10,024
2	WS_soil_temp_20cm_min	1.5	4	8.2	9.5	14.5	19.7	5.6	2,060
3	WS_soil_temp_20cm_min	1.5	3.5	6.5	8.3	12.6	19.4	5.6	706
1	WS_soil_temp_5cm_max	1	6.3	12.4	12.4	18.5	28.5	7.3	10,024
2	WS_soil_temp_5cm_max	1	6.1	11.7	11.8	17.7	28.5	7	2,060
3	WS_soil_temp_5cm_max	1	5.4	8.3	10.5	16.3	28.5	6.9	706
1	WS_soil_temp_5cm_med	0.7	4.4	9.6	10.4	16.4	22.6	6.6	10,024
2	WS_soil_temp_5cm_med	0.7	3.8	9.2	9.9	15.5	22.6	6.3	2,060
3	WS_soil_temp_5cm_med	0.7	3.5	6.1	8.6	13.4	22.6	6.3	706
1	WS_soil_temp_5cm_min	0.5	2.6	7.4	8.7	14.5	19.5	6.2	10,024

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	WS_soil_temp_5cm_min	0.5	2.6	7.1	8.2	13.7	19.5	5.8	2,060
3	WS_soil_temp_5cm_min	0.5	2	4.9	7.1	11.3	19.3	5.9	706
1	WS_temp_20cm_max	-0.4	8	17	15.9	23.6	33	9.1	10,024
2	WS_temp_20cm_max	-0.4	7.1	16.4	15.1	22.2	33	8.8	2,060
3	WS_temp_20cm_max	-0.4	5.8	13.1	13.5	20.5	33	8.8	706
1	WS_temp_20cm_med	-3.9	2.9	7.8	9.1	15.6	23.5	6.9	10,024
2	WS_temp_20cm_med	-3.9	2.3	7.6	8.4	14.4	23.5	6.6	2,060
3	WS_temp_20cm_med	-3.9	1.6	5.6	7.1	12.2	23.5	6.6	706
1	WS_temp_20cm_min	-9.6	-1.8	1.5	2.8	7.6	16.2	6.2	10,024
2	WS_temp_20cm_min	-9.6	-2.1	1.2	2.2	6.7	16.2	5.9	2,060
3	WS_temp_20cm_min	-9.6	-2.7	-0.2	1.2	5	16.1	5.9	706
1	WS_temp_2m_max	-0.7	6.8	15.1	14.5	21.8	33.4	8.6	10,024
2	WS_temp_2m_max	-0.7	6.2	14.5	13.8	19.8	33.4	8.3	2,060
3	WS_temp_2m_max	-0.7	5.4	11.6	12.3	18.6	33.4	8.3	706
1	WS_temp_2m_med	-3.4	3.4	8.6	9.4	16	23.3	6.9	10,024
2	WS_temp_2m_med	-3.4	2.7	8.4	8.8	14.7	23.3	6.6	2,060
3	WS_temp_2m_med	-3.4	2.1	5.7	7.5	13.2	23.3	6.6	706
1	WS_temp_2m_min	-7.9	-0.6	2.7	4.4	9.4	16.4	5.9	10,024
2	WS_temp_2m_min	-7.9	-0.8	2.5	3.8	8.3	16.4	5.7	2,060
3	WS_temp_2m_min	-7.9	-1.4	0.6	2.8	7.2	16.4	5.7	706
1	WS_thi_max	30.7	44.3	59.2	58	70.8	91.7	15.3	10,024
2	WS_thi_max	30.7	43.2	58.1	56.8	67.6	91.7	14.9	2,060
3	WS_thi_max	30.7	41.9	53	54.1	65.4	91.7	14.9	706
1	WS_thi_med	27.2	39.1	48.8	49.2	60.4	70.8	11.7	10,024
2	WS_thi_med	27.2	37.6	48.5	48.2	58.4	70.8	11.3	2,060
3	WS_thi_med	27.2	36.1	43.4	46	56.2	70.8	11.4	706
1	WS_thi_min	22.6	36.1	42.9	43.3	51.8	61.1	9.5	10,024
2	WS_thi_min	22.6	35.8	42.1	42.4	50.2	61.1	9.1	2,060
3	WS_thi_min	22.6	33.6	39.1	40.7	47.5	61.1	9.3	706
1	WS_wind_velocity_max	1.6	2.7	3.5	4	4.7	12.7	2	10,024

LMS	Variable	Min	Q1	Median	Mean	Q3	Max	SD	N
2	WS_wind_velocity_max	1.6	2.6	3.4	3.9	4.4	12.7	1.9	2,060
3	WS_wind_velocity_max	1.6	2.7	3.6	4.3	4.8	12.7	2.3	706
1	WS_wind_velocity_med	0.5	1.1	1.5	1.8	2	5.7	1	10,024
2	WS_wind_velocity_med	0.5	1.1	1.4	1.7	2	5.7	1	2,060
3	WS_wind_velocity_med	0.5	1.2	1.6	1.9	2.2	5.7	1.1	706
1	WS_wind_velocity_min	0	0	0	0.2	0.1	3.3	0.5	10,024
2	WS_wind_velocity_min	0	0	0	0.2	0.1	3.3	0.4	2,060
3	WS_wind_velocity_min	0	0	0	0.2	0.3	3.3	0.5	706
1	Season	1	1	2	2.1	3	4	1	19,431
2	Season	1	1	2	2.2	3	4	1	3,736
3	Season	1	1	2	2.3	3	4	1	1,416
Claw health									
1	PT	0	0	0	0.1	0	1	0.4	19,316
2	PT	0	0	0	0.2	0	1	0.4	3,678
3	PT	0	0	1	0.5	1	1	0.5	1,379
1	GSC	0	2.5	3	2.7	3	3	0.4	19,316
2	GSC	1	2.5	2.8	2.6	3	3	0.4	3,699
3	GSC	1.2	2	2.5	2.5	3	3	0.4	1,379

Table 61: Significance across all corrected locomotion score (C_LMS) groups across all farms (Kruskal-Wallis test) (parameters explained in Table 33)

Variable	Statistics	p_value
Animal characteristics		
Breed	58	<0.01
Milking		
Lactation_number	281.7	<0.01
Days_in_milk	40.5	<0.01
LKV_milk_yield_in_last_lactation	197.7	<0.01
LKV_daily_milk_yield	28.5	<0.01
LKV_urea	3.6	>0.05
LKV_somatic_cell_count	17.5	<0.01
LKV_fat	34.3	<0.01
LKV_protein	120.6	<0.01
LKV_fat_protein_ratio	32.6	<0.01
LKV_lactose	56.7	<0.01
Milkings	130.6	<0.01
Maximum_milking_interval	69.9	<0.01
Robot_daily_milk_yield	26.2	<0.01
Robot_milk_yield_in_current_lactation	7.6	<0.05
Robot_milk_yield_in_last_lactation	75.9	<0.01
Robot_daily_milk_yield_in_last_lactation	14.3	<0.01
MDi	36.4	<0.01

Variable	Statistics	p_value
Milking_flow	151.1	<0.01
Max_milking_flow	6.7	<0.05
Robot_conduct_lely	9.1	<0.05
Robot_conduct	27.1	<0.01
Robot_somatic_cell_count	9.4	<0.01
Robot_effect_of_scc	18.7	<0.01
Robot_fat	9.5	<0.01
Robot_protein	125.9	<0.01
Robot_fat_protein_ratio	11.4	<0.01
Robot_lactose	12.8	<0.01
Milking_temperature	62.1	<0.01
Constitution		
Robot_BCS	32.8	<0.01
Body_weight	171.3	<0.01
Feeding		
Concentrated_feed_intake	1.9	>0.05
Concentrated_feed_remains	20.6	<0.01
WT_feed_intake	60.2	<0.01
WT_feeding_pace	401.3	<0.01
WT_feeding_duration	171.5	<0.01
WT_feeding_duration_day	171.1	<0.01
WT_feeding_duration_day_night	3.1	>0.05
WT_trough_visits	540.5	<0.01
WT_trough_visits_day	512.2	<0.01
WT_trough_visits_day_night	3.3	>0.05
WT_feed_intake_per_visit	666.6	<0.01
WT_feeding_duration_per_visit	317.7	<0.01
WT_number_of_meals	119.8	<0.01
WT_number_of_meals_day	126.2	<0.01
WT_number_of_meals_day_night	8.4	<0.05
WT_feed_intake_per_meal	175.4	<0.01
WT_feeding_duration_per_meal	9.2	<0.05
ENGS_feeding	15.8	<0.01
ENGS_feeding_day	20.1	<0.01
ENGS_feeding_day_night	3.6	>0.05
ENGS_number_of_meals	2.3	>0.05
ENGS_number_of_meals_day	2.7	>0.05
ENGS_number_of_meals_day_night	2.3	>0.05
ENGS_feeding_duration_per_meal	7.7	<0.05
Nedap_feeding	86.5	<0.01
Rumination		
Smaxtec_rum	5.3	>0.05
SCR_rum	8.1	<0.05
SCR_rum_day	9	<0.05
SCR_rum_day_night	73.8	<0.01
Nedap_rum	144.6	<0.01
Heat detection		
SCR_heat_probability	6.5	<0.05
SCR_heat_probability_day	4.7	>0.05
Lemmer_factor_of_restlessness	292.6	<0.01
Lying		
Nedap_lying	4.1	>0.05

