The use of advanced technology to enhance monitoring of dairy cow health

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Declaration

I hereby declare that this thesis is of my own composition and that all assistance has been duly acknowledged. The results presented herein have not been previously submitted for any other degree or qualification.

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Abstract

The UK trend of increasing dairy herd size and milk yield per cow has generated challenges for dairy farmers, namely in the realm of cow health and herd management. Technology has the potential to facilitate livestock production, however the uptake of cow monitoring technologies within the UK has not been widely researched. There are key periods within the life of a cow where high levels of cow monitoring are required, for example calving, and technology has the potential to aid farmers with cow management. Calving cows require regular observation as it is a period of high risk for cow and calf; two common issues at calving are calving difficulty (dystocia) and calf mortality. However as average herd size increases, farm staff are under pressure to manage their time effectively and calving presents a management challenge. In the period surrounding calving, cows are susceptible to a range of disorders such as hypocalcaemia – a metabolic disorder which can be fatal. Automated systems could be used to detect calving and clinical hypocalcaemia on commercial dairy farms to help facilitate herd management and improve cow health and welfare.

The first study was a survey investigating the prevalence and use of automated cow technologies was completed by 122 UK dairy farmers. The results showed that approximately 3 in 5 dairy farmers utilised automated cow monitoring technology, and the main parameters that were monitored on UK dairy farms were heat detection, daily milk yield, and illness detection. Half of dairy producers that do not have automated cow monitoring technology installed will invest within the next 5 years, and it is therefore expected that the prevalence of automated cow technologies will increase. Results indicated that dairy producers were satisfied with automated cow monitoring technology on their farms. The main barrier to adoption of technology was initial investment cost.

The second study investigated the behavioural changes of eutocic and dystocic dairy cows in late gestation and on the day of calving. An accelerometer was attached to the hind leg of dairy cattle to collect lying and activity behavioural data. Data were collected from 32 multiparous and 12

primiparous Holstein dairy cattle to describe normal calving behavior and parity differences. To quantify behaviour related to calving difficulty, the data from 14 animals that had dystocia at calving were matched to cows that had an eutocic calving based on parity, locomotion score, calf breed, calf sex, month, and year of calving. Retrospective analysis was conducted on lying and activity data in the period before calving (d -4 to d -1) and on the day of calving (d 0). Findings suggest that cow behaviour on the day of calving was significantly different when compared to a non-calving control period (d -4). Important differences were found in the behaviour of primiparous and multiparous cows during the period prior to calving. In addition, the days relative to calving were found to affect activity behaviours. Three different types of machine learning methods (random forest, decision tree, and neural network) were unable to successfully use behavioural changes to classify the day before calving or the 2h period before calving. There was no difference in the behaviour between 14 cows with assisted calvings (dystocic) and 14 cows with non-assisted calvings (eutocic).

The third study was designed to describe and quantify any behavioural differences between cows diagnosed with normocalcaemia, subclinical hypocalcaemia, and clinical hypocalcaemia at calving. A total of 51 multiparous cows and 21 primiparous cows were categorised as having either clinical hypocalcaemia, subclinical hypocalcaemia, or normocalcaemia at calving. Lying and activity behaviours of multiparous and primiparous cows within each blood calcium category was assessed for differences. In the 14 d before calving, multiparous cows with normocalcaemia had fewer lying and standing bouts compared to multiparous cows with subclinical hypocalcaemia and clinical hypocalcaemia. In addition, the step count of primiparous cows with normocalcaemia decreased across the period. These results suggested behaviour could be used to categorise cows into blood calcium group categories prior to calving. Cows that had clinical hypocalcaemia at calving were less active and lay down more in the 21 d post-calving. This finding suggests that the effect of hypocalcaemia on cow behaviour was long lasting.

Overall, this thesis has shown that the use of remote sensing technology can be used to detect behavioural changes associated with calving and hypocalcaemia. These findings could be used to develop automated detection systems for calving and hypocalcaemia which could aid dairy producers in herd and cow health management. In addition, a survey of UK dairy farmers has shown that farmers are willing to invest in cow monitoring technology and 68% surveyed farmers would invest in the next 5 years. Return on investment was considered the most important criteria when selecting a technology for purchase. Therefore, it is important that technology companies can prove the monetary and non-monetary benefits of technologies.

Lay Summary

Cows are required to give birth to initiate milk production. However calving cows need regular observation. Common issues at calving include birthing difficulties and health disorders such as low blood calcium levels. In the UK, increased dairy cow herd size and milk yield can lead to herd management and cow health issues. Farm staff are under increasing pressure as the number of cows within their care increases. Automated cow behavioural monitoring systems could be used to aid dairy producers in both cow and health management.

This study assessed the use of automated cow monitoring systems on 122 UK dairy farms and assessed the ability of an automatic behavioural monitor to identify behavioural changes relating to calving and low blood calcium levels. The results show that 3 in 5 dairy farms use automated cow monitoring technology. Of the farms that did not use technology, half of these farms were willing to invest in the next 5 years. Financial implications were cited as the main reason farms had not invested in technology. Overall, technology was viewed positively by dairy farmers.

Important differences in the behaviour of first calving cows and older cows were found in the period before calving. On the day of calving, cow activity increased, lying time decreased, and the number of lying and standing bouts increased. Calcium status at calving was found to affect behaviour before calving for both first calving cows and older cows. Cows giving birth to their first calf which had normal blood calcium had a reduced activity in the pre-calving period. For older cows, low blood calcium status at calving reduced their activity and increased their lying time in the period after calving. This suggests that low blood calcium had a prolonged effect on cow behaviour after calving.

The behavioural changes identified in the period preceding calving and the diagnosis of low blood calcium have the potential to be used in the creation of

automated detection systems. These systems could be used by dairy producers to improve the management of their cows and cow health.

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Chapter 1 Introduction

1.1 General introduction

Dairy farming is the utilisation of lactating animals, predominately dairy cattle, to produce milk for liquid consumption and the manufacture of other dairy products. In 2018, dairy cows produced 81.0% of the world's milk supply, with the remaining 19.0% supplied by buffalo (15.1%), goat (2.2%), sheep (1.3%), and camel (0.4%) (FAO, 2020). By 2050, world population is anticipated to have increased by one third to reach 9.1 billion (FAO, 2009), and to sustain this population, food production must increase by 70% whilst coping with a decrease in the land available for food production (Britt et al., 2018). The demand for dairy products is projected to increase substantially by 2050 (Alexandratos and Bruinsma, 2012), and projections show that annual dairy intake (liquid milk equivalents) will increase from 87 kg per person to 119 kg per person by 2067 (Britt et al., 2018).

In the United Kingdom (UK), dairy farms are intensifying. The average herd size has nearly doubled, increasing from an average of 75 to 148 cows per herd between 1996 and 2018 (AHDB, 2020a). In the same period, average yield per cow has increased from 5,512 to 7,968 litres per cow per year (AHDB, 2019). Increased dairy consumption and dairy intensification are associated with a plethora of issues which can be divided into four categories: 1) Animal health and welfare; 2) Human health; 3) Economic and social well-being; 4) Environmental concerns (Clay et al., 2020).

The automation of dairy farming has been presented as a farm-level solution to address these key issues (Lovarelli et al., 2020). However, the adoption rate of sensor technology is relatively low, and it is thought dairy farmers are waiting for technology to advance before incorporating it into herd management strategies (Rutten et al., 2018). Further research is required to understand how sensor technology is utilised by dairy farmers in the UK and its ability to detect a change in cow status (e.g. healthy or not healthy, calving or not calving). The purpose of this chapter is to review the literature on precision dairy farming, and to introduce how automated technology could be used in the detection of calving and hypocalcaemia.

1.2 Precision livestock farming

The incorporation and connection of communication and information technologies in agricultural production systems have been called ‘Smart Farming’ (Pivoto et al., 2018), ‘Precision Agriculture’ (Zhang et al., 2002), or ‘Precision livestock farming’ (Tullo et al., 2019). Precision livestock farming has been defined as: “*the application of process engineering principles and techniques to livestock farming to automatically monitor, model and manage animal production”* (Tullo et al., 2019).

According to Norton and Berckmans (2017), precision livestock farming was generated to regularly inform farmers about the productivity, health, and welfare of their livestock, and to allow farmers to make rapid, evidence-based decisions about their animals. Precision livestock farming has presented farmers with new opportunities to capture data, and this ability to capitalise on new information has led to an increase in data driven decision-making on farm (Pham and Stack, 2018).

In recent years, the development of technological systems within agriculture has led to a revolution in the working environment on farms, and the use of technology has become of increasing importance in dairy production systems. As herd size increases and the availability of skilled labour decreases, there is a need to apply user-friendly, automated technology to facilitate herd management (Gargiulo et al., 2018). Britt et al. (2018) states that the adoption of technology could help farmers to address labour shortages, improve cow health and longevity, and maintain a profitable and sustainable dairy farm.

1.3 Automated dairy cow monitoring

Rutten et al. (2013) defined a sensor used for cow management as a device that measures a behavioural or physiological parameter of an individual animal, and alerts the farmer to a change in the status of that animal, which ultimately results in “on farm” detection (Figure 1.1). Sensor technologies have the ability to identify cattle that require attention before human observation, and this mechanism can be used to improve cattle health and welfare.

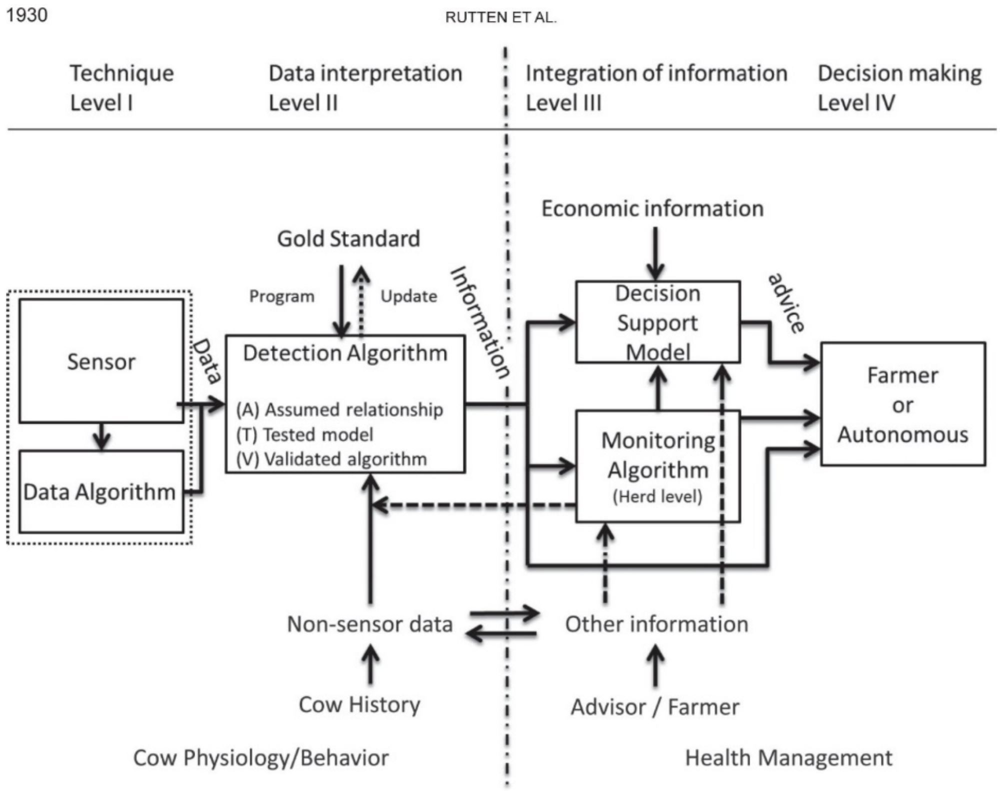


Figure 1.1 A framework to show the use of sensor information to aid in dairy farm management (Rutten et al., 2013).

Sensor technologies allow real-time monitoring of cows using production, physiological, and behavioural parameters. Technologies can be stand alone, integrated into the milking system, wearable, or incorporated into herd management software (Eckelkamp, 2019). Sensors can be attached to the animal, such as rumination collars to record rumination behaviour (Grinter et al., 2019), or accelerometers for oestrus detection (Schweinzer et al., 2019). Telemetric sensors have been developed which can be used to detect rumen acidosis (Mottram et al., 2008), core body temperature (Iwasaki et al., 2019), and heart rate (Signer et al., 2010). Automatic weighing systems have been developed to monitor changes in liveweight (Dickinson et al., 2013), and more recent innovations have seen 3D imagery technology used to monitor cows liveweight, body condition score, and mobility (Hansen et al., 2018). Sensors to quantify milk yield and milk electrical conductivity are available and are being used to predict the onset of disease (Lukas et al., 2009). Sounds, such as tooth grinding or tympanic sounds from the gastrointestinal system, have been recorded and used in the evaluation of dairy cattle pain (Gleerup et al., 2015).

1.3.1 Adoption of technology on dairy farms

Precision livestock technologies can be considered as disruptors. Disruptive technologies are new technologies which disrupt or replace an old one, leaving the original technology obsolete (Love et al., 2020). According to Danneels (2004), disruptive technologies are initially considered unsuitable for the needs of the customer as they only satisfy the needs of a small market share. However, as investments are made (through research and development) and as the technologies mature, the performance of these technologies improve to the point where they can fulfil the requirements of the wider market. These technologies have the potential to transform agricultural systems (Shang et al., 2021).

The use of precision dairy technologies can provide farmers with a solution to improve management of their dairy herd and to adapt to labour shortages (Eastwood et al., 2012). Data from the European Commission (2013) showed that between 2010 and 2013 the number of farms within the European Union decreased by 11.5% (12.0 million to 10.8 million holdings), and the remaining holdings became larger, with the hectares per holding increasing by 12.2%. In the same period, the number of agricultural workers decreased by 12.8%. The trend of increasing farm size (hectares and animals per unit) is coupled with a workforce crisis.

In addition to a reduced workforce, it is reported that UK agriculture is relying on an ageing workforce (median age of 60) with 40% of farm holders 65 years of age or older (Defra, 2019a). Agricultural work is physically and mentally demanding and the jobs available are perceived to be of low appeal by new entrants (Hostiou et al., 2020). Factors that contribute to the negative view of farm work include low wages and repetitive and physically demanding jobs (Marinoudi et al., 2019). Farm worker health and safety are affected by numerous factors such as hazardous working conditions, large workloads, time and weather pressures, lone working, and the handling of machinery and chemicals (Lunner-Kolstrup et al., 2018). The fatality rate of workers within UK agriculture is 18 times higher than the average rate across all other main industrial sectors (Health and Safety Executive, 2019). When job control is low and job demand is high, stress can occur (Hansen and Østerås, 2019). External conditions that can act as stressors for farmers and farm workers include farmgate prices, weather, regulations, disease outbreaks, and societal stance towards farming (Lunner-Kolstrup et al., 2013). A survey of 265 farmers indicated that the main external factors contributing to stress were volume of work, volatility, and animal disease. Severe burnout was reported by 9% of farmers surveyed (Kallioniemi et al., 2016).

In Australia, precision dairy technologies that reduce labour requirements have most commonly been adopted (Gargiulo et al., 2018). This includes technologies such as automatic parlour feeding, milking unit wash systems, and teat cup removers. Although the use of wearable technologies and biosensors on dairy farms has accelerated within the realm of animal management (Neethirajan, 2017), the adoption of sensors by dairy farmers is still relatively low (Rutten et al., 2018). A survey of American dairy farmers in 2013 showed that 31% of respondents (n = 109) did not use a technology on their dairy farm (Borchers and Bewley, 2015). The most common parameters recorded by dairy farmers using technologies were daily milk yield (52%), cow activity for oestrus detection (41%), mastitis detection (26%), and milk components (25%) (Borchers and Bewley, 2015). Other parameters that can be recorded include feeding behaviour, rumen pH, rumination, lameness detection, animal location, body condition score, heart rate, and temperature (Bewley, 2010; Borchers and Bewley, 2015).

Hansen (2015) reported that skilled labour shortages and high wage rates contributed to the adoption of automatic milking systems (AMS) in Norway. Jacobs and Siegford (2012) estimated that there was an 18% labour saving when the milking system was swapped to AMS. In accordance, Bijl et al. (2007)

found farms with AMS used 29% less labour when compared to farms with a conventional milking system. Published figures assessing farm income for 2017/2018 show that, in the UK, 26% of farms failed to post a positive Farm Business Income when unpaid labour was factored in (Defra, 2019b). Technology, such as AMS, has the potential to improve farm profitability by reducing labour requirements.

Lunner-Kolstrup et al. (2018) reported that technology on dairy and arable farms improved the efficiency and accuracy of daily tasks which led to an increase in the time available for leisure. Conversely, Butler et al. (2012) reported that although AMS reduced the time spent milking, overall workload was not reduced, as time was spent completing alternative jobs. Regardless, it is accepted that within agriculture, technology can be used to reduce the effect of physically demanding jobs (Butler et al., 2012; Marinoudi et al., 2019). Incorporating technology on farms can improve working conditions for farm staff and could help change public perception of working conditions within agriculture.

1.3.2 Issues surrounding technology adoption on dairy farms

The installation of precision technologies on dairy farms could lead to a modification in the relationship between farmers and their cattle. Hostiou et al. (2017) summarised that the automation of milking could lead to an increase in the physical distance between animals and farmers. Cattle would move from manual milking twice a day to robotic milking. It was hypothesised that cattle could become more fearful as animals are deprived of human contact. In addition, direct contact between animals and the farmer could be limited to negative interactions; for example vaccination and foot trimming. Many technological systems offer cloud based computing services. However, there are security and privacy issues relating to these facilities (Brewster, 2017). In addition, the ownership and control of farm data is unclear and technology companies may contest farmers having primary control of data on farm. Occasionally technologies require repairs after equipment failures. This could increase the mental workload on farmers (Hostiou et al. 2017).

1.3.3 Behavioural monitoring of dairy cows

Animal behaviour is an important indicator of well-being and health (Weary et al., 2009), and it can be described as the manner in which an animal expresses its ability to interact with its physical environment and other organisms. The change in the behaviour of an animal can be one of the most visible and rapid changes in response to a stressor, such as an alteration in the environment or the function of an animal (Deen, 2010). To better understand the overall health, production, nutrition and management of dairy cows, the monitoring of cow behaviour has increased in importance (Mattachini et al., 2016). Currently, behavioural parameters are used by dairy farmers to provide insights into oestrus events (Shahriar et al., 2016), animal health (Rutten et al., 2013), and feed intake (Greenwood et al., 2017).

Traditionally, cow behaviour has been measured through human observation or video surveillance. However, these methods pose practical issues for implementation on farm. Measuring cow behaviour by video surveillance is time consuming and labour intensive, and direct human observation may alter behavioural outcomes; beef cattle have been observed to alter their behaviour in the presence of a human (Ishiwata et al., 2007). Methods of assessing behavioural activity have changed in recent years, with automatic recording techniques using GPS trackers, accelerometers, proximity loggers, and location sensors favoured over manual scoring (Vázquez Diosdado et al., 2015). In comparison to manual scoring, automated behavioural technologies are less labour intensive, can relay large quantities of data, can provide higher sampling rates, and are less invasive (Krause et al., 2013). The most common method of behavioural monitoring in dairy cows is the use of sensor devices that can be attached to the hind leg or neck of the dairy cow.

In general, devices called accelerometers are used to automatically classify cow behaviours (Vázquez Diosdado et al., 2015). Accelerometers are electrical sensors that measure acceleration (the change in velocity over a known time) across multiple axes (Yang and Hsu, 2010). They can measure inertial acceleration caused by body movement, as well as gravitational acceleration (Brown et al., 2013). This makes accelerometers suitable to monitor animal behaviour, as both postural orientation and activity can be determined from the processed values (Mathie et al., 2004). Accelerometers can collect and store behavioural data using two different methodologies, generally known as 'bio-loggers' or 'bio-telemetry' sensors. Bio-loggers typically store data on an internal memory card and consume little battery power, however the animal needs to be restrained in order to recover the data. Bio-telemetry sensors transmit data to a central data hub; however, this can lead to increased battery drain (Vázquez Diosdado et al., 2015).

1.3.4 Scientific validation of the IceQube

The IceTag and IceQube (IceRobotics, Edinburgh, UK) are triaxial accelerometers that measure movement in three planes (X, Y, and Z) (McGowan et al., 2007; Borchers et al., 2016). The IceQube samples cow behaviour at 4Hz and summarises lying time, standing time, the number of steps, the number of postural transitions from standing to lying, and motion index into 15-minute blocks (Elischer et al., 2013; Borchers et al., 2016). Motion index is the sum of net acceleration measured by the 3-axes minus an offset for gravity, and motion index can be considered an expression of leg activity (Maselyne et al., 2017). Gibbons et al. (2012) reported that there was no effect of IceTag positioning on lying behaviour or on leg health. In accordance, MacKay et al. (2012) also found that there was no effect of the IceTag on lying behaviour or feed intake. It can be concluded that IceTags, or comparable devices such as the IceQube, provide a non-invasive method of remotely and automatically recording animal behaviour. Table 1.1 summarises studies that have validated the IceTag and IceQube as a method of collecting cow behaviour data.

The IceTag's ability to accurately measure cow behaviour was first reported by McGowan et al. (2007). The distribution of each behaviour was compared to timings and frequencies of visual observations. The IceTag recorded all lying bouts within one minute of the visually observed lying bout. Results showed that the IceTag was reliable at recording lying behaviour, step count, and standing behaviour. The IceQube's capability to record lying behaviour has been evaluated and it has been reported to be strongly correlated (r = 0.97; r >0.99) to visually observed behaviour (Elischer et al., 2013; Borchers et al., 2016). Data generated by the IceQube has been found to have moderate to strong correlations between human observations in all categories of behaviour: lying, standing, walking and activity (Elischer et al., 2013). It was further reported that the IceQube generated data accounted for 81 – 94% of the variance of live observations (the gold standard) (Elischer et al., 2013). It can be concluded that previous research has shown that the IceQube can reliably measure dairy cattle behaviour.

Figure 1.2 IceTag (left) and IceQube (right) on the hind leg of adult dairy cows (Photographs courtesy of IceRobotics, 2019).

Table 1.1 A summary of research that has validated the IceTag and IceQube to measure animal behaviour.

Hz[1]	Device dimensions[2]	Sensor	Method of analysis	Behaviours validated	Reference
	190g 96 x 81 x 31 mm	IceTag	IceTags were attached to both hind legs of 16 dairy cattle. Timings and frequencies of observed cow behaviour were compared to sensor-generated data.	Lying, standing, active, lying bouts and number of steps	McGowan et al. (2007)
	197g 65 x 60 x 30 mm	IceTag	IceTags were attached to the inside or the outside of the leg of 24 dairy cattle. The effect of IceTag position on lying behaviour was analysed using a Kruskal-Wallis Test. IceTags were attached to either both hind legs, the right hind leg, the left hind leg or no IceTag was attached (control). The effect of IceTag treatment on lying behaviour was analysed.	No effect of IceTag treatment or position on lying behaviour or on leg health	Gibbons et al. (2012)
8Hz	210g 95 x 85 x 32mm	IceTag	IceTags attached to 12 cows. Observed behaviour was compared to sensor-generated behaviour. The specificity, sensitivity and predicted values were calculated.	Lying and standing behaviour	Mattachini et al. (2013)
4Hz		IceQube	Visually observed behaviour was compared to sensor-generated behaviour for 15 dairy cattle.	Lying, standing, active and number of steps	Elischer et al. (2013)
4Hz	72g 55 x 55 x 26mm	IceQube	IceQubes were attached to 48 dairy cattle. Pearson correlation coefficients was used to compare visual observations and IceQube generated data.	Lying behaviour	Borchers et al. (2016)

[1,2] Where Hz or device dimensions are blank, information for the criteria were missing from studies.

1.4 Introduction to calving

Calving is an essential process in dairy production systems, as it marks the start of lactation. Two common issues at calving are calving difficulty (dystocia) and calf mortality (Mee, 2004). Dystocia (calving difficulty) has been defined as severely assisted foetal extraction or prolonged calving. Dystocia presents a cattle welfare issue as difficult births are classed as one of the most painful conditions that a dairy cow can experience (Huxley and Whay, 2006). It has been reported that 16% of calvings within the UK require assistance (Wall et al., 2010). The increase in average herd size has resulted in an increase in the number of cows to be managed per stockman. This poses a challenge in modern dairy production, as calving requires intensive management and surveillance to maximise cow welfare by establishing whether cows have health or calving issues. An automated calving detection system could facilitate calving management by notifying farm staff when an animal is calving. This would benefit both cow and calf health and welfare. Cow behavioural changes around calving could be used as an indicator of calving and used in the prediction of calving. Therefore, research is required to understand the behavioural changes around calving.

1.5 Issues associated with calving

The timeframe surrounding calving, defined as the transition period, characterises a vulnerable time for the dairy cow (Drackley, 1999). Described as the three weeks pre- and post- calving, the transition period is a period where cows are susceptible to infectious diseases and metabolic health disorders such as hypocalcaemia, metritis, ketosis, retained foetal membrane, displaced abomasum, and laminitis (Huzzey et al., 2007; Mulligan and Doherty, 2008). A successful transition from a state of late pregnancy to early lactation is of great importance for farm profitability and the health and production of dairy cows (Drackley, 1999).

