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Replacing Subjective Assessment of Dairy Cows with Objective Measures

Caleb Sagwa Barasa

Animal Breeding and Genomics Group, Department of Animal Science, Egerton University, P.O. BOX 536 – 20115 EGERTON

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ABSTRACT

In 2067 dairy farms in developing countries will be modernized and automated systems will replace much of the manual labour on farms. Traditionally, livestock management decisions have been based on almost entirely on observations, judgement, and experience of the farmer. However, such manual systems are inherently subjective, labour intensive, time consuming, invasive and unreliable. Today technology-oriented approaches are widely in use in animal agriculture. New data obtained using fast, real time, and affordable objective measures are becoming more readily available to aid farm level monitoring, awareness, and decision making. Computer vision technology and image analysis, digital twins, artificial intelligence, sensors, big data, and machine learning are a game changer in the livestock industry. This review aims at highlighting the main areas where digital technologies for improved animal monitoring and welfare are most applicable in dairy animals. In particular, body condition scoring, lameness detection, mastitis diagnosis, oestrus detection and pregnancy diagnosis. The environmental sustainability of digital technologies is also discussed. The application of technology offers new possibilities to realize food safety and quality, efficient and sustainable animal farming, healthy animals, guaranteed wellbeing and acceptable environmental impact of livestock production.

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Introduction

There is significant interest and investment in information that can be derived from new technologies and data to support enhanced monitoring, measurement, and management of farming systems for more sustainable production (Bell and Comber, 2020). Studies have shown that by the year 2067 dairy farms in developing countries will be modernized and integrated sensors, robotics, and automated systems will replace much of the manual labour on farms, (Britt *et al*., 2018). The use of digital technologies forms the basis for successful large scale implementation of precision livestock farming in practice (Groher *et al*., 2020). With digital technologies, farmers are not only able to monitor large animal populations for health and welfare, but also detect issues with individual animals in a timely manner, and also anticipate issues before they occur, based on previous data (Benjamin and Yik, 2019). Currently, Artificial intelligence and machine learning are being used to improve the prediction of complex events such as calving time (Borchers *et al*., 2017). Accelerometers are providing a useful tool to help farmers to identify oestrus activity in cows (Mayo *et al*., 2019). An understanding of the new digital information is important for effective implementation, from support, for farmers to data analytics and the linkage actors (Bell and Comber, 2020). Innovation needs to continue if we are to supply safe and nutritious food to a population that will grow to over 9 billion by 2050 and on a planet where resources are becoming scarcer (Shepherd *et al*., 2020).

Traditionally, livestock management decisions have been based on almost entirely on observations, judgement, and experience of the farmer (Norton *et al*. 2019; Werkheiser 2020), this subjective technique scoring systems lack reliability. The usefulness of any assessment method is determined by its validity, reliability, and sensitivity (Flower and Weary, 2006). High intra assessor and inter assessor variability in subjective assessments have been reported (O'Callaghan *et al*., 2003; Flower and Weary, 2006). Objective measurement tools like sensors focus on most directly on measurable indicators of a condition rather than proxy measures (Mottram, 2016). Increasing standards for animal health and welfare has led to considerable research activity into ways to monitor animals in a continuous, dynamic and real-time manner on farm (Norton *et al*., 2019; Neethirajan and Kemp, 2021). This has facilitated phenotyping of a wide range of functional traits, particularly (fertility, legs/feet, udder, birth, feed utilization efficiency, be-

*Corresponding author: Caleb Sagwa Barasa
E-mail address: c.bsagwa@yahoo.com

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haviour, milk composition, body composition) that can be used for management and genetic selection purposes, as well as parameters of public interest (Egger-Danner *et al*., 2015). Precision livestock farming (PLF) equips farmer with more objective information about the animal to make more informed choices about the sustainability of their production systems (Norton *et al*., 2019).

Digital applications have the potential to dramatically change the way knowledge is processed, communicated, accessed, and utilised as farming processes become increasingly data driven and data enabled (Ingram and Maye, 2020). Compared with ruminant species, digital technologies are widely used in the dairy sector (Groher *et al*., 2020). The authors observed that, easy to use sensors and measuring devices for example, integrated in the milking parlour are wider spread than data processing technologies. The current study aims at assessing digital technologies for improved animal monitoring and welfare in dairy herds in the tropics. Such technologies have the potential to allow welfare and health issues to be detected quickly for more animals compared to more manual methods currently used (Bell and Tzimiropoulos, 2018). Some of the main health and fertility problems associated with dairy cows are discussed below.