Variable	Statistics	p_value
Nedap_get_ups	79.7	<0.01
ENGS_lying	2.4	>0.05
ENGS_lying_day	25.4	<0.01
ENGS_lying_day_night	141	<0.01
ENGS_lying_bouts	108.4	<0.01
ENGS_lying_bouts_day	89.8	<0.01
ENGS_lying_bouts_day_night	13.3	<0.01
ENGS_lying_duration_per_bout	59.4	<0.01
Lemmer_lying	98.4	<0.01
Lemmer_get_ups	51.9	<0.01
Activity		
Delaval_act_avg	92.4	<0.01
Delaval_act_rel	28.8	<0.01
Delaval_act_rel_min	28.5	<0.01
Delaval_act_rel_max	18.3	<0.01
ENGS_act	218	<0.01
ENGS_act_day	276.5	<0.01
ENGS_act_day_night	60	<0.01
Smaxtec_act	25.3	<0.01
Smaxtec_act_day	19.4	<0.01
Smaxtec_act_day_night	21.1	<0.01
SCR_act	366.6	<0.01
SCR_act_day	383.4	<0.01
SCR_act_day_night	68.4	<0.01
Lemmer_act	383	<0.01
Nedap_inactive	248.2	<0.01
Nedap_act_collar_median	54.6	<0.01
Nedap_act_collar_sum	55	<0.01
Nedap_act_collar_median_day	85	<0.01
Nedap_act_collar_sum_day	79.3	<0.01
Nedap_act_collar_median_day_night	57.6	<0.01
Nedap_act_collar_sum_day_night	82.7	<0.01
Nedap_act	65.9	<0.01
Nedap_act_foot_median	51.5	<0.01
Nedap_act_foot_median_day	78.8	<0.01
Nedap_act_foot_sum_day	76.2	<0.01
Nedap_act_foot_median_day_night	36.8	<0.01
Nedap_act_foot_sum_day_night	51	<0.01
Body temperature		
Smaxtec_temp_normal_median	333.4	<0.01
Smaxtec_temp_median	193.4	<0.01
Smaxtec_temp_min	129.2	<0.01
Smaxtec_temp_max	259.8	<0.01
Smaxtec_temp_without_drink_cycles_median	267.9	<0.01
Smaxtec_temp_without_drink_cycles_min	109.9	<0.01
Smaxtec_temp_without_drink_cycles_max	250.4	<0.01
Climate		
Smaxtec_climate_temp_median	60.5	<0.01
Smaxtec_climate_temp_min	39.3	<0.01
Smaxtec_climate_temp_max	65.7	<0.01
Smaxtec_climate_hum_median	12.4	<0.01
Smaxtec_climate_hum_min	27.1	<0.01

Variable	Statistics	p_value
Smaxtec_climate_hum_max	4.8	>0.05
Smaxtec_thi_median	45.9	<0.01
Smaxtec_thi_min	39.6	<0.01
Smaxtec_thi_max	63.4	<0.01
WS_thi_med	56	<0.01
WS_thi_min	56.7	<0.01
WS_thi_max	51.9	<0.01
WS_temp_2m_med	58.6	<0.01
WS_temp_2m_min	55.3	<0.01
WS_temp_2m_max	52.5	<0.01
WS_temp_20cm_med	59.4	<0.01
WS_temp_20cm_min	49.6	<0.01
WS_temp_20cm_max	53.2	<0.01
WS_soil_temp_5cm_med	60.2	<0.01
WS_soil_temp_5cm_min	57.9	<0.01
WS_soil_temp_5cm_max	52	<0.01
WS_soil_temp_20cm_med	59.4	<0.01
WS_soil_temp_20cm_min	58.2	<0.01
WS_soil_temp_20cm_max	59.8	<0.01
WS_rel_hum_med	24.9	<0.01
WS_rel_hum_min	19.6	<0.01
WS_rel_hum_max	23.8	<0.01
WS_wind_velocity_med	6.5	<0.05
WS_wind_velocity_min	4.5	>0.05
WS_wind_velocity_max	4.3	>0.05
WS_rain_med	6.5	<0.05
WS_rain_min	0.7	>0.05
WS_rain_max	8.7	<0.05
WS_global_rad_med	36.6	<0.01
WS_global_rad_min	22.6	<0.01
WS_global_rad_max	32.2	<0.01
Season	14.7	<0.01

Table 62: Significance of the differences between the different corrected locomotion score (C_LMS) groups for each parameter across all farms (Wilcoxon signed-rank test) (parameters explained in Table 33)

Parameters	p-value C_LMS1 vs. C_LMS2	p-value C_LMS1 vs. C_LMS3	p-value C_LMS2 vs. C_LMS3
Animal characteristics			
Breed	< 0.05	< 0.01	> 0.05
Milking			
Lactation_number	< 0.01	< 0.01	> 0.05
Days_in_milk	< 0.01	< 0.01	< 0.01
LKV_milk_yield_in_last_lactation	< 0.01	< 0.01	> 0.05
LKV_daily_milk_yield	< 0.05	< 0.01	> 0.05
LKV_urea	> 0.05	> 0.05	> 0.05
LKV_somatic_cell_count	< 0.01	> 0.05	< 0.01
LKV_fat	> 0.05	< 0.01	> 0.05
LKV_protein	< 0.01	< 0.01	< 0.01
LKV_fat_protein_ratio	< 0.01	> 0.05	< 0.01

Parameters	p-value C_LMS1 vs. C_LMS2	p-value C_LMS1 vs. C_LMS3	p-value C_LMS2 vs. C_LMS3
LKV_lactose	< 0.01	< 0.05	< 0.01
Milkings	< 0.01	< 0.01	> 0.05
Maximum_milking_interval	< 0.01	< 0.01	> 0.05
Robot_daily_milk_yield	> 0.05	< 0.01	> 0.05
Robot_milk_yield_in_current_lactation	< 0.05	> 0.05	> 0.05
Robot_milk_yield_in_last_lactation	< 0.01	< 0.01	> 0.05
Robot_daily_milk_yield_in_last_lactation	> 0.05	< 0.01	< 0.01
MDi	< 0.01	< 0.01	> 0.05
Milking_flow	< 0.01	< 0.05	< 0.01
Max_milking_flow	> 0.05	< 0.05	> 0.05
Robot_conduct_lely	> 0.05	< 0.05	> 0.05
Robot_conduct	< 0.01	> 0.05	< 0.01
Robot_somatic_cell_count	> 0.05	> 0.05	> 0.05
Robot_effect_of_scc	< 0.01	> 0.05	< 0.01
Robot_fat	< 0.05	> 0.05	> 0.05
Robot_protein	< 0.01	< 0.01	< 0.01
Robot_fat_protein_ratio	> 0.05	< 0.01	> 0.05
Robot_lactose	> 0.05	< 0.05	< 0.01
Milking_temperature	< 0.01	< 0.05	< 0.01
Constitution			
Robot_BCS	< 0.01	< 0.01	< 0.01
Body_weight	< 0.01	< 0.01	< 0.01
Feeding			
Concentrated_feed_intake	> 0.05	> 0.05	> 0.05
Concentrated_feed_remains	> 0.05	< 0.01	> 0.05
WT_feed_intake	< 0.01	< 0.05	< 0.01
WT_feeding_pace	< 0.01	< 0.01	< 0.01
WT_feeding_duration	> 0.05	< 0.01	< 0.01
WT_feeding_duration_day	> 0.05	< 0.01	< 0.01
WT_feeding_duration_day_night	> 0.05	> 0.05	> 0.05
WT_trough_visits	< 0.01	< 0.01	< 0.01
WT_trough_visits_day	< 0.01	< 0.01	< 0.01
WT_trough_visits_day_night	> 0.05	> 0.05	> 0.05
WT_feed_intake_per_visit	< 0.01	< 0.01	< 0.05
WT_feeding_duration_per_visit	< 0.01	< 0.01	> 0.05
WT_number_of_meals	> 0.05	< 0.01	< 0.01
WT_number_of_meals_day	> 0.05	< 0.01	< 0.01
WT_number_of_meals_day_night	> 0.05	< 0.05	> 0.05
WT_feed_intake_per_meal	< 0.01	< 0.01	> 0.05
WT_feeding_duration_per_meal	> 0.05	< 0.01	> 0.05
ENGS_feeding	< 0.01	> 0.05	< 0.01
ENGS_feeding_day	< 0.01	> 0.05	< 0.01
ENGS_feeding_day_night	> 0.05	> 0.05	> 0.05
ENGS_number_of_meals	> 0.05	> 0.05	> 0.05
ENGS_number_of_meals_day	> 0.05	> 0.05	> 0.05
ENGS_number_of_meals_day_night	> 0.05	> 0.05	> 0.05
ENGS_feeding_duration_per_meal	< 0.05	> 0.05	< 0.05
Nedap_feeding	< 0.01	> 0.05	< 0.01
Rumination			
Smaxtec_rum	> 0.05	> 0.05	> 0.05
SCR_rum	> 0.05	< 0.05	> 0.05