During calving, cows may need to be assisted. Assisted calving is providing timely intervention to prevent dystocia due to secondary uterine inertia and prolonged calving (Mee, 2004). The risk of dystocia has increased with domestication, evolution, and breeding programmes (Mee, 2008a). Figures from an American study investigating 7,380 individual calving events over a one-year period suggest that 36.6% of cows require assistance at calving (Lombard et al., 2007). Only 48.8% of calves born to primiparous cows were reported to be delivered with no assistance, whilst more than two thirds (70.6%) of calves were delivered unassisted from multiparous cows..

Dystocia also has a negative effect on calf health. Mee (2008b) defined perinatal mortality as the death of a calf or foetus within 48 hours after calving at full term (over 260 days), and postnatal mortality has been defined as calf death after the perinatal period until a designated timepoint such as weaning. A study by Barrier et al. (2013) assessed the effect of dystocia on mortality in heifer calves. Calves were categorised into one of three groups depending on the level of assistance given at their birth; 1) no assistance, 2) normally presented but with assistance, 3) malpresented with assistance. The study showed that mortality rates in heifer calves born without assistance was 4.9% compared to 9.4% and 40% for calves that normally presented but with assistance, or malpresented with assistance. Barrier et al. (2013) concluded that calves born from assisted calvings have lower passive immune transfer, and pre-weaning mortality is 2.8 times higher in assisted heifer calves compared to non-assisted heifer calves (Barrier et al., 2013). In support of these findings, Lombard et al. (2007) reported that the risk of a heifer calf having disease was increased by 1.5 when born from an assisted calving. This study also showed that calves born with mild dystocia (intervention by a person without the need for mechanical devices) and calves born with severe dystocia (mechanical or surgical extraction) were 2.3 and 15.4 times more likely to be stillborn compared to calves born with no assistance. Similar findings were reported by Bleul (2011) who reported that the relative risk of normal birth culminating in a stillborn calf was 12.2 times lower compared to a dystocic birth. Dystocia was reported to increase the rate of perinatal mortality, with mortality occurring in 21.0% of dystocic births compared to 1.7% of eutocic births.

1.5.1 The stages of parturition

The process of parturition occurs in three consecutive phases: Stage I, Stage II, and Stage III. Stockmen assess behavioural and physical changes that occur throughout the process to predict when a cow may be about to calve. However, as herd size and time management demands increase this has become increasingly difficult.

Prior to the start of parturition and in the last few weeks of gestation, the cow prepares for the start of lactation and the birth of the foetus. The udder begins to enlarge, and colostrum can be secreted from the udder, which often looks viscous and pale yellow in colour. Udder enlargement can occur at 5 to 6 months of pregnancy for primiparous cows, and usually occurs in the last weeks of gestation for multiparous cows (Norman and Youngquist, 2007). Prior to calving, hormonal changes cause the pelvic ligaments to relax. The tailhead becomes prominent, and the vulva starts to swell. It has been reported that these physical signs differ between individual animals and between successive parturitions, and therefore cannot be used as an accurate prediction of exact calving time (Safdar and Kor, 2014).

The first stage of labour is not externally visible, although many important changes happen which prepare the birth canal and the foetus for imminent birth (Taverne and Noakes, 2019). Mainau and Manteca (2011) state that the first stage of labour includes cervical dilation, the start of myometrial contractions, and the placement of the foetus prior to expulsion. Taverne and Noakes (2019) report that the foetus extends its extremities and rotates about its longitudinal axis. The time a cow spends in the first stage of labour typically takes between 4 and 24 hours (Jackson, 2004), and starts with restless behaviour and ceases with the chorioallantois rupturing (Wehrend et al., 2006). Restlessness behaviour is common during this stage, and it is thought to occur due to the onset of myometrial contractions which cause the cow pain (Taverne and Noakes, 2019).

Stage II is characterised by the appearance of abdominal contractions, and expulsion of the foetus. The foetus is forced against the cervix and this process initiates Ferguson reflex, a neuroendocrine reflex whereby cervical stimulation by the foetus causes oxytocin to be released. A positive feedback mechanism occurs causing additional oxytocin to be secreted, which results in further myometrial contractions (Taverne and Noakes, 2019). The foetus is forced into the pelvic inlet due to myometrial contractions, and this stimulates the pelvic reflex leading to the induction of powerful abdominal muscle contractions. As the foetus moves through the birth canal, oxytocin is released from the posterior pituitary gland further accentuating myometrial contractions, leading to a combination of abdominal and uterine expulsive efforts. It has been reported that cows typically lie down more as the foetus enters the birth canal (Schuenemann et al., 2011). The second stage of labour in eutocic cows typically takes between 38-70 minutes (Schuenemann et al, 2011). Expulsion of the foetus has been reported to take an average of 69.7 minutes from the appearance of the amniotic sac, and 64.6 minutes from the appearance of feet to expulsion of the calf (Schuenemann et al., 2011). These findings suggest that cows should be assisted if there is no calf born after 65 minutes from when the feet appear, or after 70 minutes after amniotic sac appearance.

The third stage of parturition is expulsion of the foetal membranes. This usually lasts 2-6 hours from expulsion of the calf (von Keyserlingk and Weary, 2007). When retention of foetal membranes is above 12 hours, membranes are often retained from between 3 – 10 days unless manually removed (Jackson, 2004).

1.5.2 Dystocia

Dystocia is caused by prolongation of the first or second stage of labour, and assistance is required for delivery (Norman and Youngquist, 2007). There is no uniform method of scoring dystocia. In studies, the scales used to score dystocia are ordinal and linear in progression, and it is generally accepted that the degree of dystocia is determined by the amount of assistance that is given during birth (Schuenemann et al., 2011). The number of categories used to define dystocia varies in studies, and the number of categories ranges from 3

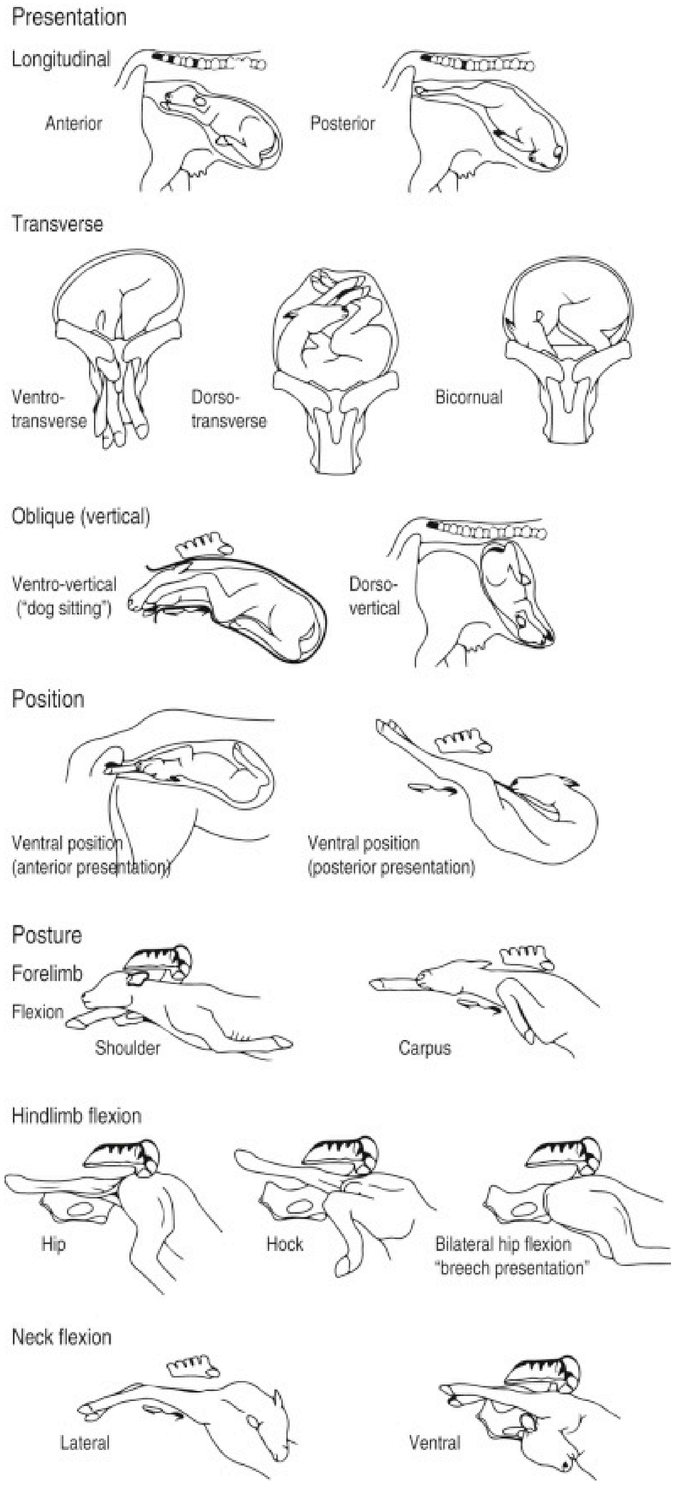
(Meyer et al., 2001) to 6 (Zaborski et al., 2019). The lack of uniformity and definition within the scales makes it difficult to compare findings between studies (Mee, 2008a).

Lombard et al. (2007) used a 1 to 5 scale (1 = no assistance, 2 = intervention by one person without mechanical assistance, 3 = assistance of 2 or more persons, 4 = mechanical assistance, 5 = surgical procedure) to describe the severity of dystocia. The accepted calving scale promoted by the Polish Federation of Cattle Breeders and Dairy Farmers is a 1-6 scale (1 = spontaneous calving, 2 = easy calving, 3 = difficult calving, 4 = a very difficult calving, 5 = an abortion, 6 = Caesarean section; Zaborski et al., 2019). Other studies have used 1 to 3 scale (1 = no assistance, 2 = slight problem, 3 = needed assistance; Meyer et al., 2001). This PhD will use a 1-5 scale (1 = no assistance, 2 = gentle traction by one person with no mechanical device used, 3 = use of calving jack or assistance with two persons, 4 = veterinary assistance, 5 = Caesarean Section) first described by Miedema et al. (2011b).

1.5.3 Causes of dystocia

The incidence of dystocia is influenced by a multitude of factors relating to the dam, calf, and environment. The principle cause of dystocia in dairy cattle is feto-pelvic disproportion which is caused when the foetus is unable to pass through the pelvis to negotiate the birth canal (Mainau and Manteca, 2011). Two determining factors of feto-pelvic disproportion are calf birthweight and dam pelvic size (Mee, 2008a). Johanson and Berger (2003) state that the odds of dystocia increase by 13% by every 1kg increase in calf birthweight, and the odds of dystocia decrease by 11% when the cow pelvic area increases by one square decimeter. The largest influence on calf birthweight is gestation length, which is in turn influenced by sire, dam breed, foetal gender, parity, and maternal nutrition (Mee, 2008a). Male calves are typically 1-3kg heavier than heifers and as a result the odds of dystocia for male calf births are 25% higher (Johanson and Berger, 2003). A study of 14,575 dairy and beef cattle calvings concluded that dystocia was predominately caused by the foetus (657/819 cases; 80.2%) rather than the dam (162/819; 19.8%) (De Amicis et al., 2018).

Another cause of dystocia is abnormal foetal presentation such as cranial malposture, breech malpresentation, or foreleg malposture (Mee, 2008a).



According to Mee (2008a), the prevalence of foetal malpresentation is low (<5%). Figure 1.3 shows abnormal birth positions of calves that require correction before delivery.

Figure 1.3 Abnormal birth positions of calves that require correction before delivery (Parkinson et al., 2019).

Other causes of dystocia include uterine inertia. This occurs when the myometrial contractions are not strong enough to expel the foetus, and it can be caused by imbalances in micronutrients (such as hypocalcaemia) or prolonged calving (Mee, 2008a). According to Jackson (2004), the most common cause of uterine inertia is hypocalcaemia. Incomplete dilation of the cervix (cervical stenosis) and incomplete dilation of the vulva (vulval stenosis) can also occur (Mee, 2008a).

1.5.4 Physiological and behavioural changes prior to parturition

Prior to calving, cows undergo a series of physiological and behavioural changes. Constant surveillance of the calving pen is required to ensure timely intervention where appropriate and it is recommended that cows are checked every 1-6 hours (Gundelach et al., 2009; Mee, 2004). However, according to Villettaz Robichaud et al. (2016), cows are observed 5 times less in the night-time (between evening-milking and morning) compared to daytime. In light of this finding, a system which can indicate and inform stockpersons of a future calving event would be useful. With the advent of cow monitoring technology and machine learning techniques, behavioural and physiological changes prior to calving could be used in the indication of calving. Behavioural changes prior to calving have been documented by numerous studies and are summarised in Table 1.2.

1.5.4.1 Vaginal and rectal temperature

The temperature of dairy cattle is influenced by physiological status such as parturition (Burfeind et al., 2011). Ouellet et al. (2016) reported that vaginal temperature decreased on the day of calving by an average of 0.3 ± 0.03°C compared to the 4 days prior to calving. Similar findings were reported by Burfeind et al. (2011), and it was shown that vaginal temperature was 0.6 to 0.7°C and 0.2 to 0.3°C lower on the day of calving when compared to the 48h and 24h before calving. Rectal temperature was also found to decrease, and it was reported to be 0.4 to 0.6°C and 0.3 to 0.5°C lower in the 48h and 24h prior to calving.

1.5.4.2 Rumination and feeding behaviour

A number of studies have evaluated rumination behaviour in prepartum cattle using a range of different devices (Schirmann et al., 2013; Büchel and Sundrum, 2014; Ouellet et al., 2016; Krieger et al., 2019).

To monitor rumination time, Schirmann et al. (2013) fitted cows with a rumination logger which contained a microphone that recorded the sounds of rumination. This study evaluated the difference in rumination times between a baseline (-4 d to -1 d before calving), and the day of calving. It was concluded that cows spent 63 ± 30 min/ d less time ruminating on the day of calving when compared to the baseline, and there was a decrease in rumination time 4h before calving.

Büchel and Sundrum (2014) used an electromyography system to automatically record rumination time. The system incorporates 2 electrodes within a head collar, and these electrodes measure the electrical impulses of the musculus masseter at a resolution of 10 datapoints per second. It was observed that rumination time decreased by 27% in the last 6 hours prior to birth when compared to a reference period, defined at the previous 66h before the final 6h block before calving.

A triaxial accelerometer contained within an eartag was used by Ouellet et al. (2016) and Krieger et al. (2019) to quantify rumination time based on ear movements. Ouellet et al. (2016) established that rumination time was 41 ± 17 min/ d lower on the day of calving, when compared to the 4 days preceding calving (-4 d, -3 d, -2 d, -1 d). Similarly, Krieger et al. (2019) found that rumination started to drop -7 d prior to calving and was lowest on the day of calving.

Schirmann et al. (2013) reported that cows spend approximately 66 ± 16 min/ d less time feeding on the day of calving, when compared to the preceding 4 d before calving, and there was a decline 8h prior to calving in the amount of time spent feeding. In addition, Büchel and Sundrum (2014) showed a 57% (20.8 min/6 h) and 56% (1.9 kg/6 h) reduction in feeding time and DMI within the 6h before calving compared to a control period.

1.5.4.3 Lying Behaviour

Previous studies have reported changes in standing and lying behaviour in periparturient cattle as calving approaches. Jensen (2012) reported that overall lying time gradually decreased from 4 days pre-calving (998 minutes) until the day of calving (894 minutes). When data were analysed in 2-hour blocks on the day of calving, it was observed that lying time increased in the last 12 hours prior to calving (31.4 minutes) to 2 hours prior to calving (42.8 minutes). Miedema et al. (2011a) compared cow behaviour on the day of calving to a pre-calving control observation period (median = 3 days pre-calving) with each cow acting as its own control. This study also reported that lying times were lower on the day of calving (12.6 ± 1.8 hours) when compared to the control period (13.6 ± 1.8 hours) but that lying time duration increased in the last 6 hours before calving. The increased number of lying bouts before calving coincided with an increase in the duration of contractions and the number of times the cows turned the head towards their abdomen.

A standing bout can be defined as the interval between two lying events, whilst a lying bout can be defined as the interval between two standing events (Miedema et al., 2011a). As standing and lying bouts assess the number of transitions from one postural state to the other, the number of standing and lying bouts can be compared within literature. Huzzey et al. (2005) concluded that the number of standing bouts increased by 80% on the day of calving. A similar finding was reported by Miedema et al. (2011a) who showed that the number of lying bouts increased significantly on the day of calving (24.2 ± 6.8 no. transitions) when compared to a control period (16.4 ± 4.8 no. transitions). When data were analysed in 6-hour periods before calving (24-18 hours; 18-12 hours; 12-6 hours; 6-0 hours), it was observed that the number of lying bouts significantly increased in the final 6 hours before calving. Jensen (2012) reported that from 12 hours before calving to 2 hours before calving, the number of lying bouts increased from 0.83 per hour to 2.79 per hour.

1.5.4.4 Activity and tail raising

Overall activity has been reported to increase on the day of calving, and this is attributed to discomfort around calving. It was observed that the number of walking bouts increased on the day of calving (529.3 ± 186.9 walking bouts/ d vs. 388.0 ± 105.1 walking bouts/ d) when compared to a control period (Miedema et al., 2011a). Borchers et al. (2017) found an increase in step count on the day of calving compared to 14 days before calving; however, the difference was not significant. Jensen (2012) used IceTags to assess the activity index of animals prior to calving and on the day of calving, and it was concluded that activity started to increase throughout the 6 hours prior to calving. Miedema et al. (2011a) reported that the most significant behavioural change on the day of calving was increased frequency of tail raising in the 6 hours prior to calving. Other papers have also reported a significant increase in tail raising 6-2 hours before calving (Barrier et al., 2012).

Table 1.2 A summary of physiological and behavioural changes prior to calving in dairy cattle.

Change detected	Behaviours validated	Reference
Rumination	↓ 3-8h before calving, ↓ The day of calving	Schirmann et al. (2013); Büchel and Sundrum (2014); Ouellet et al. (2016); Borchers et. (2017); Fadul et al. (2017); Krieger et al. (2019)
Dry Matter Intake	↓ 6-8h before calving, ↓ The day of calving	Schirmann et al. (2013); Büchel and Sundrum (2014)
Feeding time	↓ 6-8h before calving, ↓ The day of calving	Schirmann et al. (2013); Büchel and Sundrum (2014)
Lying time	↑ 4h before calving, ↓ The day of calving	Miedema et al. (2011a); Ouellet et al. (2016); Borchers et al. (2017)
Postural transitions (standing bouts or lying bouts)	↑ 2-6h before calving, ↑ The day of calving	Miedema et al. (2011a); Ouellet et al. (2016); Fadul et al. (2017); Speroni et al. (2018)
Activity	↑ 2h before calving, ↑ The day of calving	Miedema et al. (2011a); Borchers et al. (2017)
Tail raising	↑ 2-6h before calving, ↑ The day of calving	Miedema et al. (2011a); Miedema et al. (2011b) Barrier et al. (2012)

1.5.5 The effect of dystocia on cow behaviour

The use of cow monitoring technology to detect calving also has the potential to identify cows with dystocia, therefore literature examining the behavioural differences between dystocial and eutocial calvings will be reviewed. The assessment of behavioural differences between beef cattle with normal and abnormal calvings showed few statistical differences (Wehrend et al., 2006). It was, however, concluded that cows with dystocia exhibited significant restless behaviours earlier than cows with eutocia. These behaviours included scraping the floor, discharge of urine, and rubbing against the wall. Barrier et al. (2012) reported similar findings in that cows with dystocia displayed greater and earlier restlessness than cows calving naturally, and animals with a malpresented calf spent longer raising their tail compared to cows with eutocia.

Proudfoot et al. (2009) observed that cows with dystocia had more cumulative standing bouts compared to cows with a normal calving. This difference was observed to commence 24 hours prior to calving (10.9 ± 0.7 vs. 8.3 ± 0.7 bouts/ day). However, Miedema et al. (2011b) and Barrier et al., (2012) reported that there was no difference between the number of postural changes from lying to standing between cows with dystocia and cows with eutocia.

Dry matter intake and water consumption in cows with dystocia was compared to cows with eutocia. It was concluded that cows with eutocia consumed 2.6 kg more dry matter in the 24 hours before calving compared to cows with dystocia (10.9 ± 0.7 vs., 8.3 ± 0.7 kg/ d) and cows with eutocia consumed more water 24 hours before calving (36.2 ± 4.4 vs., 22.4 ± 4.4 kg/ d) (Proudfoot et al., 2009). Literature assessing the effect of dystocia on pre-calving behaviour provides contradictory results. The study conducted by Proudfoot et al. (2009) had a longer period of observation, and dystocia was defined as requiring assistance from at least two stockpersons. The differences in the studies may be due to only cows with severe cases of dystocia showing behavioural differences.

1.5.6 Factors affecting dairy cow behaviour

Many factors can affect dairy cow behaviour in the prepartum period, such as parity or housing management. If remote behavioural monitoring is to be used to identify cows as calving, factors which could affect dairy cow behaviour must be considered. The following section reviews variables which may affect behaviour of cows within late gestation or during calving.

1.5.6.1 The effect of parity on behavioural changes

Previous studies have reported slight differences in the behaviour of heifers and cows on the day of calving. Wehrend et al. (2006) observed 87 beef cattle (10 heifers and 77 cows) from the first stage of labour (defined as relaxation of the pelvic ligaments, milk leakage from the teats, and swelling of the vulva) to calving. It was concluded that fewer heifers displayed calm behaviour prior to calving and pawed more with the forefeet when compared to cows. Similarly, it was reported that the period of tail raising started earlier in heifers than cows (2–4 hours vs. 2 hours before calving) (Miedema et al., 2011b). Huzzey et al. (2007) reported that in the prepartum period, primiparous cows were less aggressive at the feed bunk, displacing other cows an average of 11.5 ± 1.5 times/ d compared to multiparous cows that displaced other cows 17.9 ± 1.2 times/ d. There was no reported difference in lying behaviour between multiparous cows of different parity (Jensen, 2012). Increased signs of restlessness in heifers can be attributed to the duration of contractions being longer in lower parity cows (Jensen, 2012). The behavioural differences between heifers and cows at calving could be misinterpreted as indicators of dystocia. As a result, it is important to consider parity in the prediction of calving.

1.5.6.2 The effect of stocking density and social regrouping on prepartum behavioural changes

The differences in prepartum behaviour between a socially stable group of prepartum cattle (all-in all-out treatment) and a socially unstable group of cattle (managed traditionally) was observed for 5 weeks. There were fewer feedbunk displacements in the socially stable group of cattle in week 1 and week 5 (0.33 ± 0.06 and 0.19 ± 0.06 displacement/ d) compared to the socially unstable group in week 1 and week 5 (0.78 ± 0.07 and 0.46 ± 0.07 displacement/ d, respectively; Lobeck-Luchterhand et al., 2014). There was no difference in feedbunk occupancy during fresh feed delivery between the two treatment groups.

Lobeck-Luchterhand et al. (2015) assessed the effect of stocking density (SD) on lying, social, and feeding behaviour of prepartum cows. Prepartum cattle (254 ± 3 d from expected calving date) were allocated to a cubicle yard at stocking density of 80% or 100% (ratio of cows to headlocks and cubicles). There was a greater number of feedbunk displacements in the 100%SD group (21.3 ± 1.0 displacements/ d) compared to the 80%SD group (15.2 ± 1.0 displacements/ d). There was an effect of parity and stocking density on feeding behaviour. Multiparous cows at 80%SD spent 7.6 ± 4.5 min/ d more time feeding than multiparous cows at 100%SD, however primiparous cows at 80%SD spent 12.4 ± 5.0 min/ d less time feeding in the 28 days prior to calving compared to primiparous cows at 100%SD. There was no difference in the number of lying bouts or duration of lying time across the experimental period between the two treatment groups.

Schirmann et al. (2011) investigated the effect of regrouping prepartum dairy cattle. Cattle were housed in groups of 6, before 3 cows were moved into another group, and 3 remained within the home pen. For cows that were moved into a new pen, it was observed that DMI decreased by 9% on the day of regrouping. There was no effect of regrouping on DMI for cows that remained in the home pen. For both treatments, after regrouping, rumination decreased by 9% and feeding rate decreased by 10%.

1.5.6.3 Changes in prepartum feeding behaviour

Campler et al. (2018) observed cows for 3 weeks within the 4 weeks prior to calving. Over three weeks, feeding time increased from approximately 3.2 h/ d in week 1 to 4.8 h/ d in week 3. The average number of visits to the feedbin increased from 35.9 visits/week in week 1 to 52.9 visits/week in week 3. Multiparous cows were reported to increase their feed intake from 40.8 kg/ d in week 1 to 65.5 kg/ d in week 3, however no difference in feed intake was reported for primiparous cows. Similar findings were observed by Lobeck-Luchterhand et al. (2015), and primiparous cows spent 46.9 ± 6.6 min/ d less time feeding compared to multiparous cows.

1.6 Current methods of calving prediction

Farmers typically manage pregnant cows using the cow's expected calving date, which is calculated by adding 280 days to the date of a successful insemination (Rutten et al., 2017). The gestation period of a cow ranges from 267 to 295 days (Inchaisri et al., 2010), so the decision to manage and monitor cows using expected calving date can lead to cows calving within the wrong environment. As the average herd size within the UK increases, the amount of time required for individual animal attention at calving also increases.