Body condition

The body condition score (BCS) of dairy cattle is an assessment of the proportion of body fat that it possesses, and it is recognised by animal scientists and producers as being an important factor in dairy cattle management (Roche *et al*., 2009). The most widely used and traditional method for BCS is manual scoring of the amount of body fat reserves associated with a live animal at a given time (Edmonson *et al*., 1989; Roche *et al*., 2009). The BCS is assigned by trained assessors using predefined scoring protocol consisting of a 5 – point scoring system with 9 levels of fatness from lean to obese (Edmonson *et al*., 1989). Given the importance of body condition at different stages of production and their physiological target, a reliable phenotypic measure of BCS is extremely beneficial (Bell *et al*., 2018). Calving BCS is probably the most influential time point in the lactation calendar, as it affects early lactation dry matter intake, post calving BCS loss, milk yield cow immunity and, although it does not directly affect pregnancy rate, it does influence reproduction through its effect on nadir BCS and BCS loss (Roche *et al*., 2009). Cows with a high or low BCS have associated with health risks and low reproductive performances (Roche *et al*., 2009). Therefore, monitoring individual cow body fat and maintaining adequate body condition is essential to maintain a productive animal that has appropriate nutrition and fertility, whilst also producing acceptable amount of milk (Bell *et al*., 2018).

Ultrasonography and machine vision technology are the alternatives to manual scoring of BCS. Ultrasonography measures subcutaneous fat thickness (Domecq *et al*., 1995). This technology is labour intensive and requires handled devices (Song *et al*., 2019). Machine vision technology has been used in automated body condition score classification of dairy cows (Bewley *et al*., 2008). Recently improvement on automated BCS classification has been done by including multiple body condition related features extracted from 3 viewpoints in 8 body regions (Song *et al*., 2019). The body images of cows are recorded using 3 – dimensional cameras positioned to view the cow from top, right side, and rear. Each image is then automatically processed to identify anatomical landmarks, the bony prominences and body surface. Around these anatomical landmarks, the bony prominences are quantified to describe 8 body condition related features. They concluded that this study increased the sensitivity of BCS classification compared with that reported for current machine vision-based body condition scoring methods.

Bell *et al*. (2018) compared three different methods of measuring the body condition of dairy cows using an ultrasound scanner, manual observation, and still digital image of the cow. They found out that across all cows, the manual BCS produced the highest average BCS of 2.76, compared to 2.41 for digital BCS and 2.10 for ultrasound BCS. The ultrasound and digital methods were below the recommended "ideal" range of 2.5 -3.0 (Chagas *et al*., 2007). On average, the manual BCS over predicted body condition when compared to ultrasound measurements by 31%. They concluded that digital BCS can provide a more accurate assessment of cow body fat than manual BCS observations, with the added benefit of more automated and frequent monitoring potentially improving the welfare and sustainability of high production systems.

Lameness and mobility

Lameness or abnormal gait is a response to pain caused by a range of pathologies (Van Nuffel *et al*., 2015; Alsaaod *et al*., 2019). Literature indicates that timely detection of lameness is a big problem in the dairy industry because cattle tend to show little overt behaviour until injuries are advanced (Taneja *et al*., 2020). The most common method of lameness detection is ad hoc observation during other activities as herding (Flower and Weary, 2006; Fabian *et al*., 2014). However, Ad hoc detection is ineffective at detecting mild and even moderate lameness and this underscores the need for measurement (O'Leary *et al*., 2020). The current gold standard for the detection of lameness in dairy cows is the clinical observation by a trained professional (Alsaaod *et al*., 2017). Studies on validity of gait scoring systems report poor relationship between scores and measures of hoof and leg injuries or disease (Flower and Weary, 2006). A lack of agreement between observers has also been reported; O'Callaghan *et al*. (2003), found only 37% agreement in the score of 2 observers, and Winckler and Willen (2001) found 68% agreement among scores of 3 observers. The estimated cost of lameness varies between cost and pathology (O'Leary *et al*., 2020). Dolecheck and Bewley (2018), estimated the cost of a foot rot case at $136 on the lower side and a sole ulcer case at $960 on the higher side. The economic viability of lameness detection depends on not just on low cost and high accuracy, but also on willingness to promptly treat cow identified as lame (Van De Gucht *et al*., 2017).

Lame cows tend to lie down for longer and generally have fewer but longer lying bouts, rumination and eating, activity measurement via leg worn and neck worm accelerometers (Thorup *et al*., 2015; Weigele *et al*., 2018). Alsaaod *et al*. (2017), detected unilateral hind limb lameness and foot pathologies in dairy cattle. They concluded that use of accelerometers with a high sampling rate (400 Hz) at the level of the MT is a promising tool to indirectly measure the kinematic variables of the lateral claw and to detect unilateral hind limb lameness and hind limb pathologies in dairy cows and is highly accurate. Flower and Weary (2006), split gait into six attributes: back arch, head bob, tracking up, joint flexion, asymmetric gait, and reluctance to bear weight and assessed using a continuous 100 –unit scales.