Parameters	p-value C_LMS1 vs. C_LMS2	p-value C_LMS1 vs. C_LMS3	p-value C_LMS2 vs. C_LMS3
SCR_rum_day	< 0.05	> 0.05	< 0.05
SCR_rum_day_night	< 0.01	< 0.01	> 0.05
Nedap_rum	> 0.05	< 0.01	< 0.01
Heat **detection**			
SCR_heat_probability	> 0.05	> 0.05	> 0.05
SCR_heat_probability_day	> 0.05	> 0.05	> 0.05
Lemmer_factor_of_restlessness	< 0.01	< 0.01	> 0.05
Lying			
Nedap_lying	> 0.05	> 0.05	> 0.05
Nedap_get_ups	> 0.05	< 0.01	< 0.05
ENGS_lying	> 0.05	> 0.05	> 0.05
ENGS_lying_day	> 0.05	< 0.01	< 0.05
ENGS_lying_day_night	< 0.01	< 0.01	> 0.05
ENGS_lying_bouts	< 0.01	< 0.01	> 0.05
ENGS_lying_bouts_day	< 0.01	< 0.01	> 0.05
ENGS_lying_bouts_day_night	> 0.05	< 0.01	> 0.05
ENGS_lying_duration_per_bout	< 0.01	< 0.01	> 0.05
Lemmer_lying	< 0.05	< 0.01	> 0.05
Lemmer_get_ups	< 0.01	< 0.01	> 0.05
Activity			
Delaval_act_avg	< 0.01	< 0.01	> 0.05
Delaval_act_rel	> 0.05	< 0.01	< 0.05
Delaval_act_rel_min	> 0.05	< 0.01	> 0.05
Delaval_act_rel_max	> 0.05	< 0.01	< 0.01
ENGS_act	< 0.01	< 0.01	> 0.05
ENGS_act_day	< 0.01	< 0.01	> 0.05
ENGS_act_day_night	< 0.01	< 0.01	> 0.05
Smaxtec_act	< 0.05	< 0.01	< 0.01
Smaxtec_act_day	> 0.05	< 0.01	< 0.05
Smaxtec_act_day_night	< 0.01	> 0.05	< 0.05
SCR_act	< 0.01	< 0.01	< 0.01
SCR_act_day	< 0.01	< 0.01	< 0.01
SCR_act_day_night	< 0.01	< 0.01	> 0.05
Lemmer_act	< 0.01	< 0.01	> 0.05
Nedap_inactive	< 0.01	< 0.01	> 0.05
Nedap_act_collar_median	< 0.01	< 0.01	> 0.05
Nedap_act_collar_sum	< 0.01	< 0.01	> 0.05
Nedap_act_collar_median_day	< 0.01	< 0.01	> 0.05
Nedap_act_collar_sum_day	< 0.01	< 0.01	> 0.05
Nedap_act_collar_median_day_night	> 0.05	< 0.01	< 0.05
Nedap_act_collar_sum_day_night	< 0.05	< 0.01	< 0.05
Nedap_act	< 0.01	< 0.01	< 0.05
Nedap_act_foot_median	< 0.01	< 0.01	> 0.05
Nedap_act_foot_median_day	< 0.01	< 0.01	> 0.05
Nedap_act_foot_sum_day	< 0.01	< 0.01	< 0.05
Nedap_act_foot_median_day_night	< 0.01	< 0.01	> 0.05
Nedap_act_foot_sum_day_night	< 0.05	< 0.01	> 0.05
Body temperature			
Smaxtec_temp_normal_median	< 0.01	< 0.01	< 0.01
Smaxtec_temp_median	< 0.01	< 0.01	> 0.05
Smaxtec_temp_min	< 0.01	< 0.01	< 0.01

Parameters	p-value C_LMS1 vs. C_LMS2	p-value C_LMS1 vs. C_LMS3	p-value C_LMS2 vs. C_LMS3
Smaxtec_temp_max	< 0.01	< 0.01	< 0.01
Smaxtec_temp_without_drink_cycles_median	< 0.01	< 0.01	< 0.01
Smaxtec_temp_without_drink_cycles_min	< 0.01	< 0.01	< 0.01
Smaxtec_temp_without_drink_cycles_max	< 0.01	< 0.01	< 0.01
Climate			
Smaxtec_climate_temp_median	< 0.01	< 0.01	< 0.01
Smaxtec_climate_temp_min	< 0.01	> 0.05	< 0.01
Smaxtec_climate_temp_max	< 0.01	< 0.01	< 0.01
Smaxtec_climate_hum_median	> 0.05	< 0.01	< 0.05
Smaxtec_climate_hum_min	< 0.01	< 0.01	< 0.01
Smaxtec_climate_hum_max	> 0.05	> 0.05	> 0.05
Smaxtec_thi_median	< 0.01	< 0.05	< 0.01
Smaxtec_thi_min	< 0.01	< 0.05	< 0.01
Smaxtec_thi_max	< 0.01	< 0.01	< 0.01
WS_thi_med	> 0.05	< 0.01	< 0.01
WS_thi_min	> 0.05	< 0.01	< 0.01
WS_thi_max	> 0.05	< 0.01	< 0.01
WS_temp_2m_med	> 0.05	< 0.01	< 0.01
WS_temp_2m_min	> 0.05	< 0.01	< 0.01
WS_temp_2m_max	> 0.05	< 0.01	< 0.01
WS_temp_20cm_med	> 0.05	< 0.01	< 0.01
WS_temp_20cm_min	> 0.05	< 0.01	< 0.01
WS_temp_20cm_max	> 0.05	< 0.01	< 0.01
WS_soil_temp_5cm_med	> 0.05	< 0.01	< 0.01
WS_soil_temp_5cm_min	> 0.05	< 0.01	< 0.01
WS_soil_temp_5cm_max	> 0.05	< 0.01	< 0.01
WS_soil_temp_20cm_med	> 0.05	< 0.01	< 0.01
WS_soil_temp_20cm_min	> 0.05	< 0.01	< 0.01
WS_soil_temp_20cm_max	> 0.05	< 0.01	< 0.01
WS_rel_hum_med	< 0.01	< 0.05	> 0.05
WS_rel_hum_min	< 0.01	< 0.01	> 0.05
WS_rel_hum_max	< 0.01	> 0.05	< 0.01
WS_wind_velocity_med	> 0.05	> 0.05	< 0.05
WS_wind_velocity_min	> 0.05	> 0.05	> 0.05
WS_wind_velocity_max	> 0.05	> 0.05	> 0.05
WS_rain_med	> 0.05	> 0.05	< 0.05
WS_rain_min	> 0.05	> 0.05	> 0.05
WS_rain_max	> 0.05	> 0.05	< 0.05
WS_global_rad_med	> 0.05	< 0.01	> 0.05
WS_global_rad_min	< 0.01	> 0.05	< 0.01
WS_global_rad_max	> 0.05	< 0.01	> 0.05
Season	> 0.05	< 0.01	> 0.05

Table 63: Significance of the differences between the different locomotion score (LMS) groups for each parameter across all farms (Wilcoxon signed-rank test) (parameters explained in Table 33)

Parameters	p-value LMS1 vs. LMS2	p-value LMS1 vs. LMS3	p-value LMS2 vs. LMS3
Animal characteristics			
Breed	< 0.01	< 0.01	> 0.05
Milking			
Lactation_number	< 0.01	< 0.01	< 0.01
Days_in_milk	> 0.05	< 0.01	< 0.05
LKV_milk_yield_in_last_lactation	< 0.01	< 0.01	> 0.05
LKV_daily_milk_yield	< 0.01	> 0.05	< 0.01
LKV_urea	> 0.05	< 0.05	< 0.05
LKV_somatic_cell_count	< 0.05	< 0.01	< 0.01
LKV_fat	< 0.01	< 0.01	> 0.05
LKV_protein	< 0.01	< 0.01	< 0.01
LKV_fat_protein_ratio	> 0.05	> 0.05	> 0.05
LKV_lactose	< 0.01	< 0.01	< 0.01
Milkings	< 0.01	< 0.01	< 0.01
Maximum_milking_interval	< 0.01	< 0.01	< 0.01
Robot_daily_milk_yield	< 0.01	> 0.05	< 0.01
Robot_milk_yield_in_current_lactation	< 0.01	< 0.01	< 0.01
MDI	< 0.01	< 0.01	< 0.05
Milking_flow	< 0.01	> 0.05	< 0.01
Max_milking_flow	> 0.05	< 0.01	< 0.01
Robot_conduct_lely	< 0.01	> 0.05	> 0.05
Robot_conduct	> 0.05	> 0.05	> 0.05
Robot_milk_yield_in_last_lactation	< 0.01	< 0.01	> 0.05
Robot_daily_milk_yield_in_last_lactation	> 0.05	> 0.05	> 0.05
Robot_fat	> 0.05	< 0.01	< 0.05
Robot_protein	< 0.01	< 0.01	< 0.01
Robot_fat_protein_ratio	> 0.05	< 0.01	< 0.01
Robot_lactose	> 0.05	< 0.01	< 0.05
Robot_somatic_cell_count	< 0.01	> 0.05	> 0.05
Robot_effect_of_scc	> 0.05	> 0.05	> 0.05
Milking_temperature	< 0.01	> 0.05	> 0.05
Constitution			
Robot_BCS	> 0.05	< 0.01	< 0.01
Body_weight	< 0.01	< 0.01	< 0.05
Feeding			
Concentrated_feed_intake	> 0.05	> 0.05	< 0.01
Concentrated_feed_remains	> 0.05	< 0.01	< 0.01
WT_feed_intake	< 0.01	> 0.05	< 0.01
WT_feeding_duration	< 0.01	< 0.01	< 0.01
WT_feeding_duration_day	< 0.01	< 0.01	< 0.01
WT_feeding_duration_day_night	> 0.05	> 0.05	> 0.05
WT_feeding_duration_per_meal	> 0.05	< 0.01	< 0.01
WT_feeding_duration_per_visit	< 0.01	< 0.01	> 0.05
WT_feeding_pace	< 0.01	< 0.01	< 0.01
WT_trough_visits	< 0.01	< 0.01	< 0.01
WT_trough_visits_day	< 0.01	< 0.01	< 0.01
WT_trough_visits_day_night	> 0.05	> 0.05	> 0.05