Dairy cows face physiological and physical complications around calving, so careful management is required to optimise cattle health and welfare. Induction of parturition in 12 heifers concluded that assessment of udder swelling, and pelvic ligament relaxation were the best method of predicting calving within the next 12 hours (Kornmatitsuk et al., 2000). It was reported that objective measurement of pelvic ligament relaxation could predict calving in 93.9% of cases when the pelvic ligaments sank by more than 5mm from the previous day's measurement (Shah et al., 2006).

Streyl et al. (2011) combined and compared 7 clinical signs (udder oedema, vulvar oedema, tail relaxation, udder hyperplasia, pelvic ligament relaxation, vaginal secretion, and teat filling) in periparturient dairy cattle to evaluate which clinical signs would give the best prediction of calving. A parturition scoring system was created that scored changes in clinical signs on a scale of 0-3. It was reported that if the scores for teat filling and relaxation of the pelvic ligaments were below a score 4, calving in the next 12 hours could be eliminated with a high degree of accuracy (> 99% in cows and > 95% in heifers).

1.6.1 Automated methods of calving prediction

New technologies in the area of health monitoring are continuously being developed, and there are commercial devices available on the market for calving detection. These devices fall into one of four categories: the monitoring of uterine contractions, the monitoring of activity and tail raising, detection of the expulsion of the allantochorion and change in vaginal in temperature, and the detection of calf expulsion (Saint-Dizier and Chastant-Maillard, 2015).

1.6.2 Machine learning and calving prediction

Previous studies have used machine learning methods and cow behavioural data to predict calving events. Machine learning methods can be used to provide a better understanding of data by generating trends, models, information, and useful knowledge through the analysis of complex datasets or large, noisy and incomplete data sets (Gupta and Gupta, 2019). According to Shahinfar et al. (2014), machine learning methods can be used to build predictive tools within agriculture as they have the ability to utilise incomplete and complex data sets, and do not presume normal data assumptions. Machine learning algorithms can handle non-linear interactions and relationships between input variables (Shine et al., 2018), and also offer a solution with regards to multicollinearity of input variables (Caraviello et al., 2006a).

Maltz and Antler (2007) created an algorithm based on three variables - changes in lying behaviour, daily step count and movements through the feeding area – and monitored dairy cow behaviour over 7 days. The day of calving was predicted correctly for 10 out of 12 animals, with a high degree of sensitivity (83.3%) and specificity (95.2%). Although the results were promising, the algorithm was not validated on a large number of animals. A larger study on 42 multiparous cows combined three variables - lying behaviours, rumination time and vaginal temperature – to predict calving with a sensitivity of 77% and a specificity of 77% (Ouellet et al., 2016).

Borchers et al. (2017) used a rumination collar and accelerometer to collect rumination, lying and activity behaviours to predict calving in 20 heifers and 33 cows. The study used machine methods such as artificial neural networks, random forest and linear discrimination, to predict the day before calving and the 8-hour period before calving. The results indicate that a neural network that used variables from both the accelerometer and rumination collar, could identify the day of calving with a sensitivity of 100% and a specificity of 86.8%. For identification at 8 hours pre-calving, a neural network combining variables from the two technologies resulted in a sensitivity of 82.8% and specificity of 80.4%.

From this study, it can be concluded that combining multiple technologies typically predicts calving with greater success than using a standalone system.

1.7 The effect of transition disease on cow behaviour

There is potential to detect transition diseases through cow behavioural changes in the pre-calving period. Numerous studies have reported behavioural differences in the pre-calving period between healthy cows (cows that do not develop a transition disease) and diseased cows (cows that develop a transition disease).

Kaufman et al. (2016) investigated rumination differences between cows with subclinical ketosis (SCK) and healthy cows across 4 commercial farms. Multiparous cows with SCK ruminated for 25 ± 12.8 min/ d less than healthy cows during wk -2 to wk +4 post-calving. In support of these findings, Schirmann et al. (2016) found that the rumination time of cows with SCK was lower than that of healthy cows by average of 14%. Dry matter intake of ketotic cows was reported to be 18% lower than that of healthy cows in wk -1 before calving, and ketotic cows visited the feedbin 18% and 27% less than healthy cows in wk -2 and wk -1 (Goldhawk et al., 2009). In the pre-calving period (-7 to -2 d), the feeding time of cows with SCK was reported to be lower than that of healthy cows (168 ± 5 vs., 236 ± 5 min/ d; Schirmann et al., 2016).

Cows diagnosed with retained foetal membranes post-calving were reported to have reduced activity in the pre-calving (444.3 ± 11.0 vs. 466.5 ± 4.3 unit/ d) and post-calving (488.2 ± 14.5 vs. 538.8 ± 5.7 unit/ d) period (Liboreiro et al., 2015). The odds of metritis diagnosis are increased by a cow having retained foetal membranes (Daros et al., 2020). Cow that developed severe metritis post-calving consumed less dry matter (kg/ d) and had a lower feeding time (min/ d) compared to healthy cows in wk -2 (d -13 to d -8) and wk -1 (d -7 to d -1) relative to calving (Huzzey et al., 2007). In addition, severely metritic cows had fewer aggressive interactions at the feed bin in the 2 weeks prior to calving, displacing others 12.2 ± 1.58 times/ d compared to healthy cows that displaced others 16.8 ± 1.74 times/ d. Similar findings were reported by Schirmann et al. (2016), for interactions at the feed bin, finding that cows that developed metritis were replaced 33% times more often than healthy cows between -7 to -2 d pre-calving. In the prepartum period, dry matter intake as a percentage of bodyweight was higher for healthy cows compared to cows that were diagnosed with postpartum clinical mastitis (1.65 ± 0.02 vs., 1.56 ± 0.04 %/ d; Pérez-Báez et al., 2019).

1.8 Hypocalcaemia

Hypocalcaemia is a metabolic disease caused by low blood calcium concentration (Goff, 2008). According to Horst et al. (1994) most cows have a degree of hypocalcaemia at calving. When cows are unable to maintain blood calcium concentration within the normal range, clinical signs such as excitability, lethargy, and prolonged recumbency are seen (Oetzel, 2011).

The individual herd incidence rate for clinical hypocalcaemia is reported to range from between 0-41% (Whitaker et al., 2002). It is reported that subclinical hypocalcaemia affects 43.3% of multiparous cows (Ribeiro et al., 2013) and 25% of first lactation cows (Reinhardt et al., 2011). In accordance with Reinhardt et al. (2011), Caixeta et al. (2017) reported that the incidence of chronic subclinical hypocalcaemia (low blood calcium on 3 consecutive days post-calving) increased with parity (46% of parity ≥ 3, 32% of parity 2, 20% of parity 1 animals). A fatal case of hypocalcaemia can cost NZD$1,854 (UK£967.21 at a conversion rate of NZD$1.00/UK£0.52; Kerslake et al., (2018)). The estimated cost for a non-fatal case of hypocalcaemia is US$246.23 ± 52.25 (UK£195.23 ± 41.43 at a conversion rate of US$1.00/UK£0.79; Liang et al., 2017).

1.8.1 Calcium

The onset of colostrogenesis and lactogenesis results in a large requirement for calcium. It is reported that cows require >23g calcium to produce 10L of colostrum (Goff, 2008), and around 50g per day for milk production during lactation (DeGaris and Lean, 2008). Milk contains 1.1 g/Ca per kg, and colostrum contains 1.7-2.3 g/Ca per kg, and to prevent prolonged hypocalcaemia, extracellular calcium must be replaced (Goff, 2014). Circulating calcium levels are rapidly depleted during colostrum and milk synthesis, and this can often lead to hypocalcaemia. Horst et al. (1997) reported that hypocalcaemia affects many cows at calving, as calcium homeostasis adapts to meet the challenge.

Calcium has a fundamental role in many biological processes within the body. Calcium ions, present in extracellular and intracellular fluids, are involved in numerous biochemical processes (El-Samad et al., 2002). Calcium ions present in extracellular fluid are important for blood clotting, hormone secretion, and neuro-muscular excitability, whilst intracellular calcium ions are required for enzyme activity, and in cell signalling. Calcium salts are integral in the maintenance of skeletal integrity (El-Samad et al., 2002). Bone mineralisation, muscle contraction, cardiac action potential, and coagulation all require calcium (Wilkens et al., 2020). As impairments in calcium homeostasis can affect muscle, immune, and endocrine function (Wilkens et al., 2020), blood calcium concentration in healthy dairy cows is regulated to be between 2.1 and 2.5 mmol/L (Goff, 2014).

1.8.1 Calcium homeostasis

Given the wide-ranging roles of calcium, optimum cow health is dependent on a cow's ability to maintain circulating calcium concentration. Weaver et al. (2016) stated that hypocalcaemia is predominately caused by the failure of a dairy cow to manage calcium homeostasis during milk production. According to Goff (2014), circulating calcium occurs in an ionised form (42-48%), bound to proteins (50%) such as albumin, or joined to soluble anions (3-7%) such as phosphate. The cow has abundant body reserves of calcium: the skeleton contains 7.8-8.5 kg of calcium, whilst there is 8-9 g in the extracellular fluids, and 3.0-3.5 g of calcium in the plasma pool. In the first days of lactation, a cow will withdraw approximately 20-30 g of calcium from her body reserves. The 3 main methods of calcium homeostasis regulation are bone resorption, decreased renal excretion, and increased intestinal absorption (Weaver et al., 2016). Increased intestinal passive transport and reduced active transport in the kidneys are insufficient to meet the mammary gland demand for calcium, therefore bone resorption is the main source of calcium (Weaver et al., 2016).

The parathyroid gland predominately controls calcium homeostasis. When a drop in blood calcium is detected, the parathyroid gland secretes parathyroid hormone (El-Samad et al., 2002). The main action of parathyroid hormone is to trigger osteocytic osteolysis, leading to the mobilisation of phosphorus and calcium from the skeleton (El-Samad et al., 2002). Calcium exists within bone crystals called hydroxyapatite (Goff, 2014). To liberate the calcium from hydroxyapatite, parathyroid hormone binds to osteoblasts. Osteoblasts secrete cytokine factors which trigger lacunar osteocytes to remove bone salts from the bone matrix (El-Samad et al., 2002; Goff, 2014). Vranković et al. (2018) reported an increase in serum inorganic phosphorus concentration at 12 and 48h post-calving, which suggests that reduced kidney excretion and increased resorption of bone occurs shortly after calving.

Another calcium homeostatic mechanism is the dietary absorption of calcium. Parathyroid hormone stimulates the kidney to secrete 1,25-dihydroxyvitamin D (1,25[OH]2D) (a vitamin D metabolite), which binds to vitamin D receptors on epithelial cells (Goff, 2014). The main function of 1,25[OH]2D is the stimulation of active transport of calcium across the duodenum and jejunum epithelial by increasing the formation of calcium-binding protein on the cell wall (El-Samad et al., 2002)

Goff (2014) reports that parathyroid hormone increases the efficiency of renal absorption from renal tubular fluids. Urine excretion of calcium is reported to be low (0.5g/ Ca per day), so this mechanism alone will not restore blood calcium concentrations to normal levels during early lactation. Figure 1.4 depicts the 3 main actions of parathyroid hormone to increase extracellular calcium concentration.

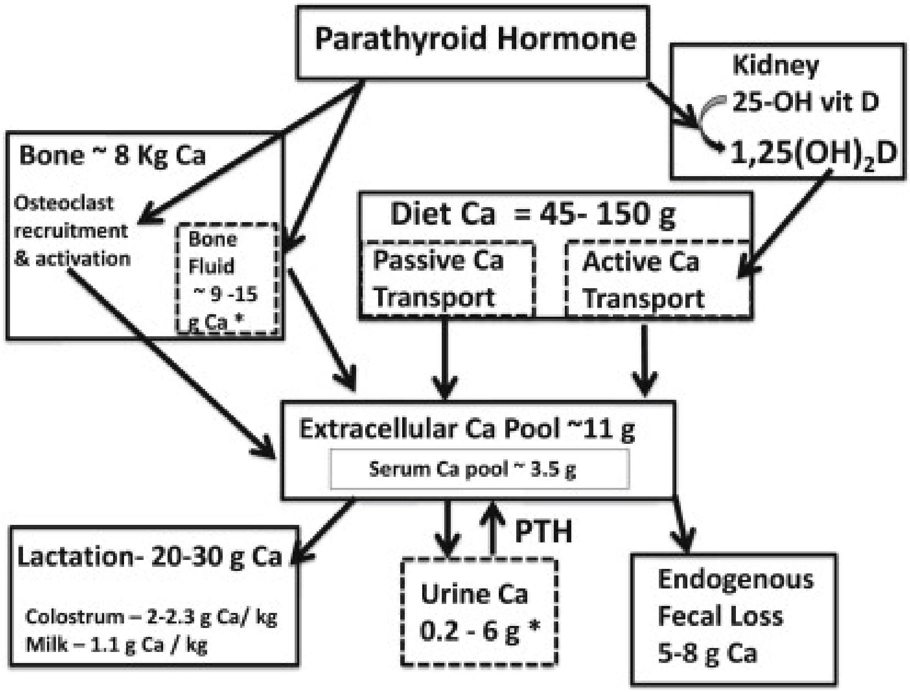


Figure 1.4 The three main methods of calcium mobilisation (renal absorption, osteoclastic bone reabsorption and dietary absorption) activated by parathyroid hormone (Goff, 2014).

1.8.2 Prevention of hypocalcaemia

Venkajob et al. (2017) questioned 115 German dairy farmers on their hypocalcaemia prevention strategies and reported that only 43% of dairy farmers (50/115) had a prevention strategy. The two methods of hypocalcaemia prevention were the inclusion of anionic salts in the diet (10/115 herds) and oral calcium products (40/115 herds).

After calving, blood calcium concentrations drop to their lowest levels between 12 to 24 hours (Goff, 2014), and oral calcium supplementation after calving can increase blood calcium and prevent hypocalcaemia (Blanc et al., 2014). Supplementation using an oral calcium bolus between 0-2h after calving, and 8-35h after calving, had a positive effect on cow health and milk production in early lactation when supplemented cows were compared to non-supplemented cows (Oetzel and Miller, 2012). Lame cows not supplemented with an oral calcium bolus had 0.34 more health events within 30 days in milk when compared to lame cows that were supplemented. Martinez et al. (2016) reported that milk production and parity affected the efficacy of oral calcium supplementation.

A common method of hypocalcaemia prevention is the feeding of an acidogenic diet that causes metabolic acidosis (Zimpel et al., 2018). This can be achieved by manipulating the mineral content of the diet, commonly known as the Dietary Cation-Anion Diet (DCAD) or Dietary Cation-Anion Balance (DCAB) (Martinez et al., 2018). Increasing the proportion of dietary anions (SO_4^{2-}, P^{3-}, Cl^{1-}) or decreasing the proportion of dietary cations (Ca^{2+}, Mg^{2+}, Na, K) will reduce the pH of the blood plasma by altering the electrical charge (Goff, 2008). According to Goff and Horst (2003), metabolic acidosis can prevent hypocalcaemia by increasing the sensitivity of tissue to parathyroid stimulation.

Zeolite A (calcium binder) can be added to the pre-calving diet to reduce calcium absorption, however often large amounts (0.25 to 1kg/d) must be fed. Crookenden et al. (2020) fed 500 g/d of sodium aluminosilicate for 14 d before expected calving date (17 ± 3 d). It was concluded that plasma calcium concentrations were higher at d 0, 1 and 4 post-calving compared to cows not fed zeolite. This finding reflects previous literature on the positive benefits of feeding zeolite on serum calcium (Kerwin et al., 2019).

1.8.3 Treatment of hypocalcaemia

Cows with clinical hypocalcaemia must be treated promptly as ischemia of the nerves and muscles can be caused by prolonged recumbency (termed ‘crush syndrome’) (Goff, 2008).

Goff (2008) reported that oral calcium treatments can be used in the prevention of clinical hypocalcaemia; however, oral calcium was not advocated for the treatment of clinical hypocalcaemia. A single oral dose of calcium within 24h post-calving was shown not to affect plasma calcium concentration within 24h after administration (Leno et al., 2018). This finding contradicts a similar study by Martinez et al. (2016) that found blood calcium concentration was increased on d 0 and 1 after 86 g/d of oral calcium. It must be noted that stopping oral calcium supplementation caused primiparous cows to experience a degree of hypocalcaemia on d 2 to 4 postpartum.

An intravenous injection of calcium salt, typically 8.5-11.5 g Ca/500 mL, is the quickest way to re-establish plasma calcium concentration. The recommended dose of intravenous calcium is 2 g Ca/100 kg of bodyweight, administered at a rate of 1 g/min to prevent fatal arrhythmia (Goff, 2008). Wilms et al. (2019) reported hypercalcaemia after treatment with intravenous calcium. Although blood calcium was high at 1h and 3h post treatment, blood calcium levels were lower at 18, 24, and 36h compared to cows that received oral calcium. Similar findings were reported by Blanc et al. (2014) who collected blood samples from cows with subclinical hypocalcaemia at 0, 1, 2, 4, 8, 12, 16, 20, 24, 36, and 48 h relative to treatment application (control (no treatment), oral calcium, or intravenous calcium). Total serum calcium concentration (mg/dL) over time is shown in Figure 1.5.

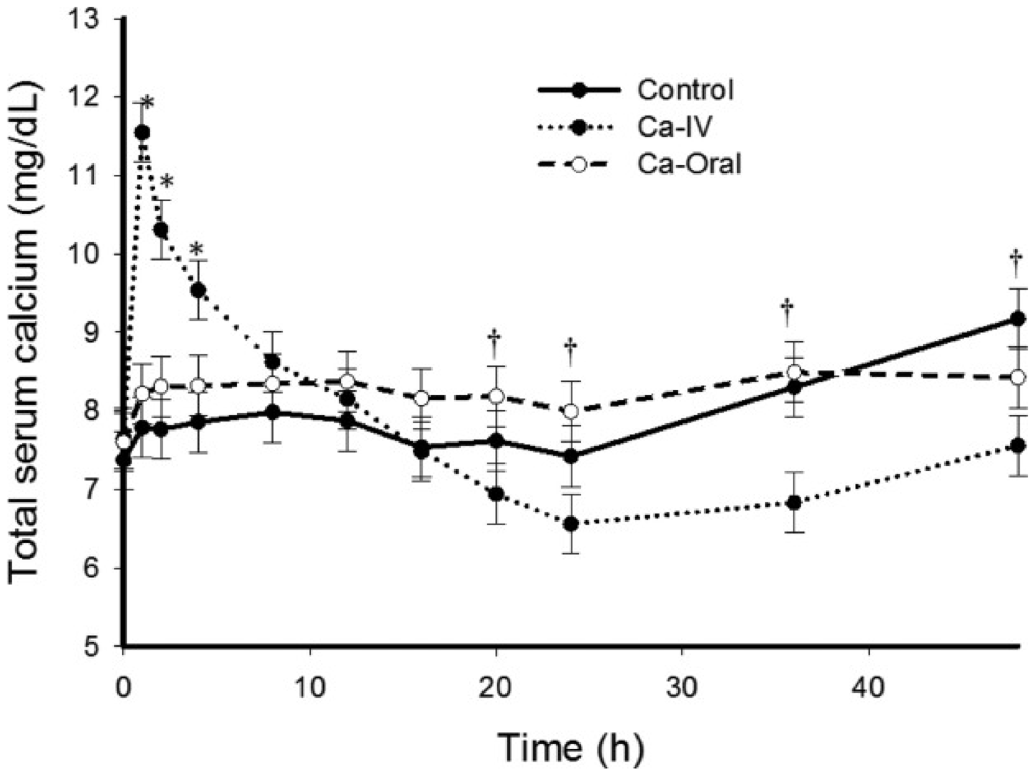


Figure 1.5 Serum calcium concentration (mg/dL) after subclinical hypocalcaemia treatment in control cows (n = 11; no calcium supplementation), oral calcium (n = 11), and intravenous calcium (n = 11) (Blanc et al., 2014).

At 1, 2, and 4h post-treatment, the serum calcium concentration was significantly higher for cows treated with intravenous calcium compared to control cows and cows treated with oral calcium. However, for cows treated with intravenous calcium, total serum calcium declined to hypocalcaemic levels at 24h. Long term hypocalcaemia can have negative consequences on cow health. Intracellular calcium signalling is important for immune cell activation, and hypocalcaemia can lead to immunosuppression (Kimura et al., 2006).

1.8.3.1 Health

The risk of cows being culled was 1.69 times higher for cows with a serum calcium concentration below <2.0 mmol/L (Venjakob et al., 2018). McArt and Neves (2020) reported that multiparous cows with persistent or delayed subclinical hypocalcaemia were 1.8 and 1.9 times more likely to be removed from the herd or develop a disease (hyperketonaemia, displaced abomasum, and metritis) in the first 60 DIM compared to cows with normocalcaemia. Cows with hypocalcaemia are more likely to incur a post-parturient disease when compared to cows with normocalcaemia, which could explain why the risk of culling is higher. Rodríguez et al. (2017) reported that cows with subclinical hypocalcaemia were 5.5, 4.3, 3.7, and 3.4 times more likely to have ketosis, metritis, displaced abomasum, and retained placenta compared to cows with normocalcaemia. Ribeiro et al. (2013) reported an association between uterine disease and hypocalcaemia; it was observed that cows with subclinical hypocalcaemia had a greater risk of developing subclinical endometritis and metritis compared to cows with normocalcaemia (24.1 vs 8.9%; 7.9 vs 4.0%, respectively). In addition, subclinical ketosis and elevated NEFA concentrations were more likely to occur in cows with subclinical hypocalcaemia when compared to cows with normocalcaemia (41.9 vs 35.3%; 27.5 vs 16.2%, respectively).

1.8.3.2 Fertility

Hypocalcaemia has an adverse effect on fertility. Caixeta et al. (2017) reported that cows with chronic subclinical hypocalcaemia (calcium serum concentration ≤ 8.6 mg/dL for the first 3 DIM) took longer to show active ovarian function when compared to cows with normocalcaemia and subclinical hypocalcaemia (at least 1 low serum calcium measurement during the first 3 DIM). In addition, only 44%

of cows with subclinical hypocalcaemia and 31% of cows with chronic subclinical hypocalcaemia become pregnant at first service compared to 63% of normocalcaemia cows. Hypocalcaemia is associated with uterine disorders, and Ribeiro et al. (2013) reported that pregnancies on 35 d and 60 d post insemination were more likely in cows that had no uterine disease.

1.8.3.3 Milk production

There are conflicting reports of the effect of hypocalcaemia on milk production, with some studies reporting hypocalcaemia causing a reduction in milk yield whilst others show an increase or no effect. According to Venjakob et al. (2018), parity influences the effect of hypocalcaemia on milk yield. In early lactation, there was no reduction in milk yield for primiparous cows with subclinical hypocalcaemia (serum calcium concentration <2.0 mmol/L). However, there was a 0.80 kg/d higher level of milk production for multiparous cows with serum concentration <2.1 mmol/L compared to cows with a serum concentration of ≥2.1 mmol/L. Similarly, Jawor et al. (2012) reported that cows with subclinical hypocalcaemia (serum calcium concentration <1.8 mmol/L) produced 5.7 kg/d more milk in wk 2, 3, and 4 compared to cows with normocalcaemia. The association between low blood calcium and increased milk production can be explained by a cow's failure to manage calcium homeostasis at the start of lactation. Cows that have higher milk production will have greater calcium requirements by the mammary gland, which is reflected in a noticeable reduction in blood calcium levels after calving. In contrast to these findings, Chapinal et al. (2012) observed that milk production was reduced by 3.8 ± 1.4 kg/d per cow when over 15% of cows in a herd had a serum calcium concentration of ≤2.1 mmol/L in wk +1.

1.9 Conclusion

Within the UK and most developed countries, dairy farms are intensifying, and average daily milk yield and average herd size have increased in the last decade. Dairy intensification is associated with many issues such as animal health, the environment, and economic and social well-being concerns. Precision livestock technologies are considered a solution which can be used on dairy farms to address these issues. The uptake of dairy cow monitoring technologies on UK dairy farms has not been researched. It is unclear what the uptake of these technologies are or the benefits and issues surrounding these technologies. As average dairy herd size increases, the number of cows under the care of farm staff increase. Calving is a high-risk period for both cow and calf as calving difficulty can occur. Calving cows require regular observation to ensure that appropriate early intervention is given where required. In addition, calving cows are susceptible to hypocalcaemia – a metabolic disorder which can be fatal. Automated detection systems that use cow monitoring technologies could be used to detect calving or hypocalcaemia which would help facilitate herd management and improve cow health.

1.10 Thesis aims and objectives

The overall aim of this thesis is to investigate the use of cow monitoring technologies on UK dairy farms, and to use automated behavioural monitoring under commercial farm conditions to examine the behaviour of dairy cattle during the critical transition period around calving. This study has 4 main objectives.

- Chapter 2 will explore the current uptake of automated cow monitoring technology on UK dairy farms. It is hypothesised that farm location, farm size, and milk yield is associated with the uptake of cow monitoring technologies. In addition, it is thought that most farms will use oestrus detection and daily milk yield to aid with cow management. The study will also identify key barriers and drivers to adoption of automated cow monitoring technology.