Mastitis

Observation of clots by use of a strip cup, swollen or heated udders and behaviour change are the commonly used methods for mastitis detection (Mottram, 2016). However, because large herd sizes, and the fact that the farmer cannot always be available to check the process visually, this has to be replaced by an automatic mastitis detection system which measure certain attributes of milk for example electric conductivity (EC), colour of milk, milk yield, and an algorithm that transforms data into alerts (Mollenhorst *et al*., 2012). The EC sensors incorporated in Automated Milking Systems (AMS) can continuously measure EC during the milking process and are termed "in line" as they monitor the level of ions in the milk during the milking process, without requiring samples to be collected and analysed (Khatun *et al*., 2017). Interest in adoption of AMS have created the demand for reliable detection of mastitis due to the reduction in time required to identify mastitic cows that need veterinary intervention (Mollenhorst *et al*., 2012).

Previous methods have shown that the use of only (EC) in different detection algorithms was unable to achieve the ISO (2017) standard specificity (>70% and specificity (>99%) for clinical mastitis detection (Khatun *et al*., 2017). Later, Khatun *et al*. (2018) developed and tested multiple measurement approach or index for inline AMS sensors to detect clinical mastitis targeting >80% sensitivity and ≥99% specificity. They reported that, best mastitis prediction was possible by incorporating 6 measurements: quarter level milk yield (MY; kg), electrical conductivity (EC; Ms/cm), average milk flow rate (MF; kg/min), occurrence of incompletely milked quarters in each milking session (IM; yes or no), MY per hour (MYH; kg/h), and EC per hour (ECH; Ms/cm/h) between successive milking sessions. The model achieved 90% sensitivity and 91% specificity and was able to detect clinical mastitis 1 -3 days before actual diagnosis of clinical mastitis.

Farmers on average prefer a clinical mastitis detection system that produces a low number of false alerts, while alerting in good time ad with emphasis on the more severe cases Mollenhorst *et al*., 2012). Iraguha *et al*. (2017) tested the specificity and sensitivity of four subclinical mastitis diagnostic tests (the UdderCheck® a lactate dehydrogenase-based test, the California Mastitis Test (CMT), Draminski® a conductivity-based test and the PortaSCC® a portable somatic cell count test) on crossbreed dairy cows using PortaSCC® as a reference. Sensitivity and specificity were 88.46% and 86.17% (CMT), 78.5% and 81.4% (Draminski®) and 64.00% and 78.95% (UdderCheck®).

Fertility

Detection of oestrus is a key determinant of profitability of dairy herds, but oestrus is increasingly difficult to observe in the modern dairy cow with shorter duration and less intense oestrus (Homer *et al*., 2013). Cow fertility is influenced most by management. It is estimated that inaccurate oestrus detection and infertility costs the dairy industry $360 per missed oestrus (Lucy, 2001; De Vries, 2006). Studies have shown that 32% of oestrus in cows is not detected by herdsmen and between 5 and 21% of cows are inseminated at the wrong time (Claus *et al*., 1983). Standing to be mounted is often construed as the gold standard. A high level of success rate of up to 89% in oestrus detection by experienced herdsmen has been reported (Hempstalk *et al*., 2013). Automated technologies have been developed to obviate the need for visual observation (Homer *et al*., 2013). Cows in oestrus exhibit different behavioural and hormonal signals which may be measured externally (Mottram, 2016).

Milk temperature has been used as a technique of detecting oestrus in cattle (Maatje *et al*., 1987) with a specificity and sensitivity of 74% %. McArthur *et al*., 1992 studied the use of milk temperature for detecting oestrus in dairy cattle. Measurements were made in both experimental (well controlled) and commercial conditions. Milk temperature was measured twice daily during milking. Milk temperature increased by 0.4°C on the day of behavioural oestrus. On commercial farm, milk temperature profiles were obtained for 18 postpartum cows which exhibited a total of 34 periods of oestrus. From their results, 50% true positives could be identified when 0.3°C elevation in above average for the previous 5 days (morning and afternoon profiles considered separately) and 81% false positives. They concluded that the twice measurement of milk temperature is not a reliable method for detecting oestrus in cattle.