Parameters	p-value LMS1 vs. LMS2	p-value LMS1 vs. LMS3	p-value LMS2 vs. LMS3
WT_number_of_meals	< 0.01	< 0.01	< 0.01
WT_number_of_meals_day	< 0.01	< 0.01	< 0.01
WT_number_of_meals_day_night	> 0.05	> 0.05	> 0.05
WT_feed_intake_per_meal	< 0.01	< 0.01	> 0.05
WT_feed_intake_per_visit	< 0.01	< 0.01	< 0.01
ENGS_feeding	> 0.05	> 0.05	< 0.05
ENGS_feeding_day	> 0.05	> 0.05	< 0.01
ENGS_feeding_day_night	> 0.05	> 0.05	> 0.05
ENGS_number_of_meals	> 0.05	> 0.05	> 0.05
ENGS_number_of_meals_day	> 0.05	> 0.05	> 0.05
ENGS_number_of_meals_day_night	> 0.05	> 0.05	> 0.05
ENGS_feeding_duration_per_meal	> 0.05	> 0.05	> 0.05
Nedap_feeding	< 0.01	< 0.01	> 0.05
Rumination			
SCR_rum	> 0.05	< 0.01	< 0.01
SCR_rum_day	> 0.05	> 0.05	> 0.05
SCR_rum_day_night	< 0.01	< 0.01	> 0.05
Nedap_rum	< 0.01	< 0.01	< 0.01
Smaxtec_rum	> 0.05	> 0.05	> 0.05
Heat detection			
SCR_heat_probability	> 0.05	> 0.05	> 0.05
SCR_heat_probability_day	> 0.05	> 0.05	> 0.05
Lemmer_factor_of_restlessness	< 0.01	< 0.01	< 0.01
Lying			
ENGS_lying	< 0.01	< 0.01	< 0.01
ENGS_lying_day	> 0.05	< 0.01	< 0.01
ENGS_lying_day_night	< 0.01	< 0.01	< 0.01
ENGS_lying_bouts	< 0.01	< 0.01	< 0.01
ENGS_lying_bouts_day	< 0.01	< 0.01	< 0.01
ENGS_lying_bouts_day_night	> 0.05	< 0.01	> 0.05
ENGS_lying_duration_per_bout	> 0.05	< 0.01	< 0.01
Nedap_lying	< 0.01	< 0.01	< 0.01
Nedap_get_ups	< 0.01	< 0.01	> 0.05
Lemmer_get_ups	> 0.05	< 0.01	< 0.01
Lemmer_lying	< 0.01	< 0.01	< 0.01
Lemmer_lying_ratio	< 0.01	< 0.01	< 0.01
Activity			
ENGS_act	< 0.01	< 0.01	< 0.01
ENGS_act_day	< 0.01	< 0.01	< 0.01
ENGS_act_day_night	< 0.01	< 0.01	> 0.05
Smaxtec_act	> 0.05	< 0.01	< 0.01
Smaxtec_act_day	> 0.05	< 0.01	< 0.01
Smaxtec_act_day_night	< 0.01	> 0.05	> 0.05
SCR_act	< 0.01	< 0.01	< 0.01
SCR_act_day	< 0.01	< 0.01	< 0.01
SCR_act_day_night	< 0.01	< 0.01	> 0.05
Nedap_act	< 0.01	< 0.01	< 0.01
Nedap_inactive	< 0.01	< 0.01	< 0.01
Nedap_act_collar_median	< 0.01	< 0.01	> 0.05
Nedap_act_collar_sum	< 0.01	< 0.01	> 0.05
Nedap_act_collar_median_day	< 0.01	< 0.01	< 0.05

Parameters	p-value LMS1 vs. LMS2	p-value LMS1 vs. LMS3	p-value LMS2 vs. LMS3
Nedap_act_collar_sum_day	< 0.01	< 0.01	< 0.05
Nedap_act_collar_median_day_night	< 0.01	< 0.01	> 0.05
Nedap_act_collar_sum_day_night	< 0.01	< 0.01	> 0.05
Nedap_act_foot_median	< 0.01	< 0.01	< 0.01
Nedap_act_foot_median_day	< 0.01	< 0.01	< 0.01
Nedap_act_foot_sum_day	< 0.01	< 0.01	< 0.01
Nedap_act_foot_median_day_night	< 0.01	< 0.01	> 0.05
Nedap_act_foot_sum_day_night	< 0.01	< 0.01	< 0.05
Lemmer_act	< 0.01	< 0.01	< 0.01
Delaval_act_avg	< 0.01	< 0.01	< 0.01
Delaval_act_rel	< 0.01	< 0.01	> 0.05
Delaval_act_rel_min	< 0.01	< 0.01	> 0.05
Delaval_act_rel_max	> 0.05	> 0.05	> 0.05
Body temperature			
Smaxtec_temp_min	< 0.05	< 0.01	< 0.01
Smaxtec_temp_max	< 0.01	< 0.01	> 0.05
Smaxtec_temp_median	< 0.01	< 0.01	< 0.01
Smaxtec_temp_without_drink_cycles_min	< 0.01	< 0.01	< 0.01
Smaxtec_temp_without_drink_cycles_max	< 0.01	< 0.01	> 0.05
Smaxtec_temp_without_drink_cycles_median	< 0.01	< 0.01	< 0.01
Smaxtec_temp_normal_median	< 0.01	< 0.01	< 0.05
Climate			
Smaxtec_climate_temp_median	< 0.05	< 0.01	< 0.01
Smaxtec_climate_temp_min	< 0.05	< 0.01	< 0.01
Smaxtec_climate_temp_max	> 0.05	< 0.01	< 0.01
Smaxtec_climate_hum_median	> 0.05	< 0.01	< 0.01
Smaxtec_climate_hum_min	> 0.05	< 0.01	< 0.01
Smaxtec_climate_hum_max	> 0.05	< 0.01	< 0.01
Smaxtec_thi_median	< 0.05	< 0.01	< 0.01
Smaxtec_thi_min	< 0.05	< 0.01	< 0.01
Smaxtec_thi_max	> 0.05	< 0.01	< 0.01
WS_thi_med	< 0.01	< 0.01	< 0.01
WS_thi_min	< 0.01	< 0.01	< 0.01
WS_thi_max	< 0.01	< 0.01	< 0.01
WS_temp_2m_med	< 0.01	< 0.01	< 0.01
WS_temp_2m_min	< 0.01	< 0.01	< 0.01
WS_temp_2m_max	< 0.01	< 0.01	< 0.01
WS_temp_20cm_med	< 0.01	< 0.01	< 0.01
WS_temp_20cm_min	< 0.01	< 0.01	< 0.01
WS_temp_20cm_max	< 0.01	< 0.01	< 0.01
WS_soil_temp_5cm_med	< 0.01	< 0.01	< 0.01
WS_soil_temp_5cm_min	< 0.01	< 0.01	< 0.01
WS_soil_temp_5cm_max	< 0.01	< 0.01	< 0.01
WS_soil_temp_20cm_med	< 0.01	< 0.01	< 0.01
WS_soil_temp_20cm_min	< 0.01	< 0.01	< 0.01
WS_soil_temp_20cm_max	< 0.01	< 0.01	< 0.01
WS_rel_hum_med	< 0.05	< 0.01	< 0.05
WS_rel_hum_min	< 0.05	< 0.01	> 0.05
WS_rel_hum_max	> 0.05	> 0.05	> 0.05
WS_wind_velocity_med	> 0.05	< 0.01	< 0.01
WS_wind_velocity_min	> 0.05	< 0.05	< 0.05

Parameters	p-value LMS1 vs. LMS2	p-value LMS1 vs. LMS3	p-value LMS2 vs. LMS3
WS_wind_velocity_max	< 0.05	> 0.05	< 0.01
WS_rain_med	> 0.05	< 0.01	< 0.01
WS_rain_min	> 0.05	> 0.05	> 0.05
WS_rain_max	> 0.05	< 0.01	< 0.05
WS_global_rad_med	< 0.01	< 0.01	> 0.05
WS_global_rad_min	> 0.05	< 0.05	> 0.05
WS_global_rad_max	< 0.01	< 0.01	> 0.05
Season	> 0.05	< 0.01	< 0.01
GSC	< 0.05	< 0.01	< 0.01
PT	< 0.01	< 0.01	< 0.01

Table 64: Odds ratios with confidence intervals and p values of each variable for C_LMS3 or LMS3 as outcome lame

	C_LMS3				LMS3			
Variable	OR	2.5%	97.5%	p_value	OR	2.5%	97.5%	p_value
Breed	0.828	0.781	0.874	<0.001	0.844	0.765	0.919	<0.001
Lactation_number	1.132	1.112	1.152	<0.001	1.178	1.148	1.209	<0.001
Days_in_milk	0.999	0.999	1.000	<0.001	0.999	0.998	0.999	<0.001
LKV_milk_yield_in_last_lactation	1.000	1.000	1.000	<0.001	1.000	1.000	1.000	<0.001
LKV_daily_milk_yield	1.012	1.008	1.016	<0.001	0.994	0.987	1.000	0.066
LKV_urea	0.999	0.999	1.000	0.009	0.998	0.997	0.999	<0.001
LKV_somatic_cell_count	1.000	1.000	1.000	0.815	1.000	1.000	1.000	<0.001
LKV_fat	0.919	0.879	0.961	<0.001	0.919	0.856	0.987	0.021
LKV_protein	0.565	0.512	0.623	<0.001	0.507	0.433	0.593	<0.001
LKV_fat_protein_ratio	1.267	1.088	1.473	0.002	1.305	1.026	1.653	0.029
LKV_lactose	0.779	0.648	0.938	0.008	0.409	0.312	0.540	<0.001
Milkings	0.792	0.755	0.830	<0.001	0.645	0.597	0.697	<0.001
Maximum_milking_interval	1.001	1.001	1.001	<0.001	1.002	1.001	1.002	<0.001
Robot_daily_milk_yield	1.010	1.006	1.013	<0.001	0.991	0.985	0.996	0.001
Robot_milk_yield_in_current_lactation	1.000	1.000	1.000	0.831	1.000	1.000	1.000	<0.001
Robot_milk_yield_in_last_lactation	1.000	1.000	1.000	<0.001	1.000	1.000	1.000	0.051
Robot_daily_milk_yield_in_last_lactation	1.016	1.005	1.026	0.003	1.013	0.995	1.030	0.164
Milking_flow	0.971	0.935	1.008	0.126	0.982	0.924	1.043	0.565
Milking_temperature	1.057	0.976	1.144	0.176	1.036	0.905	1.184	0.609