- The next objective is to describe and quantify and behavioural differences between primiparous and multiparous cows in late gestation and on the day of calving (Chapter 4). It was hypothesised that the behaviour of primiparous and multiparous cows would differ as primiparous cows had not experienced the pre-calving environment or management nor had primiparous cows experienced the calving process. In addition, any behavioural differences between dystocic and eutocic cows prior to calving would be explored. The hypothesis was that cows that had an assisted calving would have behave differently compared to cows that did not have an assisted calving.

- In Chapter 5, the objective was to explore if lying and activity behaviours could be used to identify the day before calving, and to identify calving events on the day of calving. It was hypothesised that cow behavioural changes on the day of calving and the days leading up to calving could be used to identify the day before calving or cows as calving.

- The final objective is to describe and quantify any behavioural differences between primiparous cows with normocalcaemia and primiparous cows with subclinical hypocalcaemia, and to describe and quantify any behavioural differences between multiparous cows with normocalcaemia, subclinical hypocalcaemia, and clinical hypocalcaemia (Chapter 6). The hypothesis was that low blood calcium levels would cause an alteration in cow behaviour in the pre- and post- calving periods, and cows with each blood calcium category would behave differently.

Chapter 2 The use of automated cow monitoring technology on UK dairy farms

2.1 Introduction

As reviewed in Chapter 1, the UK dairy industry has experienced rapid changes in recent years. Dairy production systems have intensified; milk yield per cow and the number of cows per farm have both increased. Trade-offs are often the consequence of increased production, and farmers have to deal with a multitude of issues such as animal health and welfare concerns (Jackson et al., 2020), environmental degradation (O'Mara, 2011), and social sustainability concerns (Britt et al., 2018).

Sustainable intensification has been described as "*a process designed to achieve higher agricultural [food] yields whilst simultaneously reducing the negative impact of farming [food production] on the environment*" (Godfray, 2015). It is a process that could help balance the trade-offs associated with increased production. According to Franks (2014), sustainable intensification on UK farms centres around increasing production, whilst preventing environmental degradation and reducing environmental impact. It has been suggested that the introduction of PLF on farms could be a solution for economic, environmental, and social sustainability of livestock production (Lovarelli et al., 2020) and help achieve sustainable intensification (Balaine et al., 2020). This is because technology can support farmers in making efficient decisions related to animal husbandry (Balaine et al., 2020) which will help improve productive efficiency. For example, disease reduces productive efficiency and is categorised as an animal welfare concern; the early treatment of disease or a reduction in disease incidence will benefit both animal health and production efficiency. Eckelkamp and Bewley (2020) reported on the ability of precision dairy monitoring technologies to alert to the presence of a disease or a change in cow management on four US dairy farms over a year. It was established that 92% of alerts were deemed accurate by farm staff, which highlights the importance of technology in aiding farm management. Disease alerts allow farm staff to instantly assess animal well-being, and this information can help decision-making and management decisions, ultimately improving cow health and improving production efficiency.

Commercially available dairy technologies have a wide variety of different functions and exist to improve labour efficiency, to reduce labour inputs, or to improve dairy farm performance and production efficiency (Gargiulo et al., 2018). Technologies that reduce labour requirements or make labour more efficient include sorting gates, calf feeders, milk plant wash systems, post milking disinfection, and automated teat cup removers. Data capturing technologies are used to improve farm performance or efficiency. These technologies can include electronic cow identification, in-line milk meters, oestrus detection systems, and herd management software (Gargiulo et al., 2018). The most adopted precision dairy technologies on Australian dairy farms were automatic cup removers, herd management software, and automatic milk plant wash systems (Gargiulo et al., 2018). Milking is a labour-intensive process, therefore automatic cup removers and automatic wash systems may have been adopted to address labour issues such as availability, efficiency, and cost.

Stone (2020) reported that the best technologies are those that improve decision making, farm efficiency, farm economics, animal welfare, and producer happiness. Although technology can be a solution to a problem, not all farms have adopted precision technology. There are numerous reasons as to why dairy farmers do not adopt automated cow monitoring technology, however economics could be the most influential. Technology investment is expensive (Stone, 2020) and financial uncertainty has been reported as a reason why Dutch dairy farmers did not invest in technological systems (Steeneveld and Hogeveen, 2015). A study of 109 US dairy farmers highlighted that benefit to cost ratio was the most important factor to consider before investing in technology (Borchers and Bewley, 2015). If technology companies cannot prove a return on investment, farmers are unwilling to invest. Another factor which is known to influence technology adoption is herd size. The adoption of precision technologies, such as herd management software, electronic cow identification, and automatic cup removers, was between 2 and 5 times higher on Australian dairy farms with over 500 cows compared to farms with fewer cows (Gargiulo et al., 2018). There might be greater adoption of technologies on larger farms to help with increased operation size or because fixed costs can be spread across more cows in larger herds. Social factors, such as whether competitors or friends have adopted technology, have been reported to influence adoption rates (Stone, 2020). Other factors that can influence technology adoption include investment cost, ease of use, and proven technology performance (Borchers and Bewley, 2015).

The adoption of precision dairy technologies has been researched in other countries such as Australia (Gargiulo et al., 2018), Italy (Abeni et al., 2019) and USA (Borchers and Bewley, 2015). However, no studies have assessed technology adoption on UK dairy farms. A study assessing the landscape of dairying in 2067 acknowledges the important role that technology will play in helping farmers to meet the world's requirement for milk (Britt et al., 2018), therefore it is important to understand technology use on UK dairy farms. This study will aim to establish an understanding of what precision dairy monitoring technologies have been adopted within the UK, and to understand the benefits and problems that technology installation can have on UK dairy farms. The study will gain an insight into why some farms do not use technology, and the factors that affect the uptake of technology and influence purchase decisions.

2.1.1 Research aims

The aim of this study was to understand the uptake of automated cow monitoring technology (ACMT) on UK dairy farms. More detailed research objectives are detailed below:

1. To identify the prevalence of UK dairy farms using ACMT.
2. To identify if farm location, herd size, or milk yield are associated with the uptake of ACMT on UK dairy farms.

3. To identify what individual cow measurements are currently recorded on UK dairy farms.
4. To ascertain the benefits and problems that UK dairy farmers have encountered after the installation of cow monitoring technologies.
5. To examine the reasons why UK dairy farmers have not adopted ACMT.
6. To identify what criteria would influence purchase of ACMT.

2.2 Materials and methods

2.2.1 Survey structure

In November 2019, a survey was created using JISC Online Surveys (Jisc, Bristol, England, UK). Dairy farmers and dairy specialists were asked to test the survey (n = 8), and appropriate amendments were made to survey phrasing and structure based on feedback. For example, the original survey asked what type of milking system a farm had. However it was felt that milking parlour was more appropriate, as milking system could refer to the mechanics of a milking parlour. The survey was approved by the Human Ethical Review Committee (Ref HERC_425-19) at the Royal (Dick) School of Veterinary Studies before the survey was launched in January 2020.

The target audience of the survey was UK dairy farmers. Potential survey respondents were reached through social media channels such as FaceBook and Twitter, emails, newsletters, and dairy farmer meetings. The survey could be accessed by respondents by a URL link or a QR code. The full survey can be found in Appendix 1 of this thesis.

For all respondents, the first 7 questions were the same. Respondents were asked for the country location their farm was situated in (England, Northern Ireland, Scotland, or Wales), their age (18-24, 25-34, 35-44, 45-54, 55-64, or 65+), the number of cows in their herd, their average milk yield per cow per year (litres), type of milking parlour (abreast, herringbone, robot [also called Voluntary or Automatic Milking Systems], rotary, or other), whether they had received a grant for ACMT (yes or no), and if they had installed ACMT (yes or no). For herd size and average milk yield, respondents were required to manually input a numerical value.

The survey then diverged into two separate sections depending on whether the respondent currently used ACMT or did not. ACMT was defined as, *'a piece of equipment that measures a physiological (i.e. heart rate), production (i.e. milk yield), or behavioural trait (i.e. activity) of an individual adult dairy cow'*. Respondents that used ACMT were asked 18 questions, whilst respondents that did not were asked a different 11 questions.

For farms that used ACMT, respondents were asked to select from a list of parameters that are currently automatically recorded on their farm using cow monitoring technology (Table 2.1). Respondents were asked if they had seen any benefits since the installation of cow monitoring technology (yes or no). If a respondent answered ‘yes’, they were asked to select benefits from a list (Table 2.2). Respondents were asked if they had encountered any problems since the installation of cow monitoring technology (yes or no). If a respondent answered ‘yes’, they were asked to select problems encountered from a list (Table 2.3). Word association is a methodology used in sociology and psychology and it is a technique used to understand the respondent’s attitudes and perceptions to a subject (Krumreich et al., 2019). Word association is commonly used in consumer and marketing studies (Soares et al., 2017), and as there are no right or wrong answers, unconscious feeling can be projected by respondents (Donoghue, 2000). Respondents were asked to select words that best described ACMT on their farm (Table 2.4) and had the option to describe ACMT using their own descriptors. So as to not influence respondent selection, words were randomly listed and were paired (practical/impractical; reliable/unreliable; high quality/ poor quality; useful/ineffective; and good value for money/overpriced). For analysis, words were classed as ‘positive’ or ‘negative’ descriptors of ACMT.

For farms that did not use ACMT, respondents were asked to select reasons as to why technology was not used from a list (Table 2.5).

The final 3 questions were the same for all respondents. Respondents were asked if they will invest in ACMT in the next 5 years (yes or no). A Likert Scale (Likert, 1932) was used to ask respondents to rank 9 criteria (Table 2.6) that would influence their purchase of ACMT. Criteria were ranked from 1 (not important) to 4 (most important), and there was a 'no opinion' option. The final question was an open-ended question asking respondents for comments about using ACMT or potentially using ACMT.

All questions were mandatory (required responses) apart from the final question, which was an open-ended question asking for respondent opinion on ACMT.

2.2.2 Statistical analysis

All analyses and data manipulations were carried out using RStudio (version 3.4.4; R Foundation for Statistical Computing, Vienna, Austria). Statistical significance was taken as $P \leq 0.05$. A generalised linear model ('ImerTest' package) with a binomial distribution was used to describe the association of herd size, yield (average litres per cow per year), and farm location (England, Northern Ireland, Scotland, and Wales) with the presence of ACMT (yes or no). Differences between the levels of location was determined using a Tukey test. A broken stick regression was used to calculate the changepoint in milk yield associated with technology adoption.

To identify if there was a difference in the number of positive descriptors and negative descriptors that farmers used to describe ACMT, a dependent 2-group Wilcoxon Signed Rank Test was used. A Chi-squared test was used to identify if there was a difference in the likelihood of ACMT purchase (yes or no) in the next 5 years between farms with no ACMT and farms with ACMT. To determine if there was a difference in criteria that would influence the purchase of AMCT between farms with ACMT and farms without ACMT, an independent 2-group Mann-Whitney Test analysis was used.

2.3 Results

The survey was completed by 122 UK dairy farmers. ACMT was used by 63.9% of farms (n = 78), and 18.8% of farms (n = 23) had received a grant for the installation of the technology. Average herd size was 293.0 ± 26.6 (mean ± SEM) cows per herd and average milk yield was 8,684.9 ± 172.9 litres per cow per annum (mean ± SEM). The most common milking system type was herringbone (84.4%; n = 103), followed by rotary (7.4%; n = 9), robot (6.6%; n = 8), abreast (0.8%; n = 1), and rapid exit (0.8%; n = 1). The majority of respondents were aged 25-34 (36.1%; n = 44), and respondents were categorised in the following groups: 18-24 (14.8%; n = 18), 35-44 (26.2%; n = 32), 45-54 (16.4%; n = 20), 55-64 (4.9%; n = 6), and 65+ (1.6%; n = 2). The majority of respondents were located in England (45.1%; n = 55), whilst 38.5% were based in Scotland (n = 47), and the remaining 16.4% were based in Northern Ireland (9.8%; n = 12), and Wales (6.6%; n = 8).

There was no association between herd size and the presence of ACMT (P = 0.2). Herd average milk yield per cow per year (litres) was higher in farms that had adopted technology (9,273.1 ± 199.9 litres per cow per year) compared to those that had not (7,642.0 ± 258.5 litres per cow per year; $P < 0.001$). A broken stick regression was used to calculate the change point in milk yield data associated with the uptake of technology. Farms producing less than 9,200 litres per cow per year were less likely to adopt ACMT ($P < 0.001$). Farm location did not influence the adoption of ACMT ($P > 0.05$).

2.3.1 Parameters recorded by ACMT

The most common parameters recorded were heat detection (58.2%), daily milk yield (45.1%), and illness detection (22.1%; Table 2.1). The least common parameters recorded were location (0%) and body condition score (0.8%). Less than 5% of respondents used ACMT to measure dry matter intake, cow body weight, milk progesterone, standing or lying behaviours, and feeding and eating behaviour.

Table 2.1 Results from a UK dairy farmer survey (n = 122) showing percentages and number of surveyed farmers recording various cow monitoring parameters[1]

Parameter	Percentage and number of respondents
Heat detection	58.2% (n = 71)
Daily milk yield	45.1% (n = 55)
Illness detection	22.1% (n = 27)
Rumination	18.0% (n = 22)
Mastitis detection	17.2% (n = 21)
Standing or lying behaviour	14.8% (n = 18)
Milk components	6.6% (n = 8)
Calving detection	6.6% (n = 8)
Cow body temperature	5.7% (n = 7)
Lameness detection or mobility scoring	5.7% (n = 7)
Dry matter intake	4.9% (n = 6)
Body weight	3.3% (n = 4)
Milk progesterone	1.6% (n = 2)
Standing/lying behaviour	1.6% (n = 2)
Other[2]	1.6% (n = 2)
Body condition score	0.8% (n = 1)
Location	0% (n = 0)

[1]Respondents were asked to select criteria from a preselected list.

[2] "Other" included feeding (n = 1) and eating (n = 1) behaviours.

2.3.2 Benefits associated with the installation of ACMT

Since the installation of technology, 96.2% (n = 75) of respondents reported one or more benefit. The average number of benefits each respondent with ACMT recorded was 4.6 ± 0.3 (mean ± SEM). The most cited benefits (Table 2.2) were improved fertility management (80.8%) and performance (70.5%), followed by improved herd management (62.8%), and time saved (62.8%).

Table 2.2 The benefits experienced on farm after the installation of ACMT[1] expressed as a percentage across all farms with ACMT (n = 78)

Benefit experienced	Percentage and number of respondents
No benefit experienced	3.8% (n = 3)
Improved fertility management	80.8% (n = 63)
Improved fertility performance	70.5% (n = 55)
Improved herd management	62.8% (n = 49)
Time saver	62.8% (n = 49)
Improved cow health management	56.4% (n = 44)
Increased milk production	39.7% (n = 31)
Increased profit margin per cow	41.0% (n = 32)
Increased disease detection rates	30.8% (n = 24)
Aids farm compliance	11.5% (n = 9)
Other[2]	0% (n = 0)

[1]Respondents were asked to select criteria from a preselected list.

[2] “Other” allowed respondents to input their own opinion.

2.3.3 Problems associated with the installation of ACMT

Since the installation of technology, 60.3% (n = 47) respondents reported one or more problems. The average number of problems each respondent with ACMT recorded was 0.86 ± 0.16 (mean ± SEM). The most cited problems of ACMT were system faults (e.g. breakage, poor battery life), which were reported by 32.1% of respondents (Table 2.3), and 9.0% reported a problem caused by non-compatibility with other systems on farm.

Table 2.3 The problems experienced on farm after the installation of ACMT[1] expressed as a percentage across all farms with ACMT (n = 78)

Problem experienced	Percentage and number of respondents
No problem experienced	39.7% (n = 31)
System faults (e.g. breakages or poor battery life)	32.1% (n = 25)
Not compatible with other systems on farm	9.0% (n = 7)
Difficult or time consuming to attach to cows	7.7% (n = 6)
Poor customer support available	7.7% (n = 6)
Poor system performance	7.7% (n = 6)
Poor broadband inhibits system performance	6.4% (n = 5)
Not easy to use	5.1% (n = 4)
Difficult to interpret results	3.8% (n = 3)
No return on investment	1.3% (n = 1)
Welfare concern – product interacts poorly with cows (i.e. technology causes rubs or sores)	1.3% (n = 1)
Low return on investment	0% (n = 0)
Other[2]	0% (n = 0)

[1]Respondents were asked to select criteria from a preselected list.

[2] “Other” allowed respondents to input their own opinion.

2.3.4 Respondent description of ACMT

There was a difference in the number of positive descriptors and negative descriptors that farmers used to describe technology ($P < 0.001$; Table 2.4). On average, farmers used 2.7 ± 0.15 positive descriptors to 0.21 ± 0.07 negative descriptors (mean ± SEM). The top 3 descriptors of automated cow technology were useful (73.1%), reliable (67.9%), and practical (66.7%).

Table 2.4 Results from a UK dairy farmer survey (n = 78) showing percentages and number of surveyed farmers describing ACMT[1]

Descriptor	Percentage and number of respondents
Useful	58.2% (n = 71)
Reliable	67.9% (n = 53)
Practical	66.7% (n = 52)
Good value for money	35.9% (n = 28)
High quality	29.5% (n = 23)
Overpriced	11.5% (n = 9)
Unreliable	6.4% (n = 5)
Poor quality	2.6% (n = 2)
Ineffective	1.3% (n = 1)
Impractical	0% (n = 0)
Other[2]	0% (n = 0)

[1]Respondents were asked to select criteria from a preselected list.

[2] “Other” allowed respondents to input their own opinion.

2.3.5 Respondent reasons for not adopting ACMT

On average, farms without ACMT cited 2.5 ± 0.2 reasons as to why it was not adopted (mean ± SEM; Table 2.5). The most common reason was initial investment cost (68.2%), followed by cost of system upkeep (50.0%), and too few cows for technology to be cost effective (27.3%).

Table 2.5 Results from a UK dairy farmer survey (n = 44) showing the reasons why farmers have not adopted ACMT[1]

Reason	Percentage and number of respondents
Initial investment cost	68.2% (n = 30)
Cost of system upkeep (e.g. maintenance and updates)	50.0% (n = 22)
Not enough cows for technology to be cost effective	27.3% (n = 12)
Low longevity of system	20.5% (n = 9)
Poor return on investment	18.2% (n = 8)
Do not think technology is worthwhile	15.9% (n = 7)
Poor farm infrastructure	15.9% (n = 7)
Poor broadband speed	13.6% (n = 6)
Other[2]	9.1% (n = 4)
Difficult or time consuming to attach to cows	6.8% (n = 3)
Lack of time to prioritise	2.3% (n = 1)
No long-term goal for dairy continuation	2.3% (n = 1)
Not easy to use	2.3% (n = 1)

1Respondents were asked to select criteria from a preselected list.

2 “Other” included low-cost system (n = 2), waiting for the right time before investing (n = 1), and poor prior experience with ACMTs (n = 1).

2.3.6 Criteria influencing ACMT purchase

It was observed that 50% of farms with no current monitoring technology were likely to purchase cow monitoring technology in the next 5 years, compared to 78% of farms already using monitoring technology. Farms that did not utilise ACMT were less likely to want to purchase cow monitoring technology in the next 5 years compared to farms that already utilise technology ($P = 0.003$). A Likert scale (Likert, 1932) was used to determine the importance of criteria that would influence the purchase of ACMT from not important (1) to very important (4). No differences in criteria that would influence purchase of ACMT were found between farms with no ACMT and farms with ACMT (Table 2.6). The most important criteria when considering the purchase of technology were return on investment (3.7 ± 0.04), good customer support (3.6 ± 0.05), ease of use (3.6 ± 0.06), and established technology with recognised performance (3.5 ± 0.05) as the most important factors (mean ± SEM).

Table 2.6 Results from a UK dairy farmer survey (n = 122) showing the criteria that influence purchase on ACMT

Criteria	1-Not important	2	3	4 -Very important	No opinion	All	With ACMT	Without ACMT	P-value
Available grants	13.9% (n=17)	16.4% (n=20)	31.1% (n=38)	36.9% (=45)	1.6% (n=2)	2.93 ± 0.09	2.80 ± 0.13	3.13 ± 0.14	0.15
Return on investment	0% (n=0)	2.5% (n=3)	20.5% (n=25)	76.2% (n=93)	0.8% (n=1)	3.74 ± 0.04	3.69 ± 0.06	3.84 ± 0.06	0.16
Initial investment cost	2.5% (n=3)	14.8% (n=18)	39.3% (n=48)	41.8% (n=51)	1.6% (n=2)	3.23 ± 0.07	3.13 ± 0.09	3.40 ± 0.12	0.06
Established technology with recognised performance	0% (n=0)	8.2% (n=10)	33.6% (n=41)	54.1% (n=66)	4.1% (n=5)	3.48 ± 0.06	3.51 ± 0.07	3.43 ± 0.11	0.64
Ease of use	0% (n=0)	7.4% (n=9)	27.9% (n=34)	62.3% (n=76)	2.5% (n=3)	3.56 ± 0.06	3.55 ± 0.08	3.58 ± 0.09	0.99
Time required to understand output/results	4.9% (n=6)	18.0% (n=22)	37.7% (n=46)	38.5% (n=47)	0.8% (n=1)	3.11 ± 0.08	3.10 ± 0.10	3.13 ± 0.14	0.85
Good customer support	0% (n=0)	3.3% (n=4)	35.2% (n=43)	59.0% (n=72)	2.5% (n=3)	3.57 ± 0.05	3.53 ± 0.07	3.65 ± 0.08	0.24
Compatibility with other systems on farm	9.0% (n=11)	15.6% (n=19)	23.8% (n=29)	49.2% (n=60)	2.5% (n=3)	3.16 ± 0.09	3.12 ± 0.12	3.23 ± 0.15	0.58
Suitable farm infrastructure (i.e. good broadband)	5.7% (n=7)	13.1% (n=16)	30.3% (n=37)	49.2% (n=60)	1.6% (n=2)	3.25 ± 0.08	3.22 ± 0.11	3.30 ± 0.13	0.78

2.4 Discussion

2.4.1 Initial findings

The average herd size of UK dairy farms is 148 cows (AHDB, 2020a) whereas it was 293 cows in this survey. In addition, the average milk yield in this survey (8, 684.9 litres per cow per year) was higher than the UK national average of 7, 968.0 litres per cow per year (AHDB, 2019). Defra (2019a) reported the average age of farm workers was 60 years of age, whilst the average age of UK farm owners was 65. The most common respondent age bracket in this survey was 25-34. Although we do not know what position respondents held on the farm – e.g. farm worker – we do know that the average respondent age was younger than the reported Defra averages for both farm owners and workers. It is advised that caution is applied whilst interpreting these results as this survey does not represent the average UK dairy farm.

In this study, 63.9% of farms utilised automated cow monitoring technology. Similar figures have been reported on USA dairy farms, with previous studies reporting that 68.8% of respondents used monitoring technology on their dairy farms (Borchers and Bewley, 2015). Rutten et al. (2018) reported that sensor technologies have great potential, and as technology becomes more reliable and capable, adoption may increase. The findings of this study support this statement, and it was observed that 50% of farms that did not have ACMT would invest in ACMT within the next 5 years.

This study identified no association between farm location (England, Northern Ireland, Scotland, or Wales) or herd size and the adoption of ACMT. Gargiulo et al. (2018) reported that precision technologies had higher adoption rates in herds with over 500 cows, compared to herds with 500 cows or fewer. There were differences in methodology between the two studies. This study focused on the adoption of ACMT, whilst Gargiulo et al. (2018) looked at the adoption of all technologies e.g. automatic cluster removal. Gargiulo et al. (2018) classified farms as either small, medium, large, X-large, and XX-large, whilst this study did not categorise herd size. The respondents in this survey had an average herd size of 293 cows, which was higher than the UK national average of 148. This is a study limitation as it suggests that the respondents are not representative of the average UK dairy farm. The findings of this study suggest that herd size has not influenced the purchase decisions of UK dairy farmers. Further research is needed to ascertain why farmers decided to purchase automated cow monitoring technologies, as this study only addresses why farmers have not invested. As there was no significant association between herd size and adoption of ACMT, it was not possible to use a breakpoint regression to calculate the number of cows in a herd associated with increased technology adoption.

Whilst no association between ACMT adoption and herd size was found, average milk yield per cow per year was higher in farms that had adopted technology (9,273.1 ± 199.9 litres per cow per year) compared to those that had not (7,642.0 ± 258.5 litres per cow per year). It is not possible to ascertain whether increased milk yield occurred after adoption of ACMT, or whether higher milk yield led to the adoption of ACMT. No previous studies have looked at the association between milk yield and the adoption of technology on dairy farms. Previous studies have reported the association between increased milk production and reduced fertility in dairy cattle (Butler, 2003), and so farms with increased milk yield could be using ACMT to manage and monitor oestrus detection in their cows more effectively. Conversely, revenue generated by milk sales is likely to be higher in farms that produce more milk. Farms with greater capital are more likely to invest, and it is suggested that increased ACMT adoption reflects the farmers' attempts to invest their capital. In support of this statement, this study found that initial investment cost was cited as the main reason farms without ACMT had not invested in technology. A breakpoint regression was used to locate the change point in the milk yield data, and it is suggested that farms producing less than 9,200 litres per cow per year were less likely to have adopted ACMT.