A decrease in vaginal temperature by 1.0 to 1.6°C the day before oestrus and a similar increase after the day of ovulation has been reported (Wren *et al*., 1958; Redden *et al*.,1993). Sakatani *et al*., 2016) compared the use of vaginal temperature and pedometers in oestrus detection in Japanese black cows. They observed that the oestrus detection of the pedometer was lower in summer and lower than that obtained using vaginal temperature. The study concluded that oestrus detection using body temperature especially measurement of the vaginal temperature could be effective throughout the year. Recently Higaki *et al*. (2019), evaluated the effectiveness of oestrus detection techniques based on continuous measurement of vaginal temperature and conductivity with supervised machine learning in cattle. They observed that detection model with features from either temperature or conductivity alone was not efficient. Best detection model was developed from features from both temperature and conductivity. Of 17 estruses, 16 were detected, with 1 false positive when the best model was used. Implying that oestrus can be detected real-time by this technique.

Automated oestrus detection and pregnancy diagnosis

Use of direct measurable indicators of a condition rather than proxy measures has been recommended (Mottram, 2016), for objectivity. Since the advent of cheap tri-axial accelerometers and digital signal processor chips the collar can detect oestrus, behaviour, lameness, location and with the collection of audio data rumination and feeding activities (Mottram, 2016). Quantifying behaviour and physiological variables with automated oestrus detection improves oestrus detection rates (Stevenson *et al*., 2014; Mayo *et al*., 2019), compared with visual observation. In a study by Stevenson *et al*. (1996) to compare oestrus detection by observation and radiotelemetry, it was observed that visual observation failed to detect 11 of 41 heifers (37%) that were detected by the radio telemetric device. The goal of continuous monitoring with automated systems is to detect animals in oestrus to predict ovulation time (Mayo *et al*., 2019). Predictors of ovulation time should have high sensitivity (89%) for detecting behaviours by 18 hours before ovulation (Trimberger, 1948). Artificial Insemination based on detection of oestrus plays an important role in overall reproductive management program on most dairies in the United States (Caraviello *et al*., 2006).

Rudimentary and invasive methods of pregnancy diagnosis like rectal palpation are too invasive. Ultrasound examination and endocrine testing are fairly less invasive and cause no trauma. Long calving intervals is the cost of inadequacies in flawed pregnancy diagnosis approaches. With PLF technologies, physiological and behavioural animal variables can be continuously monitored non – invasively using image and sound analysis from cameras and microphones respectively (Norton *et al*., 2019).

Novel traits

Novel measurements such as rumination time, eating time, lying behaviour, ultra-wide band technology to measure mounting and standing to be mounted behaviour and infrared thermography to measure temperature are being studied to further aid oestrus detection (Roelofs *et al*., 2004). A novel approach for detection of oestrus using ultra-wide band technology (UWB) was reported by Homer *et al*. (2013). The UWB technology accurately detected 9 out of 10 cows in oestrus and correctly confirmed all 6 cows not in oestrus. Ultra- wide band technology provides acuminous method of detection, operating 24 h per day, accurately detecting cows in oestrus and reporting the optimal time for AI.

In a recent study by Mayo *et al*. (2019), Oestrus detection by precision dairy monitoring technology (PDMT), an oestrus behaviour scoring system, and by visual observation of standing oestrus were compared with reference (gold) standard. Only 56% of cows that ovulated were observed standing by visual observation. These points out challenges of silent ovulation. In a review by Mottram (2016), it was argued that pedometers are not capable of providing completely reliable detection. However, monitoring the intensity of oestrus could be used to predict super ovulatory response as well as embryo quality in Holstein heifers (Madureira *et al*., 2020).

Freemartins

Freemartin is by definition, a genetically female foetus masculinised in the presence of a male co-twin, giving rise to a sterile heifer (Esteves *et al*., 2012). However, studies have shown that about 10% of heterosexual twin females are not sterile, develop correctly and can be considered for breeding (Esteves *et al*., 2012; Qiu *et al*., 2018). Freemartinism is diagnosed by physical examination, external genitalia commonly present enlarged clitoris, small vulva and a prominent, male like tuft hair (ESteves *et al*., 2012). The general rule has been that heifers born twin to a bull have to be considered sterile and should be identified as early as possible. However, ambiguity in diagnosis of freemartins has been reported (Szczerbal *et al*., 2021). According to Qiu *et al*. (2018), quantifying SRY gene by qPCR is a better detection method for diagnosis of freemartin in Holstein cattle as compared to qualitative detection of SRY gene by PCR or quantitative detection of H-Y antigen.

Using cytogenetic and molecular techniques, Kozubska-Sobocin´ska *et al*. (2019) estimated the most precise and effective diagnostic method especially useful for identification of freemartinism in young female calves. In that experiment 12.5% of the calves were found to be potentially fertile heifers which can qualify for further breeding. They concluded that precise and early identification of freemartinism can be the basis for guideline and selection recommendations concerning the reproductive performance of heifers born from heterosexual multiple pregnancies.