	C_LMS3				LMS3			
Variable	**OR**	**2.5%**	**97.5%**	**p_value**	**OR**	**2.5%**	**97.5%**	**p_value**
Max_milking_flow	1.037	1.012	1.062	0.003	1.170	1.127	1.214	<0.001
Robot_conduct_lely	1.010	0.995	1.026	0.180	1.005	0.980	1.031	0.684
Robot_conduct	1.021	0.944	1.106	0.602	0.880	0.786	0.989	0.029
Robot_somatic_cell_count	1.000	1.000	1.000	0.136	1.000	0.999	1.000	0.360
Robot_effect_of_scc	1.013	0.995	1.031	0.152	0.989	0.950	1.023	0.573
Robot_fat	0.985	0.945	1.027	0.491	1.108	1.040	1.178	0.001
Robot_protein	0.630	0.538	0.737	<0.001	0.356	0.273	0.463	<0.001
Robot_fat_protein_ratio	1.100	0.946	1.277	0.212	2.008	1.618	2.474	<0.001
Robot_lactose	0.780	0.658	0.925	0.004	0.625	0.478	0.819	0.001
MDi	1.339	1.125	1.584	0.001	1.596	1.264	1.980	<0.001
Robot_BCS	0.602	0.478	0.760	<0.001	0.532	0.383	0.744	<0.001
Body_weight	1.001	1.001	1.002	<0.001	1.001	1.000	1.002	0.039
Concentrated_feed_intake	1.002	0.986	1.019	0.817	0.964	0.938	0.990	0.007
Concentrated_feed_remains	1.213	1.123	1.308	<0.001	1.407	1.262	1.559	<0.001
WT_feed_intake	1.005	1.000	1.010	0.049	0.994	0.987	1.002	0.123
WT_feeding_pace	1.43e+174	7.05e+155	4.60e+175	<0.001	3.73e+102	4.46e+110	5.30e+149	<0.001
WT_feeding_duration	0.991	0.989	0.992	<0.001	0.985	0.982	0.987	<0.001
WT_feeding_duration_day	0.988	0.986	0.990	<0.001	0.983	0.979	0.986	<0.001
WT_feeding_duration_day_night	0.864	0.527	1.426	0.566	2.363	1.085	5.224	0.032
WT_trough_visits	0.958	0.954	0.963	<0.001	0.944	0.936	0.951	<0.001
WT_trough_visits_day	0.949	0.944	0.955	<0.001	0.936	0.927	0.945	<0.001
WT_trough_visits_day_night	0.866	0.525	1.438	0.576	2.192	0.993	4.943	0.055
WT_feed_intake_per_visit	1.951	1.820	2.095	<0.001	1.745	1.620	1.883	<0.001
WT_feeding_duration_per_visit	1.131	1.101	1.162	<0.001	1.097	1.068	1.131	<0.001
WT_number_of_meals	0.872	0.849	0.895	<0.001	0.831	0.798	0.865	<0.001
Nedap_feeding	1.000	0.999	1.000	0.223	0.999	0.998	0.999	<0.001

	C_LMS3				LMS3			
Variable	OR	2.5%	97.5%	p_value	OR	2.5%	97.5%	p_value
WT_number_of_meals_day	0.839	0.813	0.866	<0.001	0.823	0.784	0.864	<0.001
WT_number_of_meals_day_night	0.604	0.359	1.019	0.058	1.746	0.776	3.991	0.182
WT_feed_intake_per_meal	1.171	1.137	1.205	<0.001	1.136	1.090	1.182	<0.001
WT_feeding_duration_per_meal	0.990	0.980	0.998	0.028	0.974	0.956	0.990	0.003
ENGS_feeding	0.996	0.993	0.999	0.011	0.996	0.992	1.000	0.069
ENGS_feeding_day	0.994	0.990	0.998	0.003	0.994	0.989	1.000	0.037
ENGS_feeding_day_night	0.649	0.282	1.534	0.316	0.739	0.237	2.483	0.614
ENGS_number_of_meals	1.002	0.959	1.047	0.924	1.028	0.968	1.091	0.374
ENGS_number_of_meals_day	0.978	0.924	1.034	0.433	1.021	0.945	1.102	0.603
ENGS_number_of_meals_day_night	0.521	0.202	1.379	0.183	1.046	0.275	4.285	0.949
ENGS_feeding_duration_per_meal	0.971	0.947	0.996	0.025	0.969	0.934	1.003	0.084
Smaxtec_rum	1.000	0.999	1.001	0.497	1.001	0.999	1.002	0.380
SCR_rum	0.999	0.998	0.999	0.001	0.997	0.996	0.998	<0.001
SCR_rum_day	0.999	0.998	1.001	0.341	0.999	0.997	1.000	0.092
SCR_rum_day_night	42.912	12.529	149.042	<0.001	61.537	10.380	362.910	<0.001
Nedap_rum	0.997	0.996	0.997	<0.001	0.995	0.994	0.996	<0.001
SCR_heat_probability	0.991	0.977	1.002	0.138	0.986	0.964	1.004	0.167
SCR_heat_probability_day	0.990	0.979	1.001	0.094	0.987	0.968	1.003	0.147
Lemmer_factor_of_restlessness	0.998	0.998	0.999	<0.001	0.997	0.996	0.998	<0.001
Nedap_get_ups	0.884	0.855	0.913	<0.001	0.883	0.836	0.931	<0.001
ENGS_lying	1.000	1.000	1.001	0.028	1.003	1.003	1.004	<0.001
ENGS_lying_day	1.002	1.001	1.003	<0.001	1.006	1.005	1.007	<0.001
ENGS_lying_day_night	13.917	6.882	28.312	<0.001	43.845	15.916	119.980	<0.001
ENGS_lying_bouts	0.997	0.990	1.004	0.477	0.976	0.962	0.988	<0.001

	C_LMS3				LMS3			
Variable	OR	2.5%	97.5%	p_value	OR	2.5%	97.5%	p_value
ENGS_lying_bouts_day	0.997	0.987	1.008	0.631	0.968	0.949	0.986	0.001
ENGS_lying_bouts_day_night	2.164	1.254	3.750	0.006	3.417	1.501	7.848	0.004
ENGS_lying_duration_per_bout	1.008	1.007	1.010	<0.001	1.010	1.008	1.012	<0.001
Lemmer_lying	1.002	1.002	1.003	<0.001	1.005	1.004	1.005	<0.001
Nedap_lying	0.999	0.998	1.000	0.002	1.004	1.003	1.006	<0.001
Lemmer_get_ups	1.043	1.026	1.060	<0.001	1.103	1.079	1.128	<0.001
Delaval_act_avg	0.936	0.922	0.949	<0.001	0.869	0.841	0.897	<0.001
Delaval_act_rel	0.991	0.983	0.998	0.010	0.998	0.987	1.008	0.761
Delaval_act_rel_min	0.984	0.974	0.994	0.001	0.974	0.958	0.990	0.001
Delaval_act_rel_max	0.997	0.990	1.003	0.275	1.011	1.003	1.018	0.005
ENGS_act	1.000	0.999	1.000	<0.001	0.999	0.999	0.999	<0.001
ENGS_act_day	0.999	0.999	0.999	<0.001	0.999	0.999	0.999	<0.001
ENGS_act_day_night	0.096	0.046	0.201	<0.001	0.151	0.056	0.427	<0.001
Smaxtec_act	0.958	0.935	0.981	<0.001	0.918	0.884	0.953	<0.001
Smaxtec_act_day	0.953	0.931	0.976	<0.001	0.907	0.874	0.941	<0.001
Smaxtec_act_day_night	1.049	0.769	1.423	0.762	1.056	0.670	1.640	0.811
SCR_act	0.950	0.941	0.958	<0.001	0.889	0.874	0.903	<0.001
SCR_act_day	0.954	0.946	0.961	<0.001	0.908	0.896	0.920	<0.001
SCR_act_day_night	0.154	0.077	0.300	<0.001	0.095	0.034	0.263	<0.001
Lemmer_act	0.990	0.989	0.992	<0.001	0.982	0.979	0.985	<0.001
Nedap_inactive	1.003	1.002	1.003	<0.001	1.005	1.004	1.005	<0.001
Nedap_act_collar_median	0.944	0.928	0.959	<0.001	0.920	0.888	0.950	<0.001
Nedap_act_collar_sum	0.996	0.995	0.997	<0.001	0.994	0.991	0.996	<0.001
Nedap_act_collar_median_day	0.947	0.934	0.960	<0.001	0.922	0.895	0.949	<0.001
Nedap_act_collar_sum_day	0.994	0.992	0.995	<0.001	0.991	0.987	0.994	<0.001
Nedap_act_collar_median_day_night	0.427	0.314	0.576	<0.001	0.391	0.216	0.685	0.001

	C_LMS3				LMS3			
Variable	OR	2.5%	97.5%	p_value	OR	2.5%	97.5%	p_value
Nedap_act_collar_sum_day_night	0.040	0.019	0.083	<0.001	0.037	0.011	0.129	<0.001
Nedap_act	1.000	1.000	1.000	<0.001	0.999	0.999	0.999	<0.001
Nedap_act_foot_median	0.996	0.995	0.997	<0.001	0.991	0.988	0.994	<0.001
Nedap_act_foot_median_day	0.996	0.995	0.997	<0.001	0.991	0.989	0.993	<0.001
Nedap_act_foot_sum_day	1.000	0.999	1.000	<0.001	0.999	0.999	0.999	<0.001
Nedap_act_foot_median_day_night	0.405	0.239	0.667	0.001	0.195	0.073	0.482	0.001
Nedap_act_foot_sum_day_night	0.023	0.006	0.083	<0.001	0.007	0.001	0.047	<0.001
Smaxtec_temp_normal_median	5.979	4.507	7.935	<0.001	9.806	6.604	14.545	<0.001
Smaxtec_temp_median	4.255	3.305	5.479	<0.001	11.629	8.271	16.353	<0.001
Smaxtec_temp_min	0.815	0.782	0.849	<0.001	0.779	0.735	0.826	<0.001
Smaxtec_temp_max	2.055	1.755	2.404	<0.001	1.723	1.378	2.134	<0.001
Smaxtec_temp_without_drink_cycles_median	4.000	3.106	5.151	<0.001	7.176	5.103	10.072	<0.001
Smaxtec_temp_without_drink_cycles_min	2.219	1.710	2.879	<0.001	4.478	3.099	6.457	<0.001
Smaxtec_temp_without_drink_cycles_max	2.051	1.751	2.401	<0.001	1.697	1.356	2.104	<0.001
Smaxtec_climate_temp_median	0.976	0.966	0.986	<0.001	0.946	0.930	0.963	<0.001
Smaxtec_climate_temp_min	0.981	0.969	0.992	0.001	0.958	0.939	0.977	<0.001
Smaxtec_climate_temp_max	0.976	0.968	0.984	<0.001	0.949	0.935	0.963	<0.001
Smaxtec_climate_hum_median	1.007	1.002	1.011	0.004	1.015	1.007	1.022	<0.001
Smaxtec_climate_hum_min	1.006	1.003	1.009	<0.001	1.017	1.011	1.022	<0.001