2.4.2 Parameters recorded by ACMT

The most recorded parameters in this study were heat detection (58.2%), daily milk yield (45.1%), and illness detection (22.1%). Heat detection and disease affect farm profitability (Dolecheck et al., 2016; Kaniyamattam et al., 2020), and so the adoption of these technologies present an opportunity to invest in a tool to help improve herd health and management. Less than 10% of farmers used technology to record parameters such as calving detection (6.6%), milk components (6.6%), lameness detection or mobility scoring (5.7%), dry matter intake (4.9%), body weight (3.3%), milk progesterone (1.6%), and standing and lying behaviour (1.6%). Rutten et al. (2018) investigated why some sensor technologies were more widely adopted than others. It was concluded that delayed investment could be caused by farmers waiting for improved versions with better decision support mechanisms. In time, there could be an increase in the adoption of these less commonly recorded parameters on farms.

This study did not investigate the parameters dairy farmers would find most useful to record. The monitoring of hoof health/locomotion problems and milk progesterone monitoring were reported as parameters of the greatest interest for Italian dairy farmers to record (Abeni et al., 2019). US dairy producers reported that the most useful parameters to record were mastitis, standing oestrus, and daily milk yield with 98.1%, 96.3%, and 92.6% of respondents categorising the parameters as 'somewhat useful' or 'useful' (Borchers et al., 2016).

2.4.2.1 Heat detection

The main source of revenue on dairy farms is through the sale of milk. One of the largest influences on dairy farm profitability is reproductive performance, due to its direct relationship with milk production (Dolecheck et al., 2016). Failure to detect oestrus will directly increase the calving interval and prevent cows from returning to a state of lactation, negatively affecting milk production. In this study, heat detection was the most common monitoring parameter, and it was recorded by 58.2% of UK dairy farmers. Traditionally, oestrus detection was achieved through human visual observation. Caraviello et al. (2006b) reported that cows are visually observed for signs of oestrus for 2.8 times/d for 27 min per observation on the weekday, and 2.5 times/d for 25 min per observation on the weekend. There is a labour cost to visual oestrus detection, and it was reported that visual heat detection methods were more sensitive to labour fluctuations (Olynk and Wolf, 2008). Compared to automatic oestrus detection systems, visual oestrus detection performs poorly. At-Taras and Spahr (2001) reported that heat detection rates were 54.4% for visual observation compared to 86.8% for a heat detection system. In At-Taras and Spahr (2001), visual detection occurred when farm staff saw cows attempting to mount or standing to be mounted during daily routine. The adoption of heat detection systems highlights how farmers have moved from a labour-intensive system (human visual detection) to an automatic monitoring system which can improve detection rates.

The adoption of technology for oestrus detection is higher in this study compared to previous studies. In the US, it was reported that 41.3% of farms recorded cow activity (Borchers and Bewley, 2015) whilst in Italy, 48.6% of farmers recorded a parameter for the detection of oestrus (i.e. neck or leg activity; Abeni et al., 2019). In North America, it was reported that 30% of all inseminations were timed AI after an oestrus synchronisation programme (Souza et al., 2013). Synchronisation programmes require hormones and although this practice is common in the US, within the UK 69% and 48% of practitioners believe the long-term routine prescription of hormones for immediate fixed-time AI and immediate oestrus induction is ’unacceptable’ (Higgins et al., 2013). In the UK, there are negative connotations associated with the use of hormones in food production (Higgins et al., 2013). A reason for increased adoption of heat detection systems in the UK compared to other countries could be to tackle fertility problems caused by limited use of synchronisation programmes.

2.4.2.2 Daily milk yield

Milk is the primary product produced on dairy farms, yet over half of UK farms in this study did not record the daily milk output of individual cows. Knowledge of the daily milk output of individual cows can help selection for breeding strategies and aid in cow management (Klopčič et al., 2013). Gargiulo et al. (2018) surveyed 199 Australian dairy farmers, and it was reported that 72% of

Australian milking systems were built over 10 years ago. In addition, it was reported that 60% of farms upgraded their milking facilities over 5 years ago. It is hypothesised that as farms upgrade their milking equipment and as precision dairy technologies develop, the use of inline milk meters will increase in the future (Eastwood et al., 2012).

The adoption of sensors for daily milk yield recording was surprisingly low (45.1%), however similar adoption rates in other countries have been cited at 39.4% (Abeni et al., 2019) and 52.3% (Borchers and Bewley, 2015). In Australia, 57.8% of dairy farmers and 54.9% of service providers believe that inline milk meter adoption will increase on Australian dairy farms by 2025 (Gargiulo et al., 2018). It is possible that a respondent with no ACMT had milk meters but did not view daily milk yield as an as an individual cow monitoring parameter. In this study, the most common milking system type was herringbone (84.4%), followed by rotary (7.4%), robot (6.6%), abreast (0.8%) and rapid exit (0.8%). In a study of 199 Australian dairy farmers, 70% were reported to have a herringbone parlour, whilst 26% used a rotary and 4% an automatic milking system.

2.4.2.3 Illness detection

In this study, 22.1% of farms had illness detection, 17.2% mastitis detection, and 4.6% lameness detection or mobility scoring. Similar figures were identified by Borchers and Bewley (2015) who reported that 25.7% of farms had mastitis detection systems and 4.5% had lameness detection.

Disease has a significant economic impact on dairy farms (Kaniyamattam et al., 2020), however the uptake of sensor technology to monitor disease e.g. lameness is relatively low. Fabian et al. (2014) reported that only 27.3% of farmers correctly identified cows with reduced mobility, so the adoption of automatic mobility scoring could improve animal health and welfare. The effect of disease on cow behaviour is an area which is still being widely researched (Warner et al., 2020). Producers have been reported to be unwilling to invest in technology with unproven performance (Borchers and Bewley, 2015), and it is possible that farmers are waiting for improved systems prior to investment.

Rutten et al. (2018) states that the performance of oestrus detection systems increased rapidly within a 20-year period. It is expected that the performance of disease detection systems will also improve in this manner, which could lead to increased farm uptake.

Further research is required to understand the reasons why farms have not adopted automated disease detection technology. This study did not allow for illness detection to be categorised into specific diseases after respondent selection. Future studies should allow farmers to select the diseases that their system monitors to give an accurate depiction of recorded parameters on UK dairy farms.

2.4.3 Farmer perceptions of ACMT after its installation

From the results of this survey, it was concluded that farmers regarded the installation of ACMT positively. When asked if there had been a benefit seen after ACMT installation, 96.2% of farmers said ‘yes’. The main benefits reported were improved fertility management (80.8%) and performance (70.5%), improved herd management (62.8%), and time saved (62.8%). These findings were expected, as the most common parameter farmers recorded was heat detection. Visual oestrus detection is characterised by poor detection and high labour inputs (At-Taras and Spahr, 2001; Olynk and Wolf, 2008), so improved fertility performance and reduced time inputs were anticipated.

Improved cow health management was reported by 56.4% of farmers, however only 30.8% of farmers reported an increased disease detection rate. A recent study by Eckelkamp and Bewley (2020) reported that dairy farmers were more likely to ignore disease alerts over time, and it is possible that this is a contributory reason for farmers not seeing a benefit in increased disease detection rates. Eckelkamp and Bewley (2020) suggested that disease alerts need to be improved to ensure farmer action, and that this could be achieved through the incorporation of herd management software and creating alerts by lactation stage.

No previous studies have assessed the problems associated with ACMT installation. Overall, 60.3% of farmers reported a problem following the installation of ACMT. For respondents that stated they have experienced an issue post-installation, over half (53.2%) stated this was due to a system fault such as breakages or poor battery life. This is a limitation in the ability of a system to perform, and technology companies should work to minimise the number of faults in their systems. Only one respondent reported technology interacted poorly with their cattle, causing rubs or sores. This suggests that technology does not pose a major welfare concern, which agrees with the findings of Gibbons et al. (2012) and Mackay et al. (2012) that reported that leg accelerometers did not affect leg health.

Despite 60.3% of farmers with ACMT stating that there was a problem after installation, when asked to select words to describe ACMT, farmers used more positive descriptors (2.7 ± 0.15 no./positive descriptors) compared to negative descriptors (0.21 ± 0.07 no./negative descriptors). The top 3 descriptors of automated cow technology were useful (73.1%), reliable (67.9%), and practical (66.7%). Only 7% of descriptors selected were associated with a negative connotation. In addition, farmers reported 4.6 ± 0.3 benefits compared to 0.86 ± 0.16 problems post installation. These findings suggest that ACMT is viewed positively on farm, and that the expectations of farmers are being fulfilled.

2.4.4 Reasons for not adopting ACMT

Farmers without ACMT cited an average of 2.5 ± 0.2 reasons as to why ACMT had not been adopted. Although Gargiulo et al. (2018) reported that small herds were less likely to adopt technology, in this study only 27.3% of farms with no ACMT believed herd size was a contributory factor for their lack of adoption. Initial investment cost and cost of system upkeep were the most cited reasons for farmers not investing in ACMT. These findings are reflective of previous studies that investigated why Dutch dairy farmers did not invest in sensor systems (Steeneveld and Hogeveen, 2015). Their study reported that 48% of respondents selected ‘prefer to invest money in other things for the farm’ and 38% stated ‘uncertainty about the profitability of the investment’.

From these two studies, it can be concluded that financial implications are the main reason why farms do not invest in technology. Another reason as to why farmers have not invested in technology could be that technologies are not deemed suitable for the needs of the farm. Danneels (2004) states that new technologies are, at first, regarded as unsuitable for the needs of the customer. Over time, as technology performance increases, these technologies can satisfy the needs and requirements of the wider market. If technology companies can improve the efficacy of their systems, reduce the cost of sensor systems, and are able to prove a return on investment post-installation, the uptake of sensor systems may increase within the future.

2.4.5 Criteria influencing ACMT purchase

No differences were found between farms with or without ACMT for criteria that would influence purchase of technology. When asked to score criteria on their importance when considering the purchase of technology, farmers scored return on investment (3.74 ± 0.04), good customer support (3.57 ± 0.05), ease of use (3.56 ± 0.06), and established technology with recognised performance (3.48 ± 0.06) as the most important factors. These results are similar to Borchers and Bewley (2015) where US dairy producers ranked benefit-to-cost ratio, total investment cost, simplicity and ease of use, and proven performance as the most important criteria prior to investment.

From the present study and Borchers and Bewley (2015), it can be concluded that sensor systems must have a benefit or return on investment. Technology manufacturers can use this information to improve how technology is marketed to farmers, with focus on a cost-benefit analysis (non-monetary and monetary).

2.4.6 Open ended question

When asked to state their opinion on ACMT, two farmers indicated that the incorporation of sensor software systems would be beneficial, whilst one farmer indicated that the amalgamation of sensors would be useful. The integration of sensor software systems or sensor systems could benefit the farmer by ensuring all information is centralised, however complications such as data ownership between companies could arise.

- *'The biggest drawback to investing in technology is that various systems are not compatible and requires different computers!!'*

- *'Too many systems are stand alone or "plug and play", with no ability to incorporate the data into a single interface without double handling'*

- *'Having a "one for all" sensor approach instead of having 2 or 3 different devices recording different things'*

In addition, one farmer raised a concern that there was a disparity between the need of the farmer and the data outputs that companies provide. Two farmers believed ACMT systems must be kept simple, as well as ensuring a return on investment and product quality. These suggestions provide useful information that technology manufacturers could use to improve their software systems.

- *'There is a gulf of understanding between practical daily use and software engineers/technicians: both the farmer and the on-farm technician need to understand the management implications of the data collected and its interpretation.'*

- *'Keep it simple, with as long a useful lifespan as possible.'*

- *'KISS: Keep It Simple Stupid. All this technology must be paid for!!'*

2.4.7 Potential bias and survey limitations

This study had a selection bias as the main method in which survey responses were collated, via the internet, could have limited the population of dairy farmers that were accessed. In 2015, it was reported that 85% of UK farms had internet access (Farmers Weekly, 2015). Across UK households, internet infiltration increased from 86% in 2015 to 93% in 2019 (Statista, 2020). It is likely that the percentage of UK farms with internet has increased since 2015, and the sample collected could be representative. Farmer meetings were attended, although these were attended only in Scotland due to geographical travel restrictions. As farmers completed the survey voluntarily, those that had an interest in ACMT could have been more likely to complete the survey, and the percentage of farms with ACMT stated in this survey may be higher than the average UK prevalence.

A potential limitation of the survey is that the questions were not generated by listening to farmers talking about technology in their own words. According to Artino et al. (2014), this method would have ensured that the wording of the survey would closely resemble that of dairy farmers. Another limitation of the survey is that if favoured closed-ended questions and there was only one open-ended question. Limiting the ability of respondents to answer freely may have led respondents to choose criteria that was not entirely applicable to their situation. There was an option for respondents to select 'other' and to input their own opinions, although this was not widely used. In addition, this survey could have better explored including additional questions which assessed the same research question (the construct; Artino et al. (2014)). This would have generated more accurate measurement of farmers' opinions to ACMT.

2.5 Conclusion

This study found that ACMT was used by 63.9% of UK dairy farmers, and those dairy farmers view ACMT positively. Farms producing under 9,200 litres per cow per year were less likely to invest in ACMT. The most recorded parameters on dairy farms were heat detection (58.2%), daily milk yield (45.1%), and illness detection (22.1%). The main reasons why farmers did not invest in ACMT were financially related. No differences were found between farms with ACMT and farms without ACMT on criteria that would influence purchase of ACMT. It was discovered that farms with ACMT were more likely to invest in further technology, compared to farms without ACMT.

Chapter 3 Materials and Methods

3.1 Animals and Housing

Behavioural data were collected at the University of Edinburgh Langhill Farm (Roslin, Midlothian, United Kingdom) between November 2016 and April 2018. The Royal Dick School of Veterinary Studies Veterinary Ethical Review Committee (Ref 82-16) and Home Office Project Licence 70/8105 approved the experimental work.

The milking herd consisted of approximately 220 Holstein dairy cattle. Pregnant cows were dried off approximately 8 wk before their expected calving date. After drying off, cows were housed in a cubicle shed (Figure 2.1) and fed a dry cow ration consisting of straw, silage, and dry cow minerals.

Approximately 3 wk prior to expected calving date, cows were moved into a transition group within the cubicle shed (14m x 12m). Cows were fed a total mixed ration once a day that consisted of wholecrop wheat, grass silage, dry cow mineral, and concentrate. The ration had a 1:4 concentrate: forage ratio.

Around 10 days before expected calving date, cows were moved onto a 11 m x 18.4 m straw-bedded shed (Figure3.1) where they calved. Approximately 5 – 15 heifers and cows were present in the calving environment at each point in time. There was a space allowance of between 2.4 m^2 – 7.3 m^2 on a concrete loafing area next to the feed face, and on the straw bedded area, there was a space allowance of between 11.1 m^2 – 33.2 m^2. Cows were fed the transition cow ration once a day.

After calving, cows were housed in a straw bedded pen (11 m x 9 m) with other calved cows for approximately 24h. Cows were fed the high yielding milking ration (providing the energy needs of maintenance plus 40 litres of milk), which consisted of wholecrop wheat, silage, concentrate, molasses, yeast and mineral supplementation once a day. A day after calving, cows joined the milking herd and were housed in cubicles. All mains water was supplied by self-filling water troughs (0.95 m x 0.4 m x 0.35 m).

Cows in the calving pen were observed for signs of calving approximately 12 times during the day by farm staff. After calving, colostrum was harvested within 4 hours to ensure the calf was fed 10% of its bodyweight in colostrum within 4 hours of birth.

Figure 3.1 Image of dry cow cubicle housing (left) and the calving shed (right).

3.2 Video recordings

Observations for time of calving were made when cows were housed in the straw yard, which was also the calving pen. The exact time of calving (to the nearest minute) and date of calving was ascertained by retrospective analysis of video recordings. One webcam (AXIS P5414-E PTZ Network Camera), with HDTV 720p performance and 18x optical zoom, was installed in an overhead position that gave a good overview of the calving shed (Figure 3.2). Video files were automatically downloaded and saved onto a computer, where they could be opened for retrospective analysis. A timestamp (hour:min:sec) and a date (year:month:day) were visible on all video files. The time and date were automatically synchronised with the computer’s clock. The calving shed was lit naturally by sunlight during daylight hours (08:00 – 16:00) and artificial lighting remained on during the night (16:00 – 08:00).

Figure 3.2 Image of calving shed from the webcam prior to retrospective video analysis to ascertain the time and date of calving.

The time of calving was taken to be the point where the foetus was fully expelled from the cow or when the calf's hips were expelled, and the hind legs remained inside the birth canal. This occurred at the end of Stage II of parturition and was a comparable definition to previous studies (Campler et al., 2015). Parturition occurs in three stages: Stage I, Stage II, and Stage III. Stage I comprises of cervical dilation, the start of myometrial contractions, and placement of the foetus prior to expulsion. Stage II includes visible abdominal contractions, the rupture of the allantochorion sac and foetal expulsion from the birth canal. The final stage of parturition, Stage III, comprises of foetal membrane expulsion (Mainau and Manteca, 2011).

3.3 Calving records

After each calving, a calving record was completed by a stockperson. The following information was recorded for each individual cow: Animal ID, Date of Calving, Time of calving, Calf live/dead, Calf sex, degree of assistance, and Notes/Problems.

Animal ID was a unique individual freeze brand number which allowed each cow to be individually identified. Although stockpersons recorded date and time of calving, this information was ascertained through retrospective analysis of video files. From the calving date an additional column, called 'academic year', was generated (Year 1: November 2016 – April 2017, and Year 2: November 2017 – April 2018). Another column, 'Gestation Length' was calculated by subtracting the date of artificial insemination prior to pregnancy diagnosis. Assistance level at calving was scored between 1-5 using a farm specific scale:

1) No assistance
2) Gentle traction by one person with no mechanical device used
3) Use of calving jack or assistance with two persons
4) Veterinary assistance
5) Caesarean Section

Farm protocol dictated when assistance could be given at calving. If the calf was not presented normally, or if calving progress has ceased for 30 minutes, or if the calf showed reduced vigour (Mee, 2008b), a decision was made to assist.

3.4 Behavioural recording

To record lying and standing time duration, step count, number of postural transitions (the number of standing and lying bouts), and motion index, an IceQube (IceRobotics Ltd., South Queensferry, United Kingdom) was attached to the right hind leg of each cow enrolled within the trial. IceQubes were securely attached above the fetlock using an 18" x 1" Velcro strap, and weighed 72g and had the following dimensions: 55 x 55 x 26mm.

The IceQube contains a triaxial accelerometer. When an animal moves, the movement generates an acceleration force which is recorded by the device. A series of algorithms translate the raw data into behavioural data (Finney et al., 2018). Motion index is the sum of net acceleration measured by the 3-axis minus an offset for gravity and can be considered an expression of leg activity (Maselyne et al., 2017). The accelerometer data were sampled at 4Hz (4 samples a second), before data were summarised in 15-minute blocks, and stored in the device memory. IceQubes have a memory storage capacity of 4 days. This is rolling storage, and data is overwritten once the storage limit is reached.

Data from the IceQube was downloaded by two different mechanisms: continuous and triggered downloads. Triggered downloads occurred when cows entered the parlour, and this happened twice a day between 04:30-7:30am and 14:45-17:30pm. Continuous downloads occurred in the dry cow shed and calving pen, where IceQubes automatically transmitted their data every 2 hours. The triggered or continuous data downloads communicate with the CowAlert Farm Server at 2.4GHz. After the data is received by the CowAlert Farm Server, it is saved into ZIP files. At the CowAlert Server, a process occurs every minute that causes the datafiles to be uploaded to the CowAlert cloud database

Experimental data files were accessed from the CowAlert cloud database. For each cow, data were stored in 15-minute blocks which summarised lying time (min/ 15 min), standing time (min/ 15 min), step count (no. steps/ 15 min), motion index (unit/ 15 min), and standing change (the number of lying and standing bouts; no. bouts/ 15 min).

Chapter 4 The behaviour of dairy cattle in the transition period: Effect of parity and dystocia

The research described in this Chapter has been published: Barraclough, R. A. C., Shaw, D. J., Boyce, R., Haskell, M. J., Macrae, A. I. (2020). The behaviour of dairy cattle in late gestation: Effects of parity and dystocia. Journal of Dairy Science, 103 (1): 714-722. See Appendix 2 for published paper.

4.1 Introduction

To commence lactation, cows are required to go through parturition, and this process carries many risks. Two common issues at calving are calving difficulty (dystocia) and perinatal mortality, and therefore intensive management of cattle in late pregnancy is critical to ensure neonatal and maternal survival, health and welfare (Mee, 2004). Dystocia, defined as a difficult or prolonged calving, has been classed as one of the most painful conditions that a cow can experience (Huxley and Whay, 2006). Within the UK, 16% of cows are reported to require calving assistance (Wall et al., 2010), and it is estimated that the worldwide prevalence of dystocia in dairy heifers and cows ranges from 1.5% to 22.6% (Mee, 2008a). To prevent calving difficulties and stillbirth, it is recommended that late gestation cows should be observed frequently for signs of calving. The suggested intervals at which cows are monitored vary from 1-2 hours (Gundelach et al., 2009) to 3-6 hours (Mee, 2004).

There is potential for automated behaviour monitoring technology to facilitate calving management. If behavioural changes prior to calving can be detected, then an alert can be sent to dairy producers. In Chapter 1, changes in cow behaviour in the period surrounding calving and late gestation were discussed and changes in cow behaviour have been observed on the day of calving, compared to the days leading up to calving. Jensen (2012) reported that overall lying time gradually decreased from 4 days pre-calving (998 minutes) until the day of calving (894 minutes). When data were analysed in 2-hour blocks on the day of calving, it was observed that lying time increased in the last 12 hours prior to calving from 31.4 min /2 hours to 42.8 min /2 hours just before calving. Overall activity has been reported to increase on the day of calving, and this is attributed to pain around calving. The number of postural transitions on the day of calving increases by up to 80% when compared to a non-calving control period (Huzzey et al., 2005), and tail raising was shown to increase in the 2-6 hour period prior to calving (Miedema et al., 2011b; Barrier et al., 2012). On the day of calving, Schirmann et al. (2013) reported a 15% reduction in rumination, a 24% decrease in dry matter intake and a 32% reduction in the time spent feeding when compared to 2-4 days prior to calving. These findings suggest that behaviour alters on the day of calving and the days leading up to calving, and there is potential for these behaviours to be developed into automated calving detection systems.

It is important to investigate what factors can influence cow behaviour prior to calving – for example parity – as these factors need to be considered within the prediction of calving. In Chapter 1, inconclusive findings were reported as to the effect of parity on cow behaviour in the period surrounding calving. Borchers et al. (2017) found differences in the daily lying time between primiparous and multiparous cows in the days leading up to calving (d -7 to d -1). However, Jensen (2012) reported no effect of parity, nor an interaction between parity and day (d -4 to d -1) on lying time duration. On the day of calving, Jensen (2012) reported no effect of parity nor an interaction between parity and 2h period on the number of lying bouts, lying time duration, or the activity index. In contrast, Miedema et al. (2011b) reported that primiparous cows increased the rate of tail raising earlier than multiparous cows (2h vs 2-4h before calving). In addition, Borchers et al. (2017) found differences in neck activity and lying behaviour between primiparous cows and multiparous cows on the day of calving.

Approximately 1 in 5 cows require assistance at calving (Mee, 2008a; Wall et al., 2010). If behavioural differences can be identified between cows that require assistance at calving and cows that do not, these behaviours could be used in the development of dystocia detection systems. Wehrend et al. (2006)

reported that cows that had dystocia exhibit restless behaviour earlier than cows that calved with no assistance. In the 24 hours before calving, Proudfoot et al. (2009) observed that cows with dystocia had more frequent transitions from standing to lying when compared to cows without dystocia. In contrast, Miedema et al. (2011b) and Barrier et al., (2012) reported that there was no interaction between the number of postural changes from lying to standing between cows with assisted calvings and cows with unassisted calvings. Kovács et al. (2017) found that cows with dystocia had lower rumination times in the final 8 hours before calving when compared to cows that had unassisted calvings. However, this result was not statistically significant.

It is important to understand the changes in cow behaviour leading up to calving as behavioural changes could be used in the prediction of calving. In addition, factors which could affect cow behaviour in late gestation (such as parity) should be investigated as literature has presented contradictory evidence. Dystocia can affect both cow and calf welfare, and therefore the ability to detect a dystocic cow could increase the rate of appropriate early intervention and improve animal welfare. The aim of this study was to objectively assess, using an automated behavioural monitoring system, any behavioural differences between primiparous and multiparous cows before calving, and to quantify any behavioural differences between dystocic and eutocic calvings.

4.1.1 Research Aims

The objectives of this study were to:

1. Determine the difference in cow behaviour on the day of calving (d 0) compared to a control period (d -4).
2. Determine the difference in lying and activity behaviours between primiparous cows and multiparous cows in the 4 d before calving (d -4 to d -1) and the day of calving.

3. Determine the difference in lying and activity behaviours between cows that had dystocia at calving and cows that had eutocia at calving in the 4 d before calving (d -4 to d -1) and the day of calving.