Birth

Up to one third of calves on farms are born following dystocia and are at risk of increased disease and mortality (Barrier *et al*., 2013). Ability to predict calving time would enable prophylactic measures to adjust diets and management to reduce problems (Mottram, 2016). Manual rectal palpation is one of the methods used for predicting calving. It entails assessing the position, size, and tone of the uterus, presence, and size of placentomes and foetus, and size and feel of the middle uterine arteries and comparing these with expected findings for pregnancies of various ages (Riding *et al*., 2008). In a study by Matthews and Morton (2012) calving dates were predicted with modest accuracy using rectal palpation assisted by artificial insemination dates; 81% of study cows calved within 10 days of their predicted calving date. Accuracy was high when were between 8 – 14 compared with 7 or 15, weeks of gestation with 87% of these cows calving within 10 days of their predicted calving date. Currently, physiological signs predictive of calving include pelvic ligament relaxation, udder distention, teat filling, vaginal discharge, vulva oedema (Miedema *et al*., 2011; Streyl *et al*., 2011), which are basically subjective. Most accurate and sensitive methods to date for prediction of calving within 24 hours are the measurements of pelvic ligament relaxation and assays for circulating progesterone and oestradiol-17β (Saint-Dizier and Chastant-Maillard, 2015).

Environmental sustainability of Precision livestock farming

Concerns on the negative impact of livestock production systems on animal welfare and environmental impact have led to increasing interest in digitalization of animal agriculture through precision livestock farming (Klerkx *et al*., 2019). Environmental problems emanate from greenhouse gas emissions and nitrogen excretion from ruminant production. Objective digital technologies could mitigate against the impact of livestock production systems on the environment. For example, Biometric real-time sensors are being exploited as accurate, non-invasive, and inexpensive technique for estimating methane emissions on farm (Munoz-Tamayo *et al*., 2019). Circular bioeconomy livestock focus could be another avenue of reversing the negative environmental effects of current animal agriculture practices. Including environmental traits and their economic weights in the dairy cattle breeding goal is one of the remedies to ensure environmental sustainability. A combination of biometric sensors, big data, artificial intelligence, and bioinformatics technologies can aid to identify and select candidates with desirable traits for breeding programs

Conclusion and Recommendations

This study highlighted key areas where digital technologies are currently applicable as far as animal agriculture is concerned. It is evident that digitalization of animal agriculture not only improves efficiency of production but also caters for animal welfare and environmental sustainability. Although the proportion of farmers using technology in the tropics is relatively low at the moment, in the near future, it will be widespread. Cost implications, low level of production of genotypes kept and lack of awareness are some of the likely reasons for low rate of use of objective measures in dairy cattle. Besides that, the low stocking densities, and low production per animal in the tropics, could be some of the factors slowing down adoption rates of precision livestock farming technologies. There is need for further study to assess digital technologies (objective measures) for improved animal monitoring and where they work best in the developing countries. Secondly objective measuring tools that create more sustainable production systems in Africa need to be identified.