	C_LMS3				LMS3			
Variable	OR	2.5%	97.5%	p_value	OR	2.5%	97.5%	p_value
Smaxtec_climate_hum_max	1.003	0.996	1.010	0.391	1.011	1.000	1.022	0.051
Smaxtec_thi_median	0.993	0.988	0.998	0.009	0.985	0.977	0.993	<0.001
Smaxtec_thi_min	0.986	0.978	0.994	0.001	0.968	0.955	0.981	<0.001
Smaxtec_thi_max	0.985	0.980	0.990	<0.001	0.968	0.960	0.977	<0.001
WS_thi_med	0.984	0.980	0.988	<0.001	0.978	0.971	0.984	<0.001
WS_thi_min	0.981	0.976	0.986	<0.001	0.973	0.965	0.981	<0.001
WS_thi_max	0.989	0.986	0.992	<0.001	0.984	0.979	0.989	<0.001
WS_temp_2m_med	0.973	0.966	0.979	<0.001	0.962	0.951	0.973	<0.001
WS_temp_2m_min	0.967	0.959	0.975	<0.001	0.957	0.944	0.970	<0.001
WS_temp_2m_max	0.980	0.974	0.985	<0.001	0.971	0.962	0.980	<0.001
WS_temp_20cm_med	0.972	0.965	0.979	<0.001	0.961	0.950	0.972	<0.001
WS_temp_20cm_min	0.970	0.963	0.978	<0.001	0.960	0.948	0.973	<0.001
WS_temp_20cm_max	0.981	0.976	0.986	<0.001	0.973	0.965	0.981	<0.001
WS_soil_temp_5cm_med	0.971	0.964	0.978	<0.001	0.959	0.947	0.971	<0.001
WS_soil_temp_5cm_min	0.969	0.961	0.976	<0.001	0.957	0.944	0.969	<0.001
WS_soil_temp_5cm_max	0.975	0.969	0.982	<0.001	0.964	0.954	0.975	<0.001
WS_soil_temp_20cm_med	0.969	0.961	0.977	<0.001	0.956	0.943	0.968	<0.001
WS_soil_temp_20cm_min	0.968	0.960	0.976	<0.001	0.955	0.942	0.968	<0.001
WS_soil_temp_20cm_max	0.970	0.962	0.978	<0.001	0.957	0.945	0.969	<0.001
WS_rel_hum_med	1.005	1.001	1.008	0.006	1.014	1.009	1.020	<0.001
WS_rel_hum_min	1.003	1.001	1.004	0.005	1.005	1.003	1.008	<0.001
WS_rel_hum_max	1.003	0.993	1.014	0.558	1.065	1.036	1.100	<0.001
WS_wind_velocity_med	1.034	0.988	1.081	0.145	1.129	1.055	1.206	<0.001
WS_wind_velocity_min	1.067	0.968	1.172	0.181	1.148	0.990	1.317	0.058
WS_wind_velocity_max	1.006	0.982	1.029	0.633	1.064	1.028	1.101	<0.001
WS_rain_med	0.365	0.070	1.750	0.218	3.103	0.273	28.774	0.339
WS_rain_min	0	0	1.43e+14	0.279	4.94e+24	0	4.83e+56	0.223

	C_LMS3				LMS3			
Variable	OR	2.5%	97.5%	p_value	OR	2.5%	97.5%	p_value
WS_rain_max	0.966	0.920	1.009	0.134	0.979	0.904	1.045	0.556
WS_global_rad_med	0.999	0.998	0.999	<0.001	0.998	0.997	0.999	<0.001
WS_global_rad_min	0.963	0.808	1.138	0.670	1.341	1.055	1.671	0.012
WS_global_rad_max	1.000	0.999	1.000	<0.001	0.999	0.999	1.000	<0.001
Season	1.061	1.026	1.098	0.001	1.153	1.093	1.216	<0.001

Table 65: Reduced Spearman's rank correlation table by farm, displaying only the parameters varying between the different farms (+ = positive correlation, - = negative correlation, / = not recorded on that farm) (parameters explained in Table 33)

Parameter	RF 1	RF 2	RF 3	CDF 1	CDF 2	CDF 3	CDF 4	CDF 5
Breed	+	/	/	/	/	/	/	-
Concentrated_feed_intake	+	-	+	-	+	+	-	-
Days_in_milk	-	-	-	+	-	-	-	+
GSC	0	+	-	+	-	+	-	-
Lactation_number	+	+	+	+	-	+	-	+
LKV_daily_milk_yield	+	-	+	+	+	+	+	-
LKV_fat	-	-	-	+	+	+	-	+
LKV_fat_protein_ratio	-	-	+	+	+	+	+	+
LKV_lactose	-	-	0	+	+	+	-	+
LKV_milk_yield_in_last_lactation	+	-	+	+	+	+	+	+
LKV_protein	-	-	-	-	-	-	-	+
LKV_somatic_cell_count	-	+	-	+	+	-	+	-
LKV_urea	-	+	+	+	-	-	-	+
Max_milking_flow	+	-	-	+	/	+	/	+
Maximum_milking_interval	0	+	-	+	+	+	+	+
MDi	+	/	/	/	/	0	/	/
Milking_flow	0	-	-	+	/	+	/	+
Milking_temperature	/	+	-	+	/	/	/	+
Robot_conduct_lely	/	+	+	-	/	/	/	+
Robot_daily_milk_yield	+	-	+	+	+	+	+	-
Robot_daily_milk_yield_in_last_lactation	+	-	+	+	+	+	+	+
Robot_effect_of_scc	/	0	-	-	/	/	/	/
Robot_fat	/	+	-	+	-	/	+	+
Robot_fat_protein_ratio	/	+	-	+	0	/	+	+
Robot_lactose	/	-	-	+	+	/	-	+
Robot_milk_yield_last_lactation	/	-	+	-	0	+	+	+
Robot_protein	/	+	-	-	-	-	-	+
SCR_act_day_night	-	/	+	-	/	/	/	-
SCR_heat_probability	/	/	+	-	/	/	/	-
SCR_heat_probability_day	/	/	+	-	/	/	/	-
SCR_rum	-	/	-	+	/	/	/	+
Season	+	+	-	/	/	+	+	/

Parameter	RF 1	RF 2	RF 3	CDF 1	CDF 2	CDF 3	CDF 4	CDF 5
Smaxtec_act	+	/	-	/	/	/	-	/
Smaxtec_act_day	+	/	-	/	/	/	-	/
Smaxtec_act_day_night	-	/	-	/	/	/	+	/
Smaxtec_climate_hum_max	+	/	-	/	/	/	+	/
Smaxtec_climate_hum_median	+	/	-	/	/	/	+	/
Smaxtec_climate_hum_min	+	/	-	/	/	/	+	/
Smaxtec_climate_temp_max	+	/	-	/	/	/	-	/
Smaxtec_climate_temp_median	+	/	-	/	/	/	-	/
Smaxtec_climate_temp_min	+	/	-	/	/	/	-	/
Smaxtec_rum	-	/	+	/	/	/	+	/
Smaxtec_thi_max	+	/	-	/	/	/	-	/
Smaxtec_thi_median	+	/	-	/	/	/	-	/
Smaxtec_thi_min	+	/	-	/	/	/	-	/
WS_rain_max	-	+	+	/	/	/	/	/
WS_rain_med	-	+	+	/	/	/	/	/
WS_rel_hum_max	+	-	0	/	/	/	/	/
WS_wind_velocity_max	-	+	+	/	/	/	/	/
WS_wind_velocity_median	-	+	+	/	/	/	/	/
WS_wind_velocity_min	0	+	+	/	/	/	/	/

Table 66: Reduced Odds ratio table by farm, displaying only the parameters varying between the different farms (>1 = positive association according to the odds ratio, <1 = negative association according to the odds ratio, n.s. = not significant, / = not recoded) (parameters explained in Table 33)

Parameter	RF 1	RF 2	RF 3	CDF 1	CDF 2	CDF 3	CDF 4	CDF 5
Body_weight	>1	/	/	/	/	/	/	n.s.
Concentrated_feed_intake	>1	<1	>1	n.s.	>1	n.s.	>1	<1
Days_in_milk	<1	<1	<1	n.s.	<1	<1	<1	>1
GSC	n.s.	>1	<1	>1	n.s.	n.s.	n.s.	<1
Lactation_number	>1	>1	>1	>1	n.s.	n.s.	n.s.	n.s.
Lemmer_act	/	/	/	/	n.s.	/	<1	/
Lemmer_factor_of_restlessness	/	/	/	/	n.s.	/	<1	/
Lemmer_get_ups	/	/	/	/	n.s.	/	>1	/
LKV_daily_milk_yield	>1	n.s.	>1	n.s.	>1	>1	>1	<1
LKV_fat	<1	<1	n.s.	n.s.	n.s.	>1	n.s.	n.s.
LKV_fat_protein_ratio	<1	<1	>1	n.s.	>1	>1	>1	>1
LKV_lactose	<1	<1	n.s.	n.s.	n.s.	>1	<1	>1
LKV_milk_yield_in_last_lactation	1	1	1	1	1	1	n.s.	1
LKV_protein	<1	<1	<1	<1	<1	<1	<1	n.s.
LKV_somatic_cell_count	1	n.s.	n.s.	n.s.	n.s.	n.s.	1	<1
LKV_urea	<1	n.s.	>1	n.s.	<1	n.s.	<1	>1
Max_milking_flow	>1	n.s.	>1	>1	/	>1	/	>1
Maximum_milking_interval	n.s.	>1	n.s.	n.s.	<1	n.s.	>1	>1
MDi	>1	/	/	/	/	n.s.	/	/
Milking_flow	>1	n.s.	>1	n.s.	/	>1	/	>1
Milking_temperature	/	>1	<1	>1	/	/	/	>1
Milkings	n.s.	<1	n.s.	n.s.	<1	n.s.	<1	<1
Nedap_feeding	/	n.s.	<1	/	/	/	/	/