4.2 Materials and Methods

4.2.1 Animals and Housing

Overall details of the cows and system have been described in Chapter 2. This study was conducted at the University of Edinburgh Langhill Farm (Roslin, Midlothian, United Kingdom) between November 2016 and April 2018. The experimental work was approved by The Royal Dick School of Veterinary Studies Veterinary Ethical Review Committee (Ref 82-16). The farm has a milking herd of approximately 220 Holstein cows. The calving environment was a straw-bedded shed (11 m x 18.4 m) which was kept at a stocking rate of 5-15 heifers and cows. Cows had a space allowance of between 11.1 m^2 – 33.2 m^2 on a straw bedded area, and a space allowance of between 2.4 m^2 – 7.3 m^2 on a concrete loafing area. Animals were moved into the straw-bedded calving shed approximately 6.8 ± 4.6 days before their actual calving date. Once a day, cows were fed a total mixed ration consisting of grass silage, wholecrop, concentrate, molasses, and dry cow mineral. The ration had a 4:1 forage:concentrate ratio. Cows had access to self-filling water troughs (0.95 m x 0.4 m x 0.35 m) which supplied mains water. The decision to give assistance at calving was based on farm protocol. Assistance was given if calving was progressing slowly (if calving progress had ceased over a 30-minute period, or if the calf started to show signs of reduced vigour; Mee, 2008b) or if the calf was not presented normally. Ease of calving was recorded using a farm specific 5-point scale: (1) no assistance, (2) gentle traction by one person with no mechanical device used (3) use of calving jack or assistance with two persons (4) veterinary assistance, and (5) Caesarean Section. Calving scores of 2 or above were classed as assisted calving.

4.2.2 Behavioural measurements

An IceQube (IceRobotics Ltd., South Queensferry, United Kingdom) was fitted to the right hind leg of each cow 4 weeks before the predicted calving date. Overall details of the behavioural monitoring used have been described in Chapter 2.2. In summary, observations for time of calving were made when cows were housed in the straw yard calving shed. The exact time of calving (to the nearest minute) was ascertained by retrospective analysis of video recordings. The time of calving was taken to be the point where the foetus was fully expelled from the cow or when the calf's hips were expelled, and the hind legs remained inside the birth canal. This occurred at the end of Stage II of parturition and was a comparable definition to previous studies (Campler et al., 2015).

4.2.3 Statistical Analysis

Dataset 1 was used to analyse normal calving behaviour and parity differences, and comprised of 44 animals; 12 primiparous cows and 32 multiparous cows (calving score 1, parity 0-7, mean 1.2 ± 0.2). Animals within dataset 1 calved between 2016-2017.

Dataset 2 was used to analyse the difference in behaviour between animals that had dystocic calvings (n =14; calving score of 2 or above; parity 0-3, mean 1.1 ± 0.1) and animals that had eutocic calvings (n =14; calving score 1; parity 0-3, mean 1.1 ± 0.1). The 14 eutocic cows included 8 cows from Dataset 1 (7 multiparous, 1 primiparous) and 4 separate eutocic cows that calved between 2017 and 2018. Animals within dataset 2 calved between 2016-2018. A case-control study design was used to compare the behavioural difference between animals that had dystocic calvings and animals that had eutocic calvings. The fourteen animals with dystocic calvings were exactly matched to cows that had an eutocic calving based on lactation number (n = 14 pairs), calving date ± 28 d (n = 14 pairs), and year of calving (n = 14 pairs). Cows were also matched as closely as possible based on locomotion score (n = 11 pairs), calf breed (n = 9 pairs), calf sex (n = 12 pairs). Of the 14 animals that calved with dystocia, 9 cows were assisted by gentle traction (Score 2) and 5 cows were calved with a calving jack (Score 3).

A further 54 animals were observed but excluded from the analysis for various reasons including incomplete datasets (*n* = 2), presence of clinical milk fever (*n* = 15), severe lameness (*n* = 3; mobility score 2 and 3 using 0 – 3 point scale: AHDB, 2020b), no recorded time of calving (*n* = 10), or were not present in the straw yard for >5 d (*n* = 24). Only cows that were present in the straw yard for five or more days prior to the day of calving were used for the analyses to ensure cows were within the same environment when analyses were conducted.

To investigate the behaviour of dairy cattle in late gestation, the duration of lying time, the number of steps, the motion index, and the total number of standing and lying bouts (the number of postural positions) from dataset 1 and dataset 2 were each summarised from the time of calving into two datasets: behaviour in 2h periods and 24h periods (behaviour per day). The bihourly datasets were used for the analyses of cow behaviour on the day of calving, and data were analysed in 2h periods from -24 h to 0 h (the time of calving). The dataset containing cow behaviour per day were used to analyse cow behaviour in the days before calving (d -4 to d -1), and to compare the change in behaviour on the day of calving (d 0) compared to a control period (d -4). In this study, the number of lying and standing bouts were combined to provide a value for the number of postural of transitions within a period. All datasets were summed from the time relative to calving (i.e. calving was used as time 0), which ensured all cows followed the same timeline.

All analyses and data manipulations were carried out using R (version 3.4.4; R Foundation for Statistical Computing, Vienna, Austria). To assess data assumptions of normality, residual plots, histogram plots and data normality tests were examined. Mixed-effect analyses were carried out using the ‘lmerTest’ package. Residual plots were examined to ascertain the best model fit for the data. Statistical significance was taken as $P \leq 0.05$. Non-significant ($P > 0.05$) interactions were removed from models. Degrees of freedom were calculated using the Satherthwaite approximation for linear models and polynomial regression models, whilst Laplace Approximation was used to calculate degrees of freedom for generalised piecewise regression models.

4.2.3.1 Behavioural differences between the day of calving and control period

To explore the behavioural changes that occur on the day of calving (d 0) compared to a control period (d -4), the duration and frequencies of behaviours in each 24h period were compared for primiparous cows (n =12), multiparous cows (n =32), dystocic cows (n =14), and eutocic cows (n =14). The step count and motion index were $\log_{10}$ transformed to meet normal residual data distribution assumptions. Paired t-test were used to analyse normally distributed data (lying time, step count, and motion index), and Wilcoxon signed rank tests were used to analyse non-normally distributed data that did not fit normal data assumptions after $\log_{10}$ transformation (the number of postural transitions). In this study, there was no difference between behaviour variables on d -4 and d -3 when each variable was compared using the appropriate statistical test, and so d -4 was chosen as the control period.

4.2.3.2 Last 4 days prior to calving

For further investigation of the behavioural differences between primiparous cows and multiparous cows, and between dystocic and eutocic cows in late gestation, a linear mixed-effect model was used to assess behavioural changes in the last 4 days before calving (d -4 to d -1). To investigate behavioural differences between primiparous (n = 12), and multiparous cows (n = 32), the linear mixed-effect model included days to calving (d -4, d -3, d -2, d -1), parity (multiparous and primiparous), and the interaction between days to calving and parity as fixed effects, and cow ID was included as a random effect to account for repeated measurements per cow. The dataset contained 176 data points, and each cow had 4 repeated observations. To investigate behavioural differences between dystocic (n = 14) and eutocic (n = 14) cows, the linear mixed-effect model included days to calving (d -4, d -3, d -2, d -1), assistance level at calving (dystocia and eutocia), and the interaction between days to calving and assistance level at calving as fixed effects. To account for repeated measurements per cow, and the pair that cows were assigned to, a nested random effect containing pair and cow ID was used (pair/cow ID). The dataset contained 112 data points, and each cow had 4 repeated observations. Animals were pair matched using lactation number, and as this variable was already controlled for within the random effect, parity (multiparous and primiparous) was not included in the final model. The step count and motion index were $\log_{10}$ transformed to meet normal residual data distribution assumptions.

4.2.3.3 The last 24 hours before calving

To ascertain the pattern of behaviour exhibited on the day of calving, a set of mixed-effect models with different temporal relationships were fitted to behavioural variables contained within the bihourly dataset. Data were analysed over 12 2h periods from -24 h to 0 h (the time of calving). A generalised piecewise regression models (or “broken-stick” models – where a step change in behaviour at a certain time point is observed; Das et al., 2016), polynomial regression models (where there is either a decrease and then increase, or increase and then decrease in behaviours; Ostertagová, 2012), and linear models (Bangdiwala, 2018) were fitted to each behavioural variable. Residual plots were examined to ascertain the best model fit for the data. A piecewise regression model provided the best description of the change in the number of postural transitions, whilst a polynomial regression model best described the change in lying time. Linear models best described the change in step count and motion index. To investigate behavioural differences between primiparous (n = 12) and multiparous cows (n = 32), each model included time relative to calving (-24h to 0h), parity (multiparous and primiparous), and the interaction between time relative to calving and parity as fixed effects, and cow ID was included as a random effect to account for repeated measurements per cow. The dataset contained 528 data points, and each cow had 12 repeated observations. To investigate behavioural differences between dystocic (n = 14) and eutocic cows (n = 14), each model included time relative to calving (-24h to 0h), assistance level at calving (dystocia and eutocia), and the interaction between time relative to calving and assistance level at calving as fixed effects. To account for repeated measurements per cow, and the pair that cows were assigned to, a nested random effect containing pair and cow ID was used (pair/cow ID). The dataset contained 336 data points, and each cow had 12 repeated observations. The step count and motion index were $\log_{10}$ transformed to meet normal residual data distribution assumptions.

4.3 Results

4.3.1 Behavioural differences between the day of calving and control period

The lying time (h /d) of primiparous cows, multiparous cows, dystocic cows, and eutocic control cows decreased on the day of calving when compared to a control period (d -4) (Table 4.1). On the day of calving, the average number of postural transitions increased by 29.6% for primiparous cows (v_{11} = 0, P < 0.01), 45.6% for multiparous cows (v_{31} = -14.5, P < 0.01), 42.4% for dystocic cows (v_{13} = 6, P < 0.01), and 44.0% for eutocic control cows (v_{13} = 8, P < 0.01) when compared to the control period (Table 4.1). There were no differences in the average number of steps (no. /d) and motion index (unit /d) in primiparous cows on the day of calving when compared to the control period. In contrast, the step count of multiparous cows (t_{31} = -4.09, P < 0.001), dystocic cows (t_{13} = -3.72, P < 0.01), and eutocic control cows (t_{13} = -2.62, P < 0.05) increased on the day of calving when compared to the control period (Table 4.1). Additionally, the motion index of multiparous cows (t_{31} = -5.84, P < 0.001), dystocic cows (t_{13} = -4.41, P < 0.001), and eutocic control cows (t_{13} = -3.65, P < 0.001) also increased on the day of calving compared to the control period (Table 4.1). Appendix 3 includes behavioural graphs which show the change in behaviour on the day of calving compared to the control period for individual animals within each group (primiparous cows, multiparous cows, dystocic cows, eutocic cows)

Table 4.1 The mean (± SE) duration and frequency of behaviours during a control period (d -4) and the day of calving (d 0), and the average change (Δ ± SE) in each behaviour between d 0 and d -4, for primiparous, multiparous, dystocic, and eutocic cows.

Behaviour	Primiparous cows (n = 12)				Multiparous cows (n = 32)				Dystocic (Assisted) cows (n = 14)				Eutocic (Unassisted) cows (n = 14)			
	d -4	d 0	Δ	*P*	d -4	d 0	Δ	*P*	d -4	d 0	Δ	*P*	d -4	d 0	Δ	*P*
Lying time (h/d)	13.0 ± 0.4	10.5 ± 0.8	-2.5 ± 0.5	***	14.2 ± 0.4	11.6 ± 0.4	-2.6 ± 0.4	***	14.0 ± 0.4	11.7 ± 0.8	-2.3 ± 0.6	***	13.9 ± 0.7	11.8 ± 0.8	-2.1 ± 0.5	***
Postural transitions (no./d)	36.8 ± 2.7	49.6 ± 2.7	12.8 ± 3.4	**	28.3 ± 1.3	45.0 ± 2.2	16.7 ± 2.5	***	33.6 ± 2.2	51.7 ± 3.4	18.1 ± 4.0	**	28.2 ± 2.1	44.1 ± 3.5	15.9 ± 4.4	**
Step count (no./d)[1]	2.84 (693.4) ± 0.04	2.87 (740.1) ± 0.06	0.03 ± 0.07	n.s.	2.71 (511.6) ± 0.03	2.89 (785.0) ± 0.03	0.19 ± 0.04	***	2.77 (588.2) ± 0.05	2.97 (930.4) ± 0.05	0.20 ± 0.05	**	2.70 (496.4) ± 0.05	2.87 (746.9) ± 0.07	0.18 ± 0.07	*
Motion Index (unit/d)[2]	3.44 (2755.8) ± 0.02	3.53 (3400.1) ± 0.04	0.09 ± 0.06	n.s.	3.32 (2090.1) ± 0.03	3.52 (3299.8) ± 0.03	0.20 ± 0.03	***	3.35 (2236.7) ± 0.05	3.58 (3764.6) ± 0.05	0.23 ± 0.05	***	3.31 (2038.4) ± 0.05	3.51 (3256.0) ± 0.06	0.20 ± 0.06	**

n.s. P > 0.05
** *P* < 0.01
*** *P* < 0.001
[1]Step count (parameter submitted to logarithmic transformation; back transformed values presented in brackets).
[2]Motion Index (parameter submitted to logarithmic transformation; back transformed values presented in brackets)

4.3.2 Last 4 days prior to calving

Whilst the lying time of multiparous cows remained constant in the 4 days before the day of calving (14.2 ± 0.2 h; $F_{1,95}$ = 0.11, P = 0.74), the lying time of primiparous cows decreased by 25 min /d (13.0 ± 0.4 h to 11.6 ± 0.6 h; $F_{1,35}$ = 7.62, P = 0.009; Figure 4.1a). There was a difference in the pattern of the lying time (h /d) depending on parity, with primiparous cows on average -2.8h /d lower than that of multiparous cows across the period ($F_{1,94}$ = 17.3, P < 0.001). There was no interaction between days to calving and parity on the number of postural transitions ($F_{1,130}$ = 0.04, P > 0.83, Figure 4.1b), nor an effect of days to calving ($F_{1,130}$ = 0.67, P > 0.60, Figure 1b). Primiparous cows had an average of 9.1 ± 2.4 more postural transitions per day compared to multiparous cows ($F_{1,42}$ = 13.9, P < 0.001). There was a decrease in both step count and motion index across the period (P < 0.041, Figure 4.1c-d). In addition, the step count (steps /d; $F_{1,42}$ = 11.1, P = 0.002) and motion index (unit /d; $F_{1,42}$ = 14.5, P < 0.001) of primiparous cows was on average 14% higher per day when compared to multiparous cows.

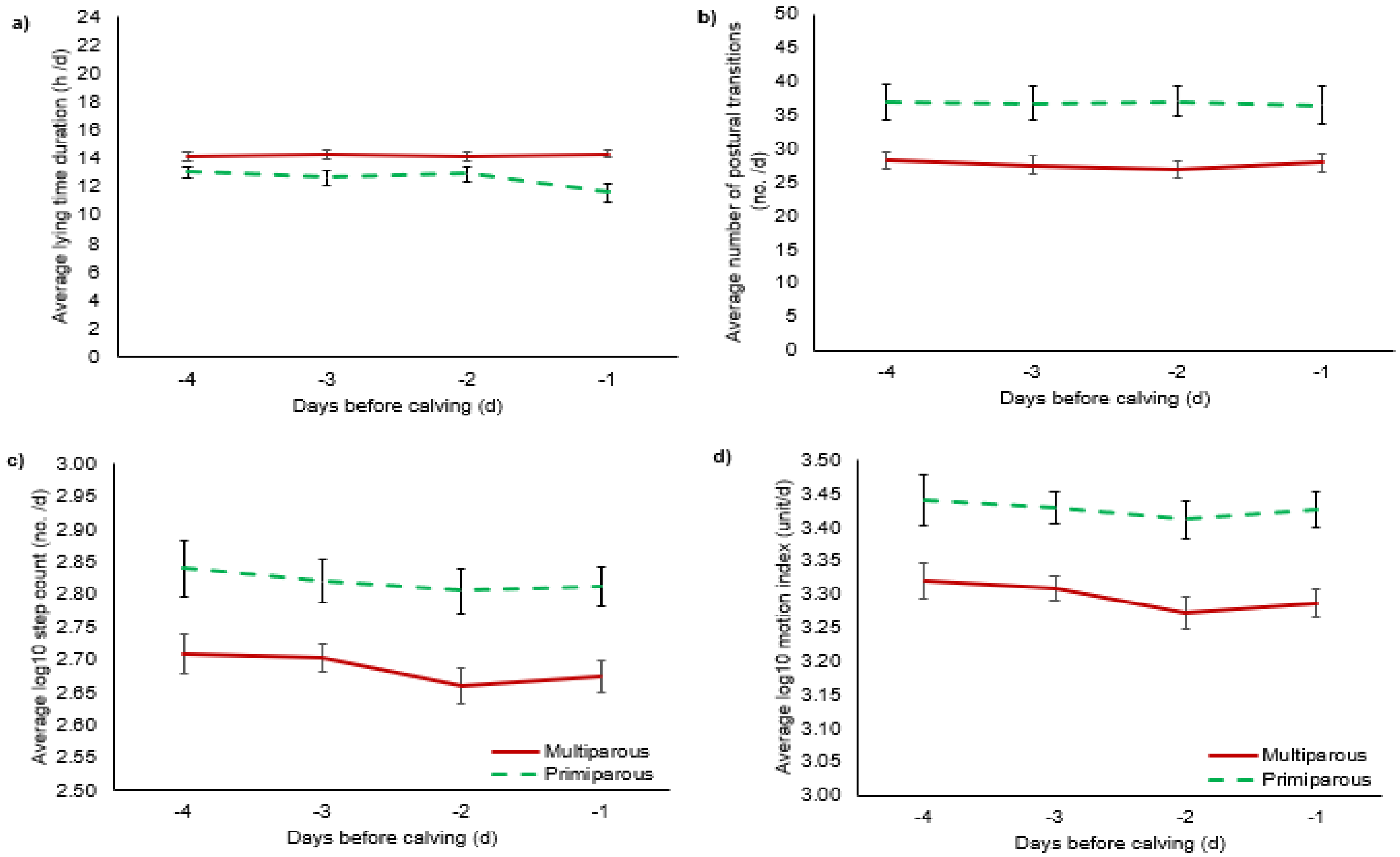


Figure 4.1 Behavioural variables for primiparous cows (green dashed line; n = 12) and multiparous cows (red solid line; n = 32) summarised into 24h periods ± SE in the 4 days before calving for (a) lying time duration (h /d); (b) number of postural transitions (no. /d); (c) Log$_{10}$ step count (no. /d); (d) Log$_{10}$ motion index (unit /d).

4.3.3 The last 24 hours before calving

There was no interaction between lying time (min /2h) and parity ($F_{1,480}$ = 3.65, P = 0.06; Figure 4.2a), nor was there an effect of parity on lying time ($F_{1,274}$ = 0.29, P = 0.59) on the day of calving. The change in lying time on the day of calving for primiparous and multiparous cows was best described by a polynomial pattern, with a decline from 65.3 min /2h at -22h to a low of 50.6 min /2h at -12h, increasing to an average of 66.8 min /2h just before birth ($F_{1,482}$ = 9.3, P = 0.002).

A piecewise regression model provided the best description of the change in the number of postural transitions on the day of calving for both primiparous and multiparous cows, with a combined breakpoint of -6.3h (Figure 4.2b). There was an effect of parity on the number of postural transitions on the day of calving, with primiparous cows having an average of 0.24 more postural transitions in each 2h period compared to multiparous cows ($z_{1,482}$ = 1.96, P < 0.05). In addition, there were increases in the average number of postural transitions in primiparous and multiparous cows from 4.4 and 3.2 at the breakpoints to 10.0 and 10.6 just before birth, respectively (P < 0.001). When a piecewise regression model was run separately for primiparous and multiparous cows, the individual breakpoints calculated were -2.0h and -6.6h, respectively.

There was no interaction between parity and hours to calving for step count ($F_{1,482}$ = 3.3, P > 0.05; Figure 4.2c) and motion index ($F_{1,482}$ = 1.86, P > 0.05; Figure 4.2d), nor an overall effect of parity on either step count ($F_{1,144}$ = 3.0, P = 0.09) or motion index ($F_{1,155}$ = 0.72, P > 0.05). Linear changes in both step count ($F_{1,483}$ = 16.5, P < 0.001) and motion index ($F_{1,483}$ = 47.9, P < 0.001) on the day of calving were observed, with increases in both parameters. Back transformation of $\log_{10}$ data show that step count increased from an average of 32.3 steps /2h at -22h to 78.8 steps /2h just before calving, and motion index increased from an average of 139.5 unit /2h at -22 to 437.5 unit /2h just before calving.

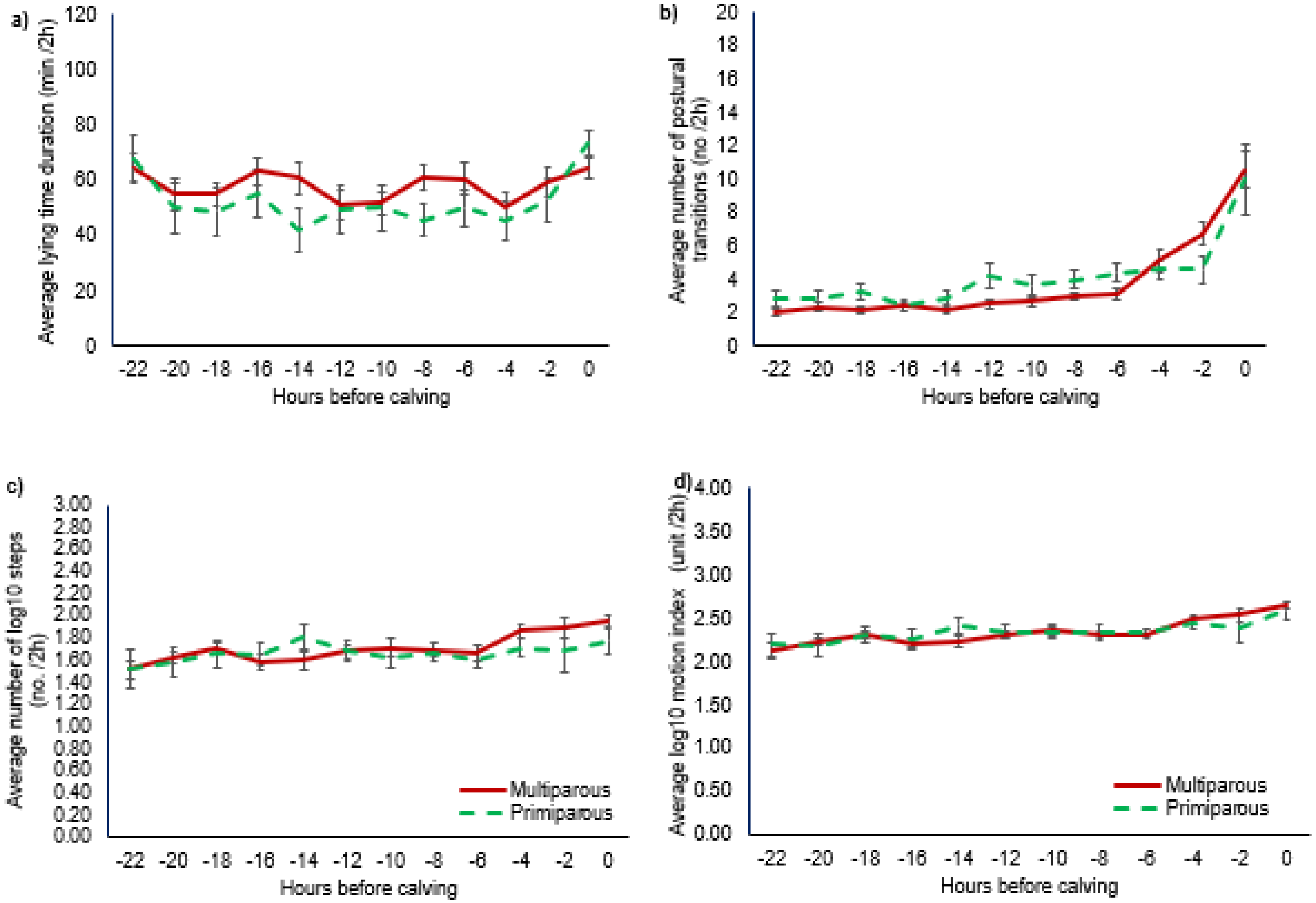


Figure 4.2 Behavioural variables for primiparous cows (green dashed line; n = 12) and multiparous cows (red solid line; n = 32) summarised into 2h periods ± SE in the 24h before calving for (a) lying time duration (min /2h); (b) number of postural transitions (no. /2h); (c) Log$_{10}$ step count (no. /2h); (d) Log$_{10}$ motion index (unit /2h).

4.3.4 Last 4 days prior to calving: dystocic and eutocic

Within the 4 d before calving (d -4, d -3, d -2, d -1), there was no difference between the 14 dystocic cows, and the 14 eutocic cows for the duration of lying time (h /d), the number of postural transitions (no. /d), the step count (no. /d), and the motion index (unit /d) ($P > 0.36$; Figure 4.3a-d). There was no interaction between days to calving and assistance level at calving for the duration of lying time, step count, and motion index within the period ($P > 0.12$). In contrast, there was an interaction between the number of postural transitions and assistance level at calving ($F_{1,82} = 6.3$; $P = 0.01$), which decreased from 33.6 ± 2.2 to 29.1 ± 2.0 for dystocic cows, but increased from 28.2 ± 2.1 to 30.4 ± 1.6 in the 14 eutocic cows.