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Conflict of interest

There is no conflict of interest

References

Alsaaod, M., Fadul, M., Deiss, R., Bucher, E., Rehage, J., Guccione, J.,

Steiner, A., 2019. Use of validated objective methods of locomotion characteristics and weight distribution for evaluating the efficacy of ketoprofen for alleviating pain in cows with limb pathologies. Plos one 14, e0218546.
Alsaaod, M., Luternauer, M., Hausegger, T., Kredel, R., Steiner, A., 2017. The cow pedogram—Analysis of gait cycle variables allows the detection of lameness and foot pathologies. J. Dairy Sci. 100, 1417-1426.
Barrier, A.C., Haskell, M.J., Birch, S., Bagnall, A., Bell, D.J., Dickinson., Macrae, A.I., Dwyer, C.M., 2013. The impact of dystocia on dairy calf health, welfare, performance and survival. Vet. J. 195, 86-90.
Bell, M.J., Comber, A., 2020. Editorial: Smarter Farming: New Approaches for Improved Monitoring, Measurement and Management of Agricultural Production and Farming Systems. Frontiers in Sustainable Food Systems 4, 121.
Bell, M.J., Maak, M., Sorley, M., Proud., R., 2018. Comparison of methods for monitoring the body condition of dairy cows. Frontiers in Sustainable Food Systems 2, 80.
Bell, M.J., Tzimiropoulos, G., 2018. Novel monitoring systems to obtain dairy cattle phenotypes associated with sustainable production. Frontiers in Sustainable Food Systems 2, 31
Benjamin, M., Yik, S., 2019. Precision livestock farming in swine welfare: a review for swine practitioners. Animals 9, 133.
Bewley, J.M., Peacock, A.M., Lewis, O., Boyce, R.E., Roberts, D.J., Coffey, M.P., Kenyon, S.J., Schutz, M.M., 2008. Potential for estimation of body condition scores in dairy cattle from digital images. J. Dairy Sci. 91, 3439-3453.
Borchers, M.R., Chang, Y.M., Proudfoot, K.L., Wadsworth, B.A., Stone, A.E., Bewley, J.M., 2017. Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle. J. Dairy Sci. 100, 5664-5674.
Britt, J.H., Cushman, R.A., Dechow, C.D., Dobson, H., Humblot, P., Hutjens, M.F., Jones, G.A., Ruegg, S., Sheldon, I.M., Stevenson J.S., 2018. Invited review: Learning from the future—A vision for dairy farms and cows in 2067. J. Dairy Sci. 101, 3722-3741.
Caraviello, D.Z., Weigel, K.A., Fricke, P.M., Wiltbank, M.C., Florent, M.J., Cook, N. B., Nordlund, K.V., Zwald, N.R., Rawson, C.L., 2006. Survey of management practices on reproductive performance of dairy cattle on large US commercial farms. J. Dairy Sci. 89, 4723–4735.
Chagas, L.M., Bass, J.J., Blache, D., Burke, C.R., Kay, J.K., Lindsay, D.R, Lucy, M.C., Martin, G.B., Meier, S., Rhodes, F.M., Roche, J. R., Thatcher, W.W., Webb, R., 2007. Invited review: New perspectives on the roles of nutrition and metabolic priorities in the subfertility of high-producing dairy cows. J. Dairy Sci. 90, 4022-4032.
Claus, R., Karg, H., Zwiauer, D., von Butler, I., Pirchner, F., Rattenberger, E., 1983. Analysis of factors influencing reproductive performance of the dairy cow by progesterone assay in milk-fat. Br. Vet. J. 139, 29–37.
De Vries., A., 2006. Economic value of pregnancy in dairy cattle. J. Dairy Sci. 89, 3876-3885.
Dolecheck, K., Bewley, J., 2018. Animal board invited review: Dairy cow lameness expenditures, losses and total cost. Anim. 12, 1462-1474.
Domecq, J.J., Skidmore, A.L., Lloyd, J.W., Kaneene, J.B., 1995. Validation of body condition scores with ultrasound measurements of subcutaneous fat of dairy cows. J. Dairy Sci. 78, 2308-2313.
Edmonson, A.J., Lean, I.J., Weaver, L.D., Farver, T., Webster, G., 1989. A body condition scoring chart for Holstein dairy cows. J. Dairy Sci. 72, 68-78.
Egger-Danner, C., Cole, J.B., Pryce, J.E., Gengler, N., Heringstad, B., Bradley, A., Stock, K. F., 2015. Invited review: overview of new traits and phenotyping strategies in dairy cattle with a focus on functional traits. Anim. 9, 191-207.
Esteves, A., Båge, R., Payan-Carreira, R., 2012. Freemartinism in cattle. Ruminants: Anatomy, Behavior and Diseases, (Marques, R.E., Ed.), 99-120.
Fabian, J., Laven, R.A., Whay, H.R., 2014. The prevalence of lameness on New Zealand dairy farms: A comparison of farmer estimate and locomotion scoring. Vet. J. 201, 31-38.
Flower, F.C., Weary, D.M., 2006. Effect of hoof pathologies on subjective assessments of dairy cow gait. J. Dairy Sci. 89, 139-146.