Parameter	RF 1	RF 2	RF 3	CDF 1	CDF 2	CDF 3	CDF 4	CDF 5
Nedap_rum	/	<1	n.s.	/	/	/	/	/
Robot_conduct	>1	/	/	/	>1	n.s.	n.s.	/
Robot_conduct_lely	/	>1	n.s.	<1	/	/	/	n.s.
Robot_daily_milk_yield	>1	<1	>1	n.s.	>1	n.s.	>1	n.s.
Robot_daily_milk_yield_in_last_lactation	/	<1	>1	n.s.	/	/	/	>1
Robot_effect_of_scc	/	<1	n.s.	n.s.	/	/	/	/
Robot_fat	/	>1	<1	>1	n.s.	/	>1	>1
Robot_fat_protein_ratio	/	>1	<1	>1	n.s.	/	>1	>1
Robot_lactose	/	<1	n.s.	>1	n.s.	/	n.s.	>1
Robot_milk_yield_last_lactation	/	1	1	n.s.	1	1	n.s.	1
Robot_protein	/	n.s.	<1	<1	n.s.	/	<1	n.s.
Robot_somatic_cell_count	/	<1	n.s.	n.s.	/	/	/	/
SCR_act_day_night	<1	/	n.s.	n.s.	/	/	/	<1
SCR_heat_probability	/	/	n.s.	<1	/	/	/	n.s.
SCR_heat_probability_day	/	/	n.s.	<1	/	/	/	n.s.
SCR_rum	<1	/	n.s.	n.s.	/	/	/	>1
Season	n.s.	>1	<1	/	/	n.s.	>1	/
Smaxtec_act	>1	/	n.s.	/	/	/	<1	/
Smaxtec_act_day	>1	/	n.s.	/	/	/	<1	/
Smaxtec_act_day_night	<1	/	<1	/	/	/	>1	/
Smaxtec_climate_hum_max	n.s.	/	<1	/	/	/	>1	/
Smaxtec_climate_hum_median	>1	/	n.s.	/	/	/	>1	/
Smaxtec_climate_hum_min	n.s.	/	n.s.	/	/	/	>1	/
Smaxtec_climate_temp_max	n.s.	/	<1	/	/	/	<1	/
Smaxtec_climate_temp_median	n.s.	/	<1	/	/	/	<1	/
Smaxtec_climate_temp_min	n.s.	/	<1	/	/	/	n.s.	/
Smaxtec_temp_median	>1	/	n.s.	/	/	/	>1	/
Smaxtec_temp_without_drink_cycles _median	>1	/	n.s.	/	/	/	>1	/
Smaxtec_temp_without_drink_cycles _min	>1	/	n.s.	/	/	/	>1	/
Smaxtec_thi_max	n.s.	/	<1	/	/	/	<1	/
Smaxtec_thi_median	n.s.	/	<1	/	/	/	<1	/
Smaxtec_thi_min	n.s.	/	<1	/	/	/	n.s.	/
WS_global_rad_max	1	<1	n.s.	/	/	/	/	/
WS_rain_max	<1	n.s.	n.s.	/	/	/	/	/
WS_rel_hum_max	n.s.	n.s.	>1	/	/	/	/	/
WS_rel_hum_med	n.s.	>1	>1	/	/	/	/	/
WS_rel_hum_min	n.s.	>1	>1	/	/	/	/	/
WS_temp_20cm_min	<1	n.s.	<1	/	/	/	/	/
WS_temp_20m_min	<1	n.s.	<1	/	/	/	/	/
WS_wind_velocity_max	<1.	n.s.	>1	/	/	/	/	/
WS_wind_velocity_median	n.s.	>1	>1	/	/	/	/	/
WS_wind_velocity_min	n.s.	n.s.	<1	/	/	/	/	/

Table 67: Reduced Spearman's rank-coefficient correlation table displaying most relevant parameter correlations with ρ > 0.4 (parameters explained in Table 33)

Parameter 1	Parameter 2	Correlation
Days_in_milk	Robot_milk_yield_in_current_lactation	0.93
WT_feeding_duration_day_night	WT_trough_visits_day_night	0.81
WT_feed_intake_per_visit	WT_feeding_duration_per_visit	0.79
Robot_daily_milk_yield	Concentrated_feed_intake	0.72
ENGS_feeding_day_night	ENGS_number_of_meals_day_night	0.71
LKV_daily_milk_yield	Concentrated_feed_intake	0.69
WT_feeding_duration_day_night	WT_number_of_meals_day_night	0.69
Milking_temperature	Smaxtec_climate_temp_max	0.67
Milking_temperature	Smaxtec_thi_max	0.67
Milking_temperature	Smaxtec_climate_temp_median	0.66
Milking_temperature	Smaxtec_thi_median	0.66
Smaxtec_climate_hum_median	Season	0.65
WT_feed_intake_per_meal	WT_feeding_duration_per_meal	0.63
Milking_temperature	Smaxtec_climate_temp_min	0.62
Milking_temperature	Smaxtec_thi_min	0.62
Milking_temperature	WS_temp_2m_med	0.62
Milking_temperature	WS_temp_20cm_med	0.62
Milking_temperature	WS_thi_med	0.61
Milking_temperature	WS_temp_2m_min	0.61
Milking_temperature	WS_soil_temp_5cm_min	0.61
Milking_temperature	WS_thi_max	0.60
Milking_temperature	WS_temp_2m_max	0.60
Milking_temperature	WS_temp_20cm_max	0.60
Milking_temperature	WS_soil_temp_20cm_med	0.60
Milking_temperature	WS_soil_temp_20cm_min	0.60
Smaxtec_climate_hum_max	Season	0.60
Milkings	Concentrated_feed_intake	0.59
Milking_temperature	WS_thi_min	0.59
Milking_temperature	WS_temp_20cm_min	0.59
Milking_temperature	WS_soil_temp_5cm_med	0.59
Milking_temperature	WS_soil_temp_20cm_max	0.59
WS_rel_hum_min	Season	0.59
Days_in_milk	LKV_protein	0.57
WT_feeding_pace	Smaxtec_act	0.56
Smaxtec_climate_hum_min	Season	0.56
WS_rel_hum_med	Season	0.55
WT_feeding_duration	Smaxtec_thi_median	0.54
Milking_temperature	WS_soil_temp_5cm_max	0.54
WT_feeding_duration	Smaxtec_climate_temp_min	0.53
Nedap_feeding	SCR_act	0.52
WT_feeding_duration_day	Smaxtec_thi_median	0.52
WT_feeding_pace	Smaxtec_act_day	0.51
WT_feed_intake	Smaxtec_thi_median	0.51
Milkings	Robot_daily_milk_yield	0.50
WT_feed_intake	WT_feeding_duration	0.50
WT_feeding_duration_day	WT_trough_visits_day	0.50
Nedap_feeding	SCR_act_day	0.50
WT_feeding_duration_day	Smaxtec_climate_temp_min	0.50
Nedap_act_foot_sum_day	WS_thi_max	0.50
Nedap_act_foot_sum_day	WS_temp_2m_max	0.50

Parameter 1	Parameter 2	Correlation
Nedap_act_foot_sum_day	WS_temp_20cm_max	0.50
Nedap_act_foot_sum_day	WS_soil_temp_5cm_max	0.50
Smaxtec_climate_hum_median	WS_rain_med	0.50
WT_feeding_duration	WT_trough_visits	0.49
Milking_temperature	Smaxtec_temp_max	0.49
WT_feeding_duration	Smaxtec_climate_temp_median	0.49
Nedap_act_foot_sum_day	Smaxtec_thi_max	0.49
Nedap_act_foot_sum_day	WS_thi_med	0.49
Nedap_act	WS_thi_max	0.49
Nedap_act_foot_sum_day	WS_temp_2m_med	0.49
Nedap_act	WS_temp_2m_max	0.49
Nedap_act_foot_sum_day	WS_temp_20cm_med	0.49
Nedap_act_foot_sum_day	WS_soil_temp_5cm_med	0.49
Nedap_act_foot_sum_day	WS_soil_temp_20cm_max	0.49
LKV_protein	Robot_fat	0.48
Lactation_number	WT_feed_intake_per_visit	0.48
Milking_temperature	Smaxtec_temp_without_drink_cycles_max	0.48
WT_feed_intake	Smaxtec_climate_temp_min	0.48
Nedap_act_foot_sum_day	Smaxtec_climate_temp_max	0.48
Nedap_act	WS_temp_20cm_max	0.48
Nedap_act_foot_sum_day	WS_soil_temp_20cm_med	0.48
LKV_protein	Robot_milk_yield_in_current_lactation	0.47
Nedap_act_foot_sum_day	Smaxtec_climate_temp_median	0.47
Nedap_act	Smaxtec_climate_temp_max	0.47
Nedap_act_foot_sum_day	Smaxtec_thi_median	0.47
Nedap_act	Smaxtec_thi_max	0.47
Nedap_act	WS_thi_med	0.47
Nedap_act_foot_sum_day	WS_thi_min	0.47
Nedap_act	WS_temp_2m_med	0.47
Nedap_act	WS_temp_20cm_med	0.47
Nedap_act_foot_sum_day	WS_soil_temp_5cm_min	0.47
Nedap_act	WS_soil_temp_5cm_max	0.47
Nedap_act_foot_sum_day	WS_soil_temp_20cm_min	0.47
Body_weight	WT_feeding_pace	0.46
Nedap_act_foot_sum_day	WS_temp_2m_min	0.46
Nedap_act_foot_sum_day	WS_temp_20cm_min	0.46
Nedap_act	WS_soil_temp_5cm_med	0.46
Nedap_act	WS_soil_temp_20cm_max	0.46
Days_in_milk	Robot_fat	0.45
LKV_urea	Robot_lactose	0.45
Max_milking_flow	Milking_temperature	0.45
WT_feeding_duration	WT_trough_visits_day	0.45
Milking_temperature	Smaxtec_temp_normal_median	0.45
WT_feed_intake	Smaxtec_climate_temp_median	0.45
WT_feeding_duration_day	Smaxtec_climate_temp_median	0.45
Nedap_act	Smaxtec_climate_temp_median	0.45
Nedap_act_foot_sum_day	Smaxtec_climate_temp_min	0.45
Nedap_act	Smaxtec_thi_median	0.45
WT_feeding_duration	Smaxtec_thi_min	0.45
Nedap_act_foot_sum_day	Smaxtec_thi_min	0.45
Nedap_act	WS_thi_min	0.45