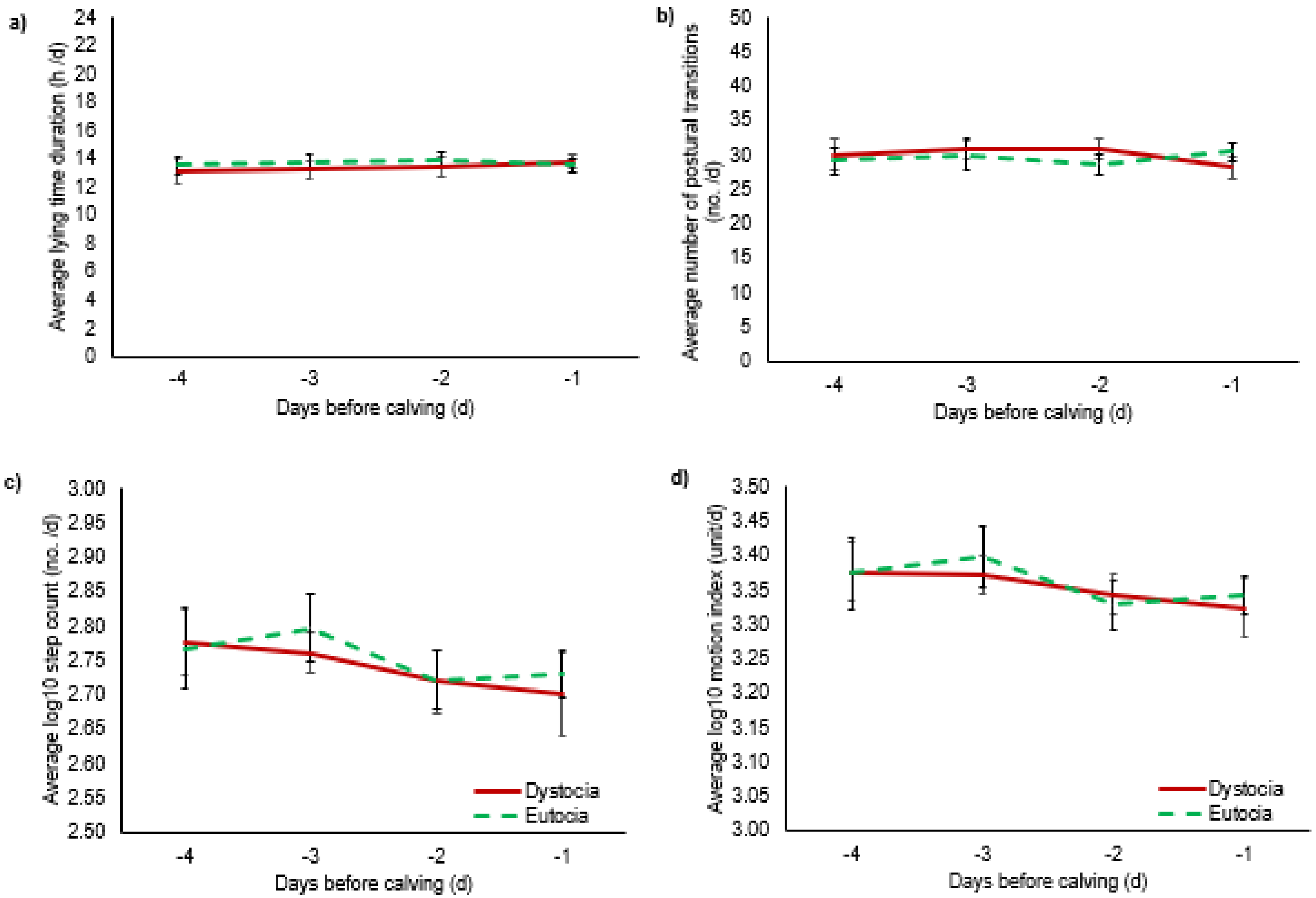


Figure 4.3 Behavioural variables for eutocic cows (green dashed line; n = 14) and dystocic cows (red solid line; n = 14) summarised into 24h periods ± SE in the 4 days before calving for (a) lying time duration (h /d); (b) number of postural transitions (no. /d); (c) Log$_{10}$ step count (no. /d); (d) Log$_{10}$ motion index (unit /d).

4.3.5 The last 24 hours before calving: dystocic and eutocic

On the day of calving, there was no interaction between hours to calving and assistance level at calving on lying time (min /2h) ($F_{1,304}$ = 0.01, P = 0.92; Figure 4.4a), nor a difference in the lying time between dystocic and eutocic cows ($F_{1,26}$ = 0.06, P = 0.81). The change in lying time on the day of calving for dystocic and eutocic cows was best described by a polynomial pattern, with a decline from 61.8 at -22h to a low of 51.6 at -10h, increasing to an average of 66.4 just before birth ($F_{1,306}$ = 4.7, P = 0.03).

Piecewise regression models provided the best description of the change in the number of postural transitions. The calculated breakpoint for the number of postural transitions was -11.0h in dystocic cows, and -8.5h for eutocic cows. Prior to the breakpoints, there was no effect of hours to calving on the number of postural transitions for both dystocic and eutocic cows ($z_{1,306}$ = 0.11, P = 0.91; Figure 4.4b). In contrast, post breakpoints, there was an effect of hours to calving on the number of postural transitions for both dystocic and eutocic cows ($z_{1,306}$ = 16.1, P < 0.001), with the average number of postural transitions increasing by an average of 0.16 and 0.15, respectively every 2h. There was no difference in the number of postural transitions between dystocic and eutocic cows on the day of calving ($z_{1,26}$ = -1.68, P = 0.07). However, cows with dystocia had numerically more postural transitions every 2h on the day of calving (4.3 ± 0.3) compared to cows which calved with eutocia (3.6 ± 0.2).

On the day of calving, there was no interaction between assistance level and hours to calving on step count ($F_{1,306}$ = 0.25, P = 0.61; Figure 4.4c) and motion index ($F_{1,306}$ = 0.27, P = 0.60; Figure 4.4d), nor was there an overall effect of assistance level on either step count ($F_{1,26}$ = 1.91, P = 0.18) or motion index ($F_{1,26}$ = 1.6, P = 0.22). Linear changes in both step count and motion index on the day of calving were observed, with increases in both parameters (P < 0.001). Back transformation of $\log_{10}$ data show that step count increased from an average of 35.2 steps /2h at -22h to 83.5 steps /2h just before calving, and motion index increased from an average of 157.8 unit /2h at -22 to 443.3 unit /2h just before calving.

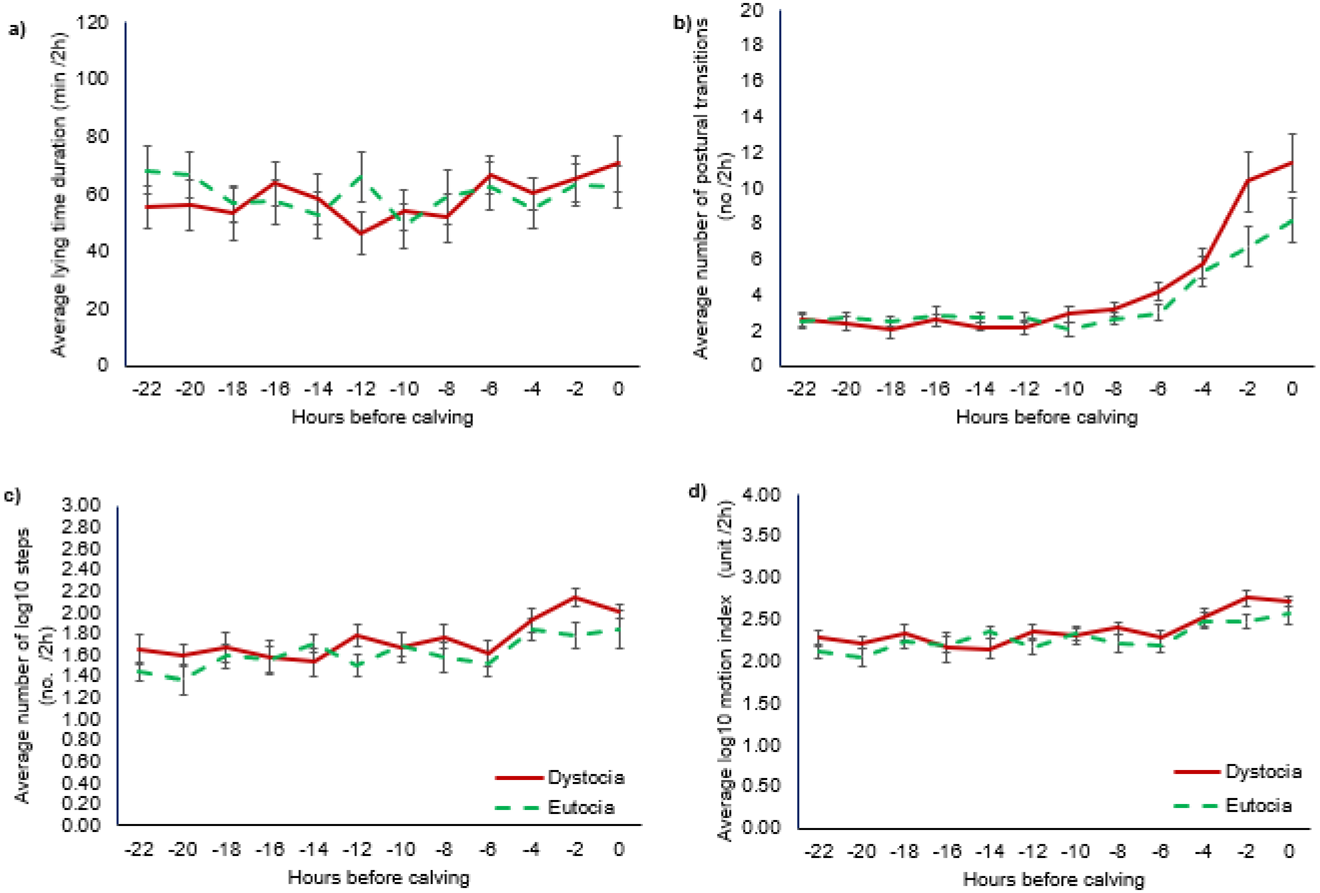


Figure 4.4 Behavioural variables for eutocic cows (green dashed line; n = 14) and dystocic cows (red solid line; n = 14) summarised into 2h periods ± SE in the 24h before calving for (a) lying time duration (min /2h); (b) number of postural transitions (no. /2h); (c) Log_{10} step count (no. /2h); (d) Log_{10} motion index (unit /2h).

4.4 Discussion

4.4.1 Behavioural differences between the day of calving and control period

For multiparous cows, dystocic cows and eutocic control cows, all behavioural variables were significantly different on the day of calving compared to the control period (d -4). On the day of calving, the number of postural transitions increased by 29.6% for primiparous cows and 45.6% for multiparous cows when compared to the control period. This study combined the number of lying bouts and standing bouts to represent the total number of postural transitions in a period. The number of lying bouts and standing bouts are comparable measurements, as the number of lying and standing bouts a cow takes in a day are proportional to each other. Similar to this study, Miedema et al. (2011a) reported that the number of lying bouts increased on the day of calving when compared to a control period and Huzzey et al. (2005) reported an 80% increase in the number of standing bouts on the day of calving. The step count and motion index of multiparous cows, dystocic cows and eutocic control cows all increased on the day of calving when compared to the control period. This study found that, on the day of calving, lying time decreased by an average of -2.55h for primiparous and multiparous cows and 2.3h and 2.1h for animals that calved with dystocia and eutocia when compared to the control period. These findings show that calving has a significant effect on cow behaviour, and the day of calving is different to a normal day (the control period).

4.4.2 Last 4 days prior to calving

An objective of this PhD was to explore if there were parity affected behaviour in the period before calving, and on the day of calving. In the last 4 days before calving (d -4 to d -1), there were parity differences for all behavioural variables. The lying time of primiparous cows was -2.8 h /d lower than that of multiparous cows and decreased by approximately 25 min /d across the period. In contrast, the lying time of multiparous cows remained constant. Borchers et al. (2017) reported a similar finding and showed that the lying time of primiparous cows decreased in the last 7 days prior to calving and was lower than that of multiparous cows. Primiparous cows had numerically more standing and lying bouts per day compared to multiparous cows, which has been reported in previous studies (Lobeck-Luchterhand et al., 2015; Neave et al., 2017). After controlling for milk production and bodyweight, Neave et al. (2017) still observed differences in the number of postural transitions during the transition period. This finding shows that differences in the standing and lying bout behaviour are independent of these two variables. The number of steps and total motion index decreased across the period for both primiparous and multiparous cows, however the number of steps /d and motion index /d were higher for primiparous cows. Wehrend et al. (2006) reported primiparous cattle to be more restless as parturition approached, and this could explain the parity differences for all behavioural variables in the days leading to calving. Another reason for the difference in behaviour between primiparous and multiparous cows is that the calving housing was a dynamic environment – cows entered and left the calving pen – and primiparous cows were experiencing the calving housing and management for the first time. Primiparous cows are more likely to be of a lower social rank compared to multiparous cows, and the higher activity sustained by primiparous cows across the pre-calving period could be due to their avoidance of more dominant older cows. Ungerfeld et al. (2014) reported cows with greater dominance indices had significantly fewer walking bouts compared to cows of a lower dominance rank, and this study found the activity of multiparous cows was 14% lower in the period before calving compared to primiparous cows.

4.4.3 The last 24 hours before calving

This study fitted mixed-effect models with different temporal relationships to describe the pattern of behaviour exhibited in the 24h before calving. Piecewise regression was a novel technique used for the analysis of the pre-calving behavioural data in this study and allowed the time when behaviour changes prior to calving to be estimated. On the day of calving, there was an effect of 2h period on all behavioural variables, and this finding indicates that labour has an effect on cow behaviour. An increase in the number of postural transitions on the day of calving has been reported in previous literature (Huzzey et al., 2005; Jensen et al., 2012), and could be explained by cows having a greater degree of pain as they enter Stage II of parturition. Stage II is characterized by uterine contractions, appearance of the amniotic sac and expulsion of the foetus. In this study, the lying time of cows increased in the last 12h before calving and peaked 2h before calving. It has been reported that cows typically lie down more as the foetus enters the birth canal (Schuenemann et al., 2011). Expulsion of the foetus has been reported to take an average of 69.7 minutes from the appearance of the amniotic sac (Schuenemann et al., 2011). The peak in lying time 2h before calving in this study can be explained by cows lying down to expel the foetus from the birth canal.

Previous studies have described the effect of parity on cow behaviour on the day of calving (Wehrend et al., 2006; Miedema et al., 2011b; Schuenemann et al., 2011). In the present study, there were no numerical differences in lying time duration, step count, or motion index when multiparous and primiparous cows were compared on the day of calving, however primiparous cows had numerically more postural transitions compared to multiparous cows. Wehrend et al. (2006) reported that fewer primiparous cows exhibited calm behaviour on the day of calving, and this restlessness behaviour may explain why primiparous cows had more postural transitions than multiparous cows. Similar findings were observed by Schuenemann et al. (2011), and it was reported that primiparous cows had an increase in the number of transitions from lying-standing at the start of labour stage.

4.4.4 Last 4 days prior to calving: dystocic and eutocic

A PhD study objective was to ascertain if cows that had an assisted calving would behave differently compared to cows that did not have an assisted calving, as the behaviour of dystocic cows in the days leading up to calving has not been widely explored in literature. Previous studies have typically focussed on the behaviour of dystocic cows on the day of calving. This study found that there was no numerical difference in the lying time duration, the number of steps, and the motion index between dystocic and eutocic cows in the last 4 days before calving. There was an interaction between the number of postural transitions and the level of assistance at calving. The average number of postural transitions decreased for dystocic cows across the period, from 33.6 ± 2.2 (d -4) to 29.1 ± 2.0 (d -1), however it is unclear why dystocic cows decreased the number of standing and lying bouts in the 4 d before calving. This study did not assess feeding behaviours nor rumination, and future studies could look at the inclusion of these parameters as a potential indicator of dystocia.

4.4.5 The last 24 hours before calving: dystocic and eutocic

Although this study found that breakpoints occurred earlier on the day of calving for dystocic cows (-11.0h) compared to eutocic cows (-8.5h), there was no significant difference in the number of postural transitions although cows that calved with dystocia had an average of 0.7 transitions /2h more than eutocic cows. The earlier breakpoint in the number of postural transitions could be due to dystocic cows having a longer calving period, and increased restlessness and postural changes could be associated with the pain caused by a protracted calving period. In contrast with our findings, Proudfoot et al. (2009) reported that cows that calved with dystocia had numerically more postural transitions on the day of calving compared to cows that did not require assistance at calving.

Proudfoot et al. (2009) categorised assistance at calving into two categories; easy assistance (whereby one person was required to pull the calf out), and difficult assistance (whereby two persons were required to pull the calf out). Only cows that were classed as having difficult assistance were used in the Proudfoot study. Our study included cows that had minor assistance at calving (gentle traction by one person with no mechanical device used), and the decision of the farm staff to assist cows by a gentle traction may have confounded the data. Cows that were classed as eutocic within this study may have experienced the same low level of difficulty at calving as cows that were calved with gentle traction, however, were unassisted due to management factors i.e. night-time calving. It is possible that comparing eutocic cows with cows that had a greater degree of assistance at calving could highlight behavioural differences in the days leading to calving. It is suggested that the earlier breakpoint calculated for dystocic cows are indicative of dystocic cows spending more time in labour before the calf was expelled from the birth canal (Barrier et al., 2012).

Farmers currently rely on expected calving dates to manage cows around calving, and direct observations to identify calving cows. Automated monitoring of cow behaviour has the potential to provide farmers with a more accurate indicator of the day and time of calving when compared to the expected calving date. For dairy farmers, predictions of the day or time of calving have the benefit of ensuring that intervention, where appropriate, can be given in a timely manner. Currently, there is no automated method to predict which cows that may need assistance at calving, and an accurate monitoring system to identify calving cows could improve neonatal and maternal survival, health, and welfare. This study found important differences in the behaviour of primiparous cows and multiparous cows, which suggest that parity must be considered when predicting the day of calving. Although no indicator of calving difficulty was identified by this research, the ability to identify calving cows and to predict the time of calving would allow farmers to monitor the progression of calving and intervene where necessary.

4.5 Conclusion

This study concluded that behaviour of dairy cattle undergoes numerous changes on the day of calving. The behaviour of multiparous and primiparous cows was significantly different in the 4 days preceding calving and it is suggested that parity must be considered when predicting the day of calving. There were no differences in parity on the day of calving for duration of lying time, step count, or motion index. Time relating to calving had a significant effect on all behavioural variables on the day of calving. It was summarised that automated behavioural monitoring systems could be used to predict calving. No indicator of calving difficulty was identified by this research.

Chapter 5 The identification of calving

5.1 Introduction

As discussed in Chapter 1, calving is a vulnerable time for the dairy cow. The number of cows per stockperson requiring supervision has increased in the last decade, and this poses a challenge as calving cows require intensive management and surveillance. Paolucci et al. (2010) concluded that timely obstetric intervention (where necessary) reduced neonatal mortality and uterine infections and improved reproductive performance post-calving. A system which automatically detects calving and notifies farm staff would be beneficial to dairy producers. It would ensure that farm staff were aware of calving cows and assistance could be given, where necessary, ultimately improving animal health and welfare.

To predict the day of calving, farmers can use artificial insemination records (Inchaisri et al., 2010) and clinical signs such as udder fill or pelvic ligament relaxation (Streyl et al., 2011). These traditional calving prediction techniques can be unreliable and can fail to generate an accurate prediction of calving. For example, physical signs are subjective and can vary between cows, and gestation period can range from 267-295 days (Inchaisri et al., 2010). In addition, visual identification of calving may be difficult for larger farms as it is costly, inefficient, and time-consuming (Keceli et al., 2020). The advent of automated cow monitoring technologies allows for the automated recording of animal behaviours on farm. In Chapter 4, it was established that cow behaviour is altered on the day of calving and in the 4 days leading up to calving. There is potential for behavioural changes to be used in the prediction of calving, and this could offer dairy producers an objective method of calving prediction rather than a subjective approach (based on traditional clinical signs and AI records).

There are commercially available systems, such as tail collars (Moocall™ calving sensor: https://moocall.com/), which detect calving. Indeed, in Chapter 2, it was established that 6.6% of UK dairy farms have a calving detection system. Tail collars contain an accelerometer that detects an increase in tail raising, which is reported to increase between 2-4 hours prior to calving (Miedema et al., 2011b), and alert farm staff to a potential calving (Saint-Dizier and Chastant-Maillard, 2015). Tail collar systems require farm staff to make a judgment on which cows may be due to calve (for attachment purposes) and this could lead to some cows not having a collar attached prior to calving. In addition, tail collar systems only have one function (calving detection) which requires dairy producers to specifically purchase the technology.

Many studies investigating cow behaviour in late gestation or on the day of calving are based on statistical methodologies (Miedema et al., 2011a; Jensen, 2012). Machine learning is a division of computer science. Its objective is to learn from data so performance tasks, such as predictions, are enhanced (Jiang et al., 2020). These methods offer a promising and feasible approach for accurate calving prediction (Keceli et al., 2020). Machine learning methodologies have been used in dairy science to identify cows as lame (Warner et al., 2020), in oestrus (Schweinzer et al., 2019), or as mastitic (Ebrahimi et al., 2020), and machine learning methods are an area of research which could be applied to calving identification. Supervised machine learning uses methods which have been created to classify or predict an outcome (Jiang et al., 2020), and these methods are applicable to the automatic detection of calving.

Recent studies have assessed the ability of technologies to successfully predict if a cow is calving. Classification-based methods have been used to identify calving 8 hours prior to the event (Borchers et al., 2017; Zehner et al., 2019). A Naïve Bayes classifier was used to classify the hour before calving using a combination of rumination behaviours; rumination boluses, eating chews, and ruminating chews (Zehner et al., 2019). The model was able to classify the hour before calving with a sensitivity of 82%, and a specificity of 87%. The positive predictive value of the model was 40%, and this indicates that numerous false positive alerts were generated. Borchers et al. (2017) used a random forest, neural network, and linear discriminant analysis to identify 2h periods in the 8-h before calving. A combination of lying time, lying bouts, step count, total motion, neck activity, and rumination were used. It was shown that neural network was the most effective in classifying the 8-h before calving, and the model had a sensitivity of 82.8% and a specificity of 80.4%. The positive predictive value was 68.6%, which shows a reduction in the number of false positives compared to Zehner et al. (2019).

The ability to identify the days before calving would allow dairy producers to improve their management of cows in late gestation. If cows are housed in an unsuitable environment prior to calving – for example, a cubicle shed – cows can be moved to a suitable straw-bedded area for calving. Similarly, the ability to identify cows as calving would allow dairy producers to give cows appropriate supervision during calving. Although studies have shown that a calving cow can successfully be identified, few studies have tried to identify the days before calving. Saint-Dizier and Chastant-Maillard (2015) reported that cow body temperature decreased in the 72h prior to calving. Ouellet et al., (2016) used a decrease in cow vaginal temperature to predict the onset of calving 24h in advance, and summarised that a decrease in vaginal temperature of >0.1°C was able to predict calving within the next 24 h. An issue with this approach is that vaginal sensors could be displaced, damaged, or lost during the delivery of the calf. A more robust approach to predicting the day before calving would be useful on commercial farms.

Literature has shown that supervised machine learning methods that classify an outcome are most suited to the identification of calving (Jiang et al., 2020; Zehner et al., 2019). This study will attempt to build on the findings of Chapter 4 and use machine learning methods to identify the day before calving and a period before calving using lying and activity behaviours. Commonly used classification methods – random forest, artificial neural network, and decision tree (Jiang et al., 2020) – will be used to identify the day before calving (d -1), the period before calving (-2h), and the 3 periods before calving (-2h, -4h, -6h).

5.1.1 Research Aims

The aim of this study was to establish if machine learning-based approaches could be used to correctly identify the day before calving, and to identify cows as calving on the day of calving. Objectives were to:

1. To identify any difference in gestation period length between primiparous and multiparous cows, and to identify other factors that could be associated with gestation period length.
2. Determine if lying and activity behaviours can identify the day before calving using machine learning methods.
3. Determine if lying and activity behaviours can identify the -2h period before calving and the -2h, -4h, or -6h period before calving using machine learning methods.

5.2 Materials and Methods

5.2.1 Animals and Housing

Cows were managed as described in Chapter 2. Calving records were collected from University of Edinburgh Langhill Farm (Roslin, Midlothian, United Kingdom) between November 2016 and April 2018.

5.2.2 Data cleaning

Behavioural records of 186 animals were summarised from the time of calving into 2 datasets: 1) 24-h periods (day), and 2) 2-h periods. The experimental period in dataset 1 was chosen to reflect the pre-calving transition period, described as the 3 wk before parturition (Drackley, 1999). However, to maximise the number of animals included in the classification of the day before calving, d -14 to d -1 was selected. The experimental period in dataset 2 was from -46h to -2h before calving (0h was the time of calving). This range was chosen because if the day before calving could be identified, another machine learning classifier could be initiated to detect the period before calving. For the -2h dataset, a rolling average per behaviour was generated. The -2h period before calving was not averaged, however each following 2h block was averaged with the preceding 2h block (e.g. -4h and -6h, and -6h and -8h).