Groher, T., Heitkämper, K., Umstätter, C., 2020. Digital technology adoption in livestock production with a special focus on ruminant farming. Anim. 14, 2404-2413.
Hempstalk, K., Burke, C.R., Kamphuis, C., 2013. Brief communication: Verification of an automated camera-based system for oestrus detection in dairy cows. In: Proceedings of New Zeland Society of Animal Production, Hamilton, New Zealand, pp. 1-3.
Higaki, S., Miura, R., Suda, T., Andersson, L.M., Okada, H., Zhang, Y., Yoshioka, K., 2019. Oestrous detection by continuous measurements of vaginal temperature and conductivity with supervised machine learning in cattle. Theriogenology 123, 90-99.
Homer, E.M., Gao, Y., Meng, X., Dodson, A., Webb, R., Garnsworthy, P.C., 2013. A novel approach to the detection of oestrus in dairy cows using ultra-wideband technology. J. Dairy Sci. 96, 6529-6534.
Ingram, J., Maye, D., 2020. What are the implications of digitalisation for agricultural knowledge?. Front. Sustain. 4, 66.
Iraguha, B., Hamudikuwanda, H., Mushonga, B., Kandiwa, E., Mpatswenumugabo, J.P., 2017. Comparison of cow-side diagnostic tests for subclinical mastitis of dairy cows in Musanze district, Rwanda. J. S. Afr. Vet. Assoc. 88, 1-6.
Khatun, M., Clark, C.E., Lyons, N.A., Thomson, P.C., Kerrisk, K.L., García, S.C., 2017. Early detection of clinical mastitis from electrical conductivity data in an automatic milking system. Anim. Prod. Sci. 57, 1226-1232.
Khatun, M., Thomson, P.C., Kerrisk, K.L., Lyons, N.A., Clark, C.E.F., Molfino, J., García, S.C., 2018. Development of a new clinical mastitis detection method for automatic milking systems. J. Dairy Sci. 101, 9385-9395.
Klerkx, L., Jakku, E., Labarthe, P., 2019. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS-WAGEN J. Life Sc. 90, 100315.
Kozubska-Sobocińska, A., Smołucha, G., Danielak-Czech, B., 2019. Early Diagnostics of Freemartinism in Polish Holstein-Friesian Female Calves. Animals 9, 971.
Lucy, M.C., 2001. Reproductive loss in high-producing dairy cattle: where will it end?. J. Dairy Sci. 84, 1277-1293.
Maatje, K., Rossing, W., Wiersma, F., 1987.Temperature and activity measurements for oestrus and sickness detection in dairy cattle. In: Proceeding of 3rd Symposium Automation in Dairying, Wageningen, The Netherlands, pp. 9-11.
Madureira, A.M.L., Burnett, T.A., Pohler, K.G., Guida, T.G., Sanches Jr.C.P., Vasconcelos, J.L.M., Cerri, R.L.A., 2020. Greater intensity of estrous expression is associated with improved embryo viability from superovulated Holstein heifers. J. Dairy Sci. 103, 5641-5646.
Matthews, B.J., Morton, J.M., 2012. Accuracy of predicted calving dates in Holstein-Friesian dairy cows based on foetal ages estimated using manual rectal palpation. N. Z. Vet. J. 60, 234-240.
Mayo, L.M., Silvia, W. J., Ray, D.L., Jones, B. W., Stone, A.E., Tsai, I.C., Clark, J.D. Bewley, J.M., Heersche, Jr.G., 2019. Automated oestrous detection using multiple commercial precision dairy monitoring technologies in synchronized dairy cows. J. Dairy Sci. 102, 2645-2656.
McArthur, A.J., Easdon, M.P., Gregson, K., 1992. Milk temperature and detection of oestrus in dairy cattle. J. Agric. Eng. Res. 51, 29-46.
Miedema, H.M., Cockram, M.S., Dwyer, C.M., Macrae, A.I., 2011. Behavioural predictors of the start of normal and dystocic calving in dairy cows and heifers. Appl. Anim. Behav. Sci. 132, 14-19.
Mollenhorst, H., Rijkaart, L.J., Hogeveen, H., 2012. Mastitis alert preferences of farmers milking with automatic milking systems. J. Dairy Sci. 95, 2523-2530.
Mottram, T., 2016. Animal board invited review: precision livestock farming for dairy cows with a focus on oestrus detection. Anim. 10, 1575-1584.
Munoz-Tamayo, R., Agudelo, J.R., Dewhurst, R.J., Miller, G., Vernon, T., Kettle, H., 2019. A parsimonious software sensor for estimating the individual dynamic pattern of methane emissions from cattle. Anim. 13, 1180-1187.
Neethirajan, S., Kemp, B., 2021. Digital Livestock Farming. Sens. Biosensing Res. 100408.
Norton, T., Chen, C., Larsen, M.L.V., Berckmans, D., 2019. Precision livestock farming: Building 'digital representations' to bring the animals closer to the farmer. Anim. 13, 3009-3017.
O'Callaghan, K.A., Cripps, P.J., Downham, D.Y., Murray, R.D., 2003. Subjective and objective assessment of pain and discomfort due