Parameter 1	Parameter 2	Correlation
Smaxtec_temp_min	WS_temp_20cm_min	0.45
Nedap_act	WS_soil_temp_20cm_med	0.45
Smaxtec_climate_hum_min	WS_rain_med	0.45
Smaxtec_climate_hum_median	WS_rain_max	0.45
WT_feeding_duration_day	WT_trough_visits	0.44
WT_feeding_duration	Smaxtec_climate_hum_median	0.44
Nedap_act	WS_temp_2m_min	0.44
Nedap_act	WS_soil_temp_5cm_min	0.44
Nedap_act	WS_soil_temp_20cm_min	0.44
Smaxtec_climate_hum_max	WS_rain_med	0.44
Milking_flow	Milking_temperature	0.43
WT_feed_intake	WT_feeding_duration_day	0.43
Lactation_number	WT_feed_intake_per_meal	0.43
WT_feed_intake	Smaxtec_act	0.43
Nedap_act	Smaxtec_climate_temp_min	0.43
WT_feeding_duration_day	Smaxtec_climate_hum_median	0.43
Nedap_act	Smaxtec_thi_min	0.43
SCR_heat_probability_day	WS_temp_2m_min	0.43
Nedap_act	WS_temp_20cm_min	0.43
LKV_daily_milk_yield	Milkings	0.42
LKV_somatic_cell_count	MDi	0.42
LKV_protein	Robot_somatic_cell_count	0.42
Lactation_number	WT_feeding_pace	0.42
Milking_temperature	Nedap_rum	0.42
Milking_temperature	Smaxtec_temp_without_drink_cycles_median	0.42
WT_feeding_duration_per_meal	Smaxtec_thi_median	0.42
SCR_heat_probability	WS_temp_2m_min	0.42
WS_wind_velocity_med	WS_rain_med	0.42
Milking_temperature	WS_global_rad_med	0.42
Robot_lactose	Concentrated_feed_intake	0.41
Robot_milk_yield_in_current_lactation	WT_feed_intake	0.41
Body_weight	WT_feed_intake_per_visit	0.41
Body_weight	Smaxtec_act	0.41
ENGS_lying	Smaxtec_temp_median	0.41
WT_feed_intake	Smaxtec_thi_min	0.41
Nedap_act_foot_median_day	WS_thi_max	0.41
WT_feed_intake	WS_soil_temp_20cm_min	0.41
WS_wind_velocity_med	WS_rain_max	0.41
Nedap_act_foot_sum_day	WS_global_rad_med	0.41

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ Activity\ +\ Body\_weight: Robot\_BCS \\
& +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 7: Expansion of Model 3 with added BCS (Body condition score) and body weight parameters

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ Milkings\ +\ LKV\_protein\ +\ Activity \\
& +\ Lying\_bouts\ +\ Lying\_bouts: Lactation\_number\ +\ Lying: Activity \\
& +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 8: Expansion of Model 3 with added lying behaviour parameters

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & LKV\_daily\_milk\_yield\ + Activity\ +\ Rumination: Lactation\_number \\
& +\ (Days\_in\_milk \mid FCN)
\end{aligned}
$$

Model 9: Expansion of Model 3 with added rumination parameters

$$
\begin{aligned}
Claw\ health\ status\ _c\sim\ & Days\_in\_milk\ +\ LKV\_protein\ +\ Lactation\_number\ +\ Activity \\
& +\ Feeding\ +\ LKV\_daily\_milk\_yield: LKV\_protein \\
& +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 10: Expansion of Model 3 with added feeding behaviour parameters

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ Activity\ +\ WT\_trough\_visits\ +\ WT\_feeding\_pace \\
& +\ WT\_trough\_visits: Days\_in\_milk\ +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 11: Expansion of Model 3 with added feeding behaviour parameters on RF1

$$
\begin{aligned}
& Claw\ health\ status_c \sim Lactation\_number\ +\ LKV\_protein \\
& +\ LKV\_milk\_yield\_in\_last\_lactation\ +\ Activity\ +\ Smaxtec\_temp\_median \\
& + Smaxtec\_temp\_normal\_median: Smaxtec\_temp\_without\_drink\_cycles\_median \\
& +\ (LKV\_daily\_milk\_yield\ +\ Days\_in\_milk \mid FCN)
\end{aligned}
$$

Model 12: Expansion of Model 3 with added body temperature parameters

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ Activity\ +\ WS\_thi\_med\ +\ Smaxtec\_thi\_median \\
& +\ Activity: Smaxtec\_thi\_median\ +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 13: Expansion of Model 3 with added climate parameters

$$
\begin{aligned}
Claw\ health\ status_n \sim\ & Days\_in\_milk\ +\ Activity\ +\ Robot\_BCS: LKV\_daily\_milk\_yield \\
& +\ Activity: Maximum\_milking\_interval\ +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 14: Expansion of Model 4 with added BCS (Body condition score) and body weight parameters

$$Claw\ health\ status_n \sim Milkings + Activity + Lying{:}Activity + Lying{:}Days\_in\_milk + (Days\_in\_milk + LKV\_daily\_milk\_yield \mid FCN)$$

Model 15: Expansion of Model 4 with added lying behaviour parameters

$$Claw\ health\ status_n \sim LKV\_protein + Activity + Rumination + Lactation\_number{:}Rumination + (Days\_in\_milk + LKV\_daily\_milk\_yield \mid FCN)$$

Model 16: Expansion of Model 4 with added rumination parameters

$$Claw\ health\ status_n \sim Lactation\_number + Activity + Feeding + LKV\_daily\_milk\_yield{:}LKV\_protein + (Days\_in\_milk + LKV\_daily\_milk\_yield \mid FCN)$$

Model 17: Expansion of Model 4 with added feeding behaviour parameters

$$Claw\ health\ status_n \sim Days\_in\_milk + Activity + WT\_feeding\_pace + Lactation\_number{:}Maximum\_milking\_interval + (LKV\_daily\_milk\_yield \mid FCN)$$

Model 18: Expansion of Model 4 with added feeding behaviour parameters on RF1

$$Claw\ health\ status_n \sim Days\_in\_milk + Activity + Smaxtec\_temp\_median + Activity{:}Smaxtec\_temp\_normal\_median + (LKV\_daily\_milk\_yield \mid FCN)$$

Model 19: Expansion of Model 4 with added body temperature parameters

$$Claw\ health\ status_n \sim Days\_in\_milk + WS\_thi\_med + Season{:}Activity + Activity{:}Smaxtec\_thi\_median + (LKV\_daily\_milk\_yield \mid FCN)$$

Model 20: Expansion of Model 4 with added climate parameters

$$Claw\ health\ status_c \sim Maximum\_milking\_interval + LKV\_protein + Lying + Smaxtec\_temp\_min + Activity{:}Lactation\_number + (Days\_in\_milk + LKV\_daily\_milk\_yield \mid FCN)$$

Model 21: Expansion of Model 3 with added lying behaviour and body temperature parameters

$$Claw\ health\ status_c \sim Days\_in\_milk + Maximum\_milking\_interval + Activity + Robot\_BCS + WT\_trough\_visits + WT\_feeding\_pace + Body\_weight{:}LKV\_daily\_milk\_yield + (LKV\_daily\_milk\_yield \mid FCN)$$

Model 22: Expansion of Model 3 with added BCS (Body condition score), body weight and feeding parameters

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ WT\_feeding\_pace\ +\ WT\_trough\_visits \\
& +\ Lying\ bouts{:}\ Lactation\_number \\
& +\ Activity{:}\ Lying\ WT\_trough\_visits{:}\ Days\_in\_milk \\
& +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 23. Expansion of Model 3 with added lying and feeding behaviour parameters on RF1

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ Lactation\_number \\
& +\ LKV\_milk\_yield\_in\_last\_lactation\ +\ Activity\ +\ Feeding \\
& +\ Rumination{:}\ LKV\_daily\_milk\_yield\ +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 24: Expansion of Model 3 with added rumination and feeding behaviour parameters

$$
\begin{aligned}
Claw\ health\ status_c \sim\ & Days\_in\_milk\ +\ Lactation\_number\ +\ Maximum\_milking\_interval \\
& +\ LKV\_protein\ +\ Activity\ +\ Smaxtec\_temp\_median \\
& +\ Rumination{:}\ Smaxtec\_temp\_min\ +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 25: Expansion of Model 3 with added rumination and body temperature parameters

$$
\begin{aligned}
Claw\ health\ status_n \sim\ & Milkings\ +\ Lying\ +\ Smaxtec\_temp\_min \\
& +\ Activity{:}\ Lactation\_number\ +\ (Days\_in\_milk \\
& +\ LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 26: Expansion of Model 4 with added lying behaviour and body temperature parameters

$$
\begin{aligned}
Claw\ health\ status_n \sim\ & Days\_in\_milk\ +\ Lactation\_number\ +\ Activity\ +\ Feeding \\
& +\ Activity{:}\ Lying\ +\ Feeding{:}\ LKV\_daily\_milk\_yield \\
& +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 27: Expansion of Model 4 with added lying and feeding behaviour parameters

$$
\begin{aligned}
Claw\ health\ status_n \sim\ & Days\_in\_milk\ +\ Activity\_day\ +\ WT\_feeding\_pace \\
& +\ Lying{:}\ Lactation\_number\ +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 28: Expansion of Model 4 with added lying and feeding behaviour on RF1

$$
\begin{aligned}
Claw\ health\ status_n \sim\ & Milkings\ +\ LKV\_protein\ +\ Activity\ +\ Feeding \\
& +\ Rumination{:}\ Days\_in\_milk\ +\ Feeding{:}\ Milkings \\
& +\ (LKV\_daily\_milk\_yield \mid FCN)
\end{aligned}
$$

Model 29: Expansion of Model 4 with added rumination and feeding behaviour parameters

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