to lameness in dairy cattle. Animal Welfare 12, 605-610.

O'Leary, N. W., Byrne, D.T., O'Connor, A.H. Shalloo, L., 2020. Invited review: Cattle lameness detection with accelerometers. J. Dairy Sci. 103, 3895-3911.

Qiu, Q., Shao, T., He, Y., Cao, B., Su, H., 2018. Applying real-time quantitative PCR to diagnosis of freemartin in Holstein cattle by quantifying SRY gene: a comparison experiment. Peer J. 6, e4616.

Redden, K.D., Kennedy, A.D., Ingalls, J.R., Gilson, T.L., 1993. Detection of estrus by radiotelemetric monitoring of vaginal and ear skin temperature and pedometer measurements of activity. J. Dairy Sci. 76, 713-721.

Riding, G.A., Lehnert, S.A., French, A.J., Hill, J.R., 2008. Conceptus-related measurements during the first trimester of bovine pregnancy. Vet. J. 175, 266-272.

Roche, J.R., Friggens, N.C., Kay, J.K., Fisher, M.W., Stafford, K.J., Berry, D.P., 2009. Invited review: Body condition score and its association with dairy cow productivity, health, and welfare. J. Dairy Sci. 92, 5769-5801.

Roelofs, J.B., Bouwman, E.G., Dieleman, S.J., Van Eerdenburg, F.J., Kaal-Lansbergen, L.M., Soede, N.M., Kemp, B., 2004. Influence of repeated rectal ultrasound examinations on hormone profiles and behaviour around oestrus and ovulation in dairy cattle. Theriogenology 62, 1337–1352.

Saint-Dizier, M., Chastant-Maillard, S., 2015. Methods and on-farm devices to predict calving time in cattle. Vet. J. 205, 349-356.

Sakatani, M., Takahashi, M., Takenouchi, N., 2016. The efficiency of vaginal temperature measurement for detection of estrus in Japanese Black cows. J. Reprod. Dev. 62, 201-207.

Shepherd, M., Turner, J. A., Small, B., Wheeler, D., 2020. Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture'revolution. J. Sci. Food Agric. 100, 5083-5092.

Song, X., Bokkers, E.A.M., van Mourik, S., Koerkamp, P.G., van der, Tol, P.P.J., 2019. Automated body condition scoring of dairy cows using 3-dimensional feature extraction from multiple body regions. J. Dairy Sci. 102, 4294-4308.

Stevenson, J.S., Hill, S., Nebel, R., DeJarnette, J., 2014. Ovulation timing and conception risk after automated activity monitoring in lactating dairy cows. J. Dairy Sci. 97:4296–4308.

Stevenson, J.S., Smith, M.W., Jaeger, J.R., Corah, L.R., LeFever, D.G., 1996. Detection of estrus by visual observation and radio telemetry in peripubertal, estrus-synchronized beef heifers. J. Sci. Food Agric. 74, 729-735.

Streyl, D., Sauter-Louis, C., Braunert, A., Lange, D., Weber, F., Zerbe, H., 2011. Establishment of a standard operating procedure for predicting the time of calving in cattle. J. Vet. Sci. 12, 177-185.

Szczerbal, I., Komosa, M., Nowacka-Woszuk, J., Uzar, T., Houszka, M., Semrau, J., Musial, M., Barczykowski, M., Lukomska M., Switonski, M., 2021. A Disorder of Sex Development in a Holstein–Friesian Heifer with a Rare Mosaicism (60, XX/90, XXY): A Genetic, Anatomical, and Histological Study. Animals 11, 285.

Taneja, M., Byabazaire, J., Jalodia, N., Davy, A., Olariu, C., Malone, P., 2020. Machine learning based fog computing assisteddata-driven approach for early lameness detection in dairy cattle. Comput Electron Agric. 171, 105286.

Thorup, V.M., Munksgaard, L., Robert, P.E., Erhard, H.W., Thomsen, P.T., Friggens, N.C., 2015. Lameness detection via leg-mounted accelerometers on dairy cows on four commercial farms. Anim. 9, 1704-1712.

Trimberger, G.W., 1948. Breeding efficiency in dairy cattle from artificial insemination at various intervals before and after ovulation. Research Bulletin: Bulletin of the Agricultural Experiment Station of Nebraska No. 153.

Van De Gucht, T., Saeys, W., Van Nuffel, A., Pluym, L., Piccart, K., Lauwers, L., Vangeyte, J., Van Weyenberg, S., 2017. Farmers' preferences for automatic lameness-detection systems in dairy cattle. J. Dairy Sci. 100, 5746-5757. `

Van Nuffel, A., Zwertvaegher, I., Pluym, L., Van Weyenberg, S., Thorup, V.M., Pastell, M., Saeys, W., 2015. Lameness detection in dairy cows: Part 1. How to distinguish between non-lame and lame cows based on differences in locomotion or behaviour. Animals 5, 838-860.

Weigele, H.C., Gygax, L., Steiner, A., Wechsler, B., Burla, J.B., 2018. Moderate lameness leads to marked behavioural changes in dairy cows. J. Dairy Sci. 101, 2370-2382.

Werkheiser, I., 2020. Technology and responsibility: a discussion of underexamined risks and concerns in precision livestock farming. Anim. Front. 10, 51-57.

Winckler, C., Willen, S., 2001. The reliability and repeatability of a lameness scoring system for use as an indicator of welfare in dairy cattle. Acta Agric Scand A Anim. Sci. 51, 103-107.

Wrenn, T.R., Bitman, J., Sykes, J.F., 1958. Body temperature variations in dairy cattle during the oestrous cycle and pregnancy. J. Dairy Sci. 41, 1071-1076.