Inchaisri et al. (2010) stated that the gestation period of a cow ranges from 267–295 d. Cows that had a gestation period outside this date range were removed from the dataset as it was deemed these cows had incorrect AI dates entered or had an issue during gestation i.e. abortion (n = 9). Cows that did not calve in the calving pen (n = 7), and cows that did not have complete datasets for 14 d before calving and the day of calving (n = 6) were removed from the dataset. This left 164 animals in the classification datasets; 50 primiparous cows and 114 multiparous cows (parity 0–8, mean 1.5 ± 0.1). It was considered to analyse parity as an ordinal variable; however this was not possible due to the distribution of parity on this farm.

5.2.3 Gestation

To ascertain the factors that may influence gestation period length, a linear mixed effect model was used to analyse if there was a difference in the gestation period between primiparous cows and multiparous cows. Parity group (primiparous and multiparous) was a fixed effect, whilst cow ID was included as a random effect to account for multiple gestation period entries per cow. A linear mixed effect model was also used to analyse other fixed effects such as month of calving, year of calving, calf sex (male or female), calf status (alive or dead), and breed of calf (dairy or beef). Calves which were sired by Aberdeen Angus, British Blue and Hereford were classed as beef breeds, whilst Brown Swiss, Holstein and Norwegian Red were classed as dairy breeds

5.2.4 Classification models

This study used 3 types of classification model – random forest, decision tree and artificial neural network - to identify the day before calving, and the period (-2h and -2h, -4h or -6h) before calving. R was used for all statistical analyses. More detailed descriptions of the classification methods are detailed below:

5.2.4.1 Random Forest

The random forest is a supervised machine learning algorithm (Breiman et al., 2001). It develops individual trees to build a ‘forest’, and classifies an output based on the prediction of the majority, rather than an individual. This format reduces the risk of overfitting, and as a result, random forest are intuitive predictors (Shalev-Schwartz and Ben-David, 2014). According to Zaborski et al. (2019), random forest has high classification accuracy and can be effectively applied to large datasets with multiple predictor variables. Additionally, random forest can process unbalanced datasets and datasets which include missing data. The randomForest package was used to provide the random forest classifier.

5.2.4.2 Decision Tree

The decision tree is a supervised machine learning algorithm (Breiman et al., 1984). It has a similar function to random forest, however the method of producing a decision threshold differs. A decision tree has an ordered set of "if-then" tests that classify data into the most likely outcome based on experience of other explanatory variables (Caraviello et al., 2006a); it does not base its prediction on the majority. The decision tree is commonly used because they are easily interpreted, simple, and intuitive (Shahinfar et al., 2014). A decision tree uses a sequence to separate data based on the value of specific features (Doupe et al., 2019). Decision trees are good at interpreting data however a disadvantage is that they often over-fit data (Doupe et al., 2019). The rpart package was used to provide the decision tree classifier.

5.2.4.3 Artificial neural network

Artificial neural networks are a versatile and robust tool to solve data-driven problems. Artificial neural networks (ANN) have been created to mimic patterns of the human nervous system in processing and learning information (Zador, 2019). ANN are computing programs which consist of processing elements, called nodes or neurons, that are highly interconnected and organised into layers (input, hidden, and output). There is no connection of neurons in the same layer, however neurons have vertical connections to the subsequent layer of neurons. Neural networks can contain two layers (input, output), however studies more frequently use the Multilayer Perceptron ANN which includes a hidden layer between the input layer and the output layer

(Valente et al., 2014). Haykin (2009) states that artificial neural networks can learn the relationship between input variables and their output regardless of non-linearity and dimensionality. The neuralnet package was used to provide the neural network classifier, and the default settings were used.

5.2.5 Identification of day before calving

Dataset 1 was used to identify the day before calving. To calculate the days from expected calving, the difference between the calving date and expected calving date was calculated (the expected calving date was taken to be 281 d post-successful insemination). The difference between the two values was added to the days from calving column to produce a new column: days from expected calving. Time to expected calving was considered an important parameter because as a cow moved closer to its expected calving date, the likelihood of calving increased. Table 5.1 summarises an example of how days from expected calving was calculated.

Table 5.1 An example of how days from expected calving was calculated.

ID	Date	Calving date	Expected calving date	Difference	Days from calving	Days from expected calving
1113	23/01/2020	06/02/2020	08/02/2020	-2	-14	-16
1113	24/01/2020	06/02/2020	08/02/2020	-2	-13	-15
1113	25/01/2020	06/02/2020	08/02/2020	-2	-12	-14
1113	26/01/2020	06/02/2020	08/02/2020	-2	-11	-13

Step count and motion index were highly correlated, and it was decided to remove motion index from the behavioural dataset to reduce multicollinearity and prevent unreliable model inferences (Farrell et al., 2019). Prior to classification using machine learning techniques, a series of linear mixed effects models were carried out on behavioural data from d -14 to d -1. This was to ascertain if behaviour of dairy cows changed in the days preceding calving, because if a behavioural parameter did not alter, then it could not be used to classify a time preceding calving. The linear mixed-effect models included days to calving (d −14 to d -1), parity (multiparous and primiparous), year, and the interaction between days to calving and parity as fixed effects. Cow ID was included as a random effect to account for repeated measurements per cow. Step count was $\log_{10}$ transformed so data met normal residual data distribution assumptions. There was no effect of days to calving on step count, so step count was removed as a variable from the classification models. Similarly, there was no effect of year on lying time or the number of postural transitions, and so this variable was removed.

Daily data (d -14 to d -1) was randomly split into 2 datasets by cow identification and year: 1) training set (70% of observations) and 2) a validation set (30% of observations). There were 1596 observations in the training set (1482 not calving, 114 day before calving) and 700 observations in the validation set (650 not calving, 50 day before calving). Daily lying time (min/d), the number of postural transitions (no. /d), and days from expected calving were scaled so that data fell between 0 and 1. Data normalisation was carried out to ensure that variables could be compared, and to prevent variables with greater numerical features (e.g. lying time) dominating variables with smaller numerical features e.g. the number of postural transitions (Singh et al., 2019). Parity group (primiparous or multiparous) and calf breed (dairy or beef) were converted into a binary variable (1 or 0).

The final models contained days from expected calving, sire (dairy or beef), parity group (primiparous or multiparous), and the scaled behavioural parameters for lying time and the number of postural transitions. Breed of sire was included in the final model, as an association between calf breed (dairy or beef) and gestation period length was found.

5.2.6 Identification of the period before calving

5.2.6.1 2h before calving

Dataset 2 was used to identify the period before calving. To help classify the 2h period from calving, the hours from expected calving was calculated. This was achieved using the method described in section 5.2.5; however, days were converted into hours.

To check that behaviour changed in the hours preceding calving (-46h to -2h), a series of linear mixed effects models were carried out on the lying time (min/ 2h), the number of lying and standing bouts (no. /2h), and step count (no. /2h). The linear mixed-effect models included hours from calving, parity (multiparous and primiparous), year, and the interaction between hours to calving and parity as fixed effects. Cow ID was included as a random effect to account for repeated measurements per cow. Step count and the number of postural transitions were log_{10} transformed to meet normal residual data distribution assumptions. There was an effect of hours to calving on all behavioural variables. In addition, there was an effect of year on lying time and the step count, so this variable was included in classification models.

Bihourly data (-46 to -2h) was randomly split into 2 datasets by cow identification and year: 1) training set (70% of observations) and 2) a validation set (30% of observations). There were 2508 observations in the training set (2394 not calving, 114 day before calving) and 1100 observations in the validation set (1050 not calving, 50 day before calving). Lying time (min /2h), the number of postural transitions (no. /2h), step count (no. /2h), hours from expected calving, and the time of day were scaled so that data fell between 0 and 1. Parity group (primiparous or multiparous), calf breed (dairy or beef), and year (year 1 or year 2) were converted into a binary variable (1 or 0).

The final models contained hours from expected calving, the time of day, sire (dairy or beef), parity group (primiparous or multiparous), year, and the scaled behavioural parameters for lying time, the number of postural transitions, and step count or the scaled rolling average for lying time, the number of postural transitions, and step count.

5.2.6.2 Classification of the -6h, -4h, or -2h period before calving

Calving is a linear process which starts with myometrial contractions and results in the birth of a foetus (Mainau and Manteca, 2011). Identifying one 2h period prior to calving as ‘calving’ may result in misclassification; Titler et al. (2015) state that cow behaviour changes on average 6h 14 min prior to calving. The correct classification of a calving cow is important and increasing the number of calving instances could help improve the models. It was theorised that behavioural changes between -2h and -6h 14 min could be used to classify a cow as calving, and behavioural changes before the -2h period could be used to improve the classification of the model.

For this classification, -2h, -4h, and -6h were selected as ‘calving’. The models were classified using the same dataset as the -2h prediction. There were 2508 observations in the training set (2166 not calving, 342 calving) and 1100 observations in the validation set (950 not calving, 150 calving). The final models contained hours from expected calving, the time of day, sire (dairy or beef), parity group (primiparous or multiparous), year, and the scaled behavioural parameters for lying time, the number of postural transitions, and step count.

5.2.7 Model classification

Classification matrices were produced for each model, which included the sensitivity (the rate of true positives) and specificity (the rate of true negatives):

Sensitivity was calculated as: True Positives / (True Positives + False Negatives)

Specificity was calculated as: True Negatives / (False Positives + True Negatives).

The positive predictive value (the percentage of positive outcomes correctly predicted) was calculated as: True Positives / (True Positives + False Positives)

The negative predictive value (the percentage of negative outcomes correctly predicted) was calculated as True Negatives / (True Negatives + False Negatives).

The accuracy (taken as the rate of outcomes predicted correctly) was calculated as: True Positives + True Negatives / (True Positives + False Negatives + False Positives + True Negatives).

5.3 Results

5.3.1 Gestation period

The average gestation period was 278.5 ± 0.1 d (mean + SE). There was no difference between the gestation period of primiparous cows (278.1 ± 0.6 d) and multiparous cows (278.6 ± 0.4 d; $F_{1,146} = 0.07$, $P = 0.79$). Figure 5.1 shows a frequency histogram of gestation period lengths for 164 primiparous and multiparous cattle.

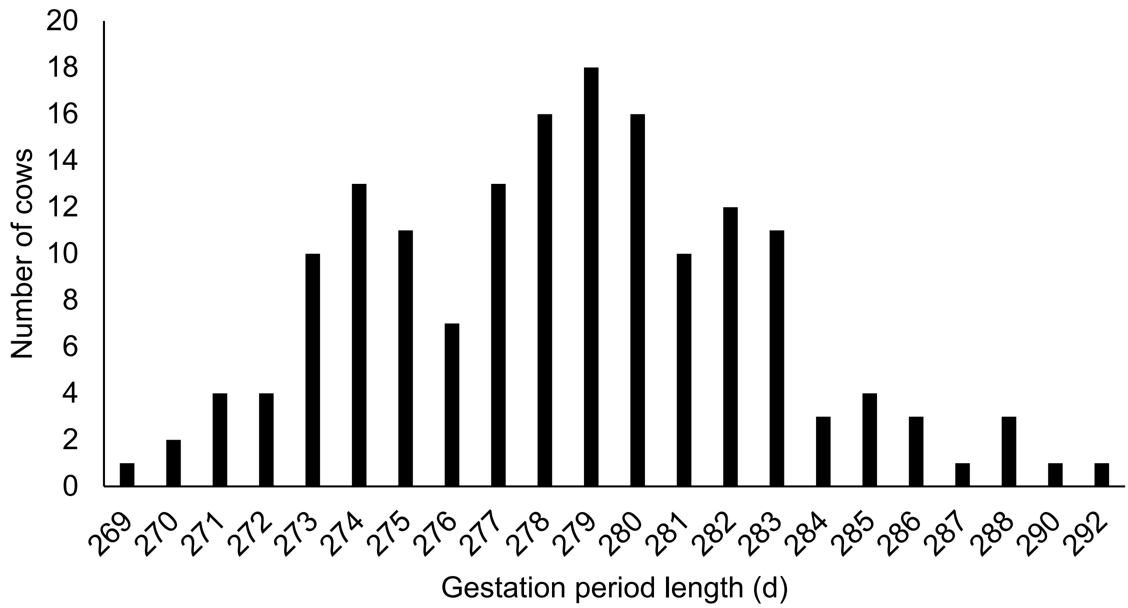


Figure 5.1 A frequency histogram showing the gestation period length (d) of 164 primiparous and multiparous cattle. The mean gestation period length was 278.5 ± 0.1 d (mean + SE).

Figure 5.2 shows a frequency histogram of average gestation length difference from the expected day of calving (281 d post successful insemination) for 164 primiparous and multiparous cattle. In this study, 6.1% of cows calved on their expected calving date.

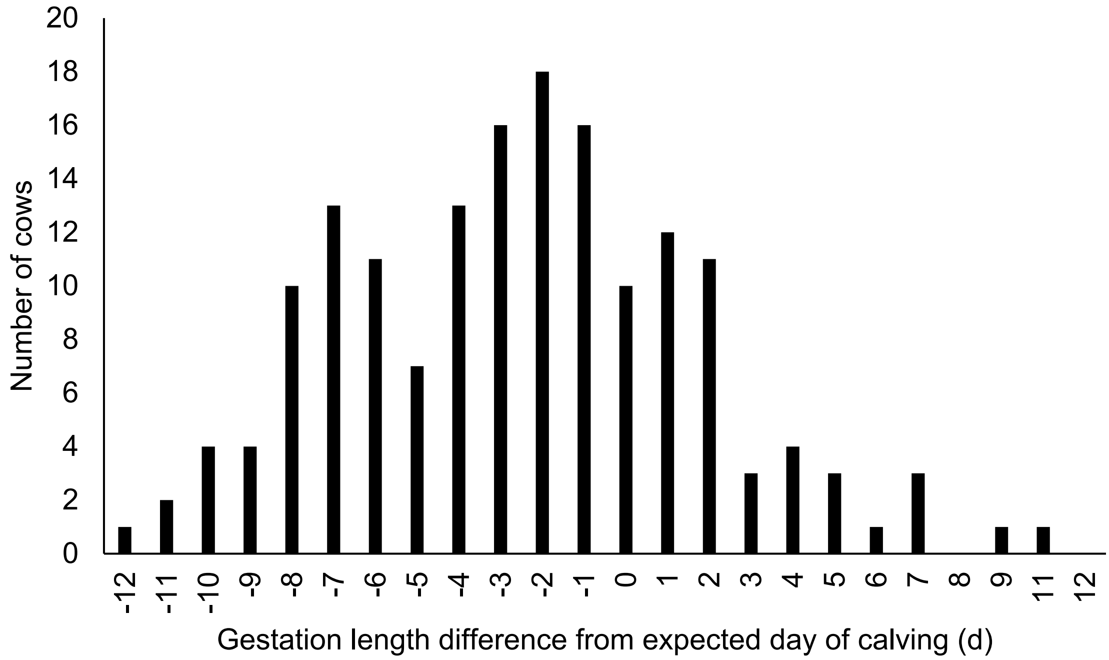


Figure 5.2 A frequency histogram showing the average gestation length difference from the expected day of calving (281 d post successful insemination) for 164 primiparous and multiparous cattle.

There was no association between gestation period length and month of calving, year of calving, calf sex and calf status (alive or dead) ($P > 0.05$). There was an association between calf breed (dairy or beef) and gestation period, and the gestation period was longer for beef-sired calves (280.2 ± 0.7 d) compared to dairy-sired calves (278.0 ± 0.4 d; $F_{1,150} = 6.3$, $P = 0.01$; Figure 5.3).

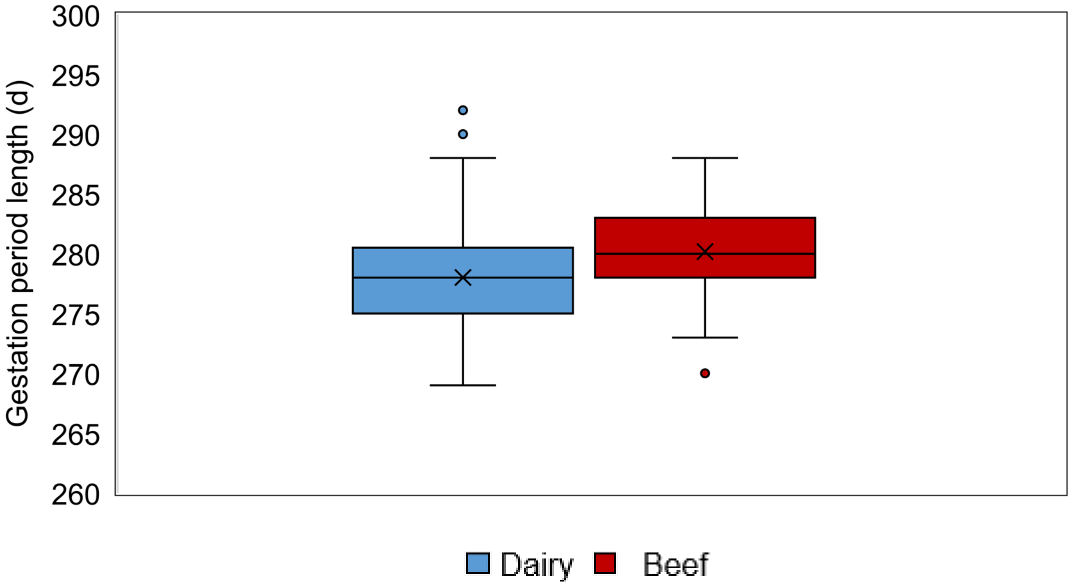


Figure 5.3 Boxplot to show the gestation period length (d) difference between animals carrying a dairy calf (blue), and animals carrying a beef calf (red). For animals carrying a dairy calf, the gestation period was 278.0 ± 0.4 d, whilst for animals carrying a beef calf, the gestation period was 280.2 ± 0.7 d (mean + SE).

5.3.2 Identification of day before calving (d -1)

Lying time (min /d) increased by 14.6 min /d from d -14 to d -1 ($F_{1,2170} = 109.9$, $P < 0.001$; Figure 5.4a). On average, primiparous cows spent 55.6 min /d less time lying down per day compared to multiparous cows ($F_{1,228} = 69.2$, $P < 0.001$). The number of postural transitions (no. /d) increased by 0.7/d from 20.5 ± 0.6/d on d -14 to 29.3 ± 0.7/d on d -1 ($F_{1,2170} = 417.5$, $P < 0.001$; Figure 5.4b). There was no effect of days to calving on step count (Figure 5.4c).

This dataset assessed 164 cows over d -14 to d -1 whereas in Chapter 4, 44 cows were assessed over d -4 to d -1. Similar to Chapter 4, it was found that primiparous cows have a lower lying time duration in the days leading to calving compared to multiparous cows. An increase in lying time and postural transitions was found from d -14 to d -1; however, this was not found in Chapter 4. The differences in the study results could have been caused by the time frame duration; Chapter 4 assessed d -4 to d -1, whilst this study assessed d -14 to d -1.

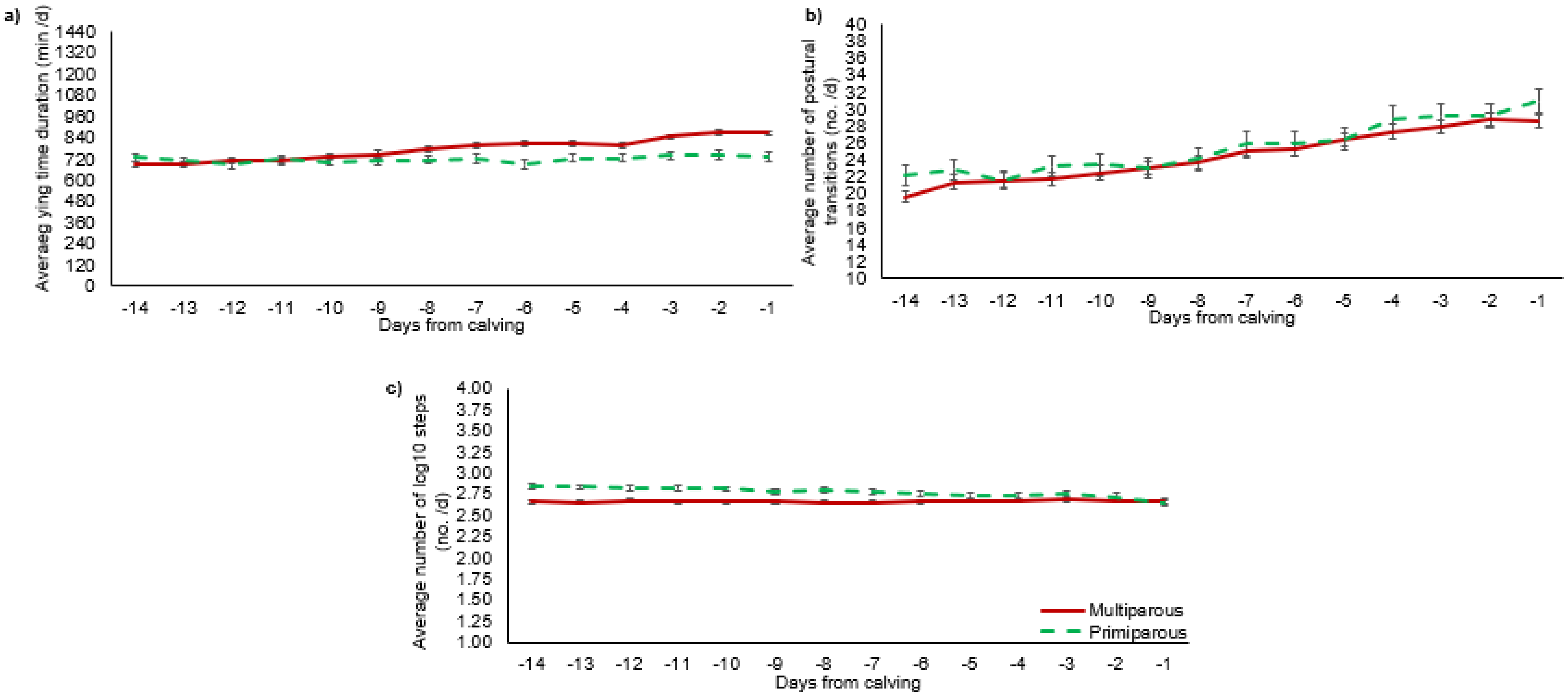


Figure 5.4 Behavioural variables for primiparous cows (green dashed line; n = 50) and multiparous cows (red solid line; n = 114) summarised into 24-h periods (+ SE) in the -14 d before calving for (a) lying time duration (min /d); (b) number of postural transitions (no. /d); (c) log$_{10}$ step count (no. /d).

The performance of the machine learning models to identify the day before calving is shown in Table 5.2. The ability to identify the day before calving was most successful when a random forest was used to assess lying time (min /d).

Table 5.2 Classification of the day before calving (d -1) using lying time (min /d), postural transitions (no. /d), and a combination of both behaviours for 14 d before calving.

Method	Behaviour	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Accuracy
Random Forest	Lying time	10%	98.2%	29.4%	93.4%	91.9%
	Postural transitions	8%	96.5%	14.8%	93.1%	90.1%
	Both	6%	97.5%	15.8%	93.1%	91.0%
ANN[1]	Lying time	4%	100%	100%	93.1%	93.1%
	Postural transitions	6%	99.4%	42.9%	93.2%	92.7%
	Both	6%	97.7%	16.7%	93.1%	91.1%
Decision Tree	Lying time	6%	99.7%	60.0%	93.2%	93.0%
	Postural transitions	0%	100%	0%	92.6%	92.9%
	Both	6%	99.7%	60.0%	93.2%	93.0%

[1] Artificial neural network

5.3.3 Identification of the period before calving

There was an effect of hours to calving on lying time, and lying time decreased from 70.3 ± 2.3 min /2h at -46h to 61.4 ± 2.3 min /2h at -2h ($F_{1,3643}$ = 126.4, P < 0.001; Figure 5.5a). Across the period (-46h to -2h), multiparous cows lay down approximately 9.8 mins more per 2h when compared to primiparous cows (67.1 ± 0.6 min /2h vs 57.3 ± 0.9 min /2h, respectively; $F_{1,597}$ = 38.4, P < 0.001; Figure 5.5a). Animals that calved in year 1 spent 4 min /2h more lying down compared to animals which calved in year 2 (65.9 ± 0.7 min /2h vs 61.9 ± 0.8 min/ 2h, respectively; $F_{1,1356}$ = 4.1, P =0.04).

The number of standing and lying bouts increased across the period ($F_{1,3761}$ = 223.1, P < 0.001; Figure 5.5b). Back transformation of $\log_{10}$ postural transitions shows that the number of transitions increased from 3.1 transitions /2h at -46 h to 6.2 transitions /2h at -2h. There was an interaction between parity group (primiparous vs multiparous) and hours to calving on the number of postural transitions ($F_{1,2592}$ = 16.5, P < 0.001 Figure 5.5b).

Back transformation of step count showed that there was an increase from an average 26.6 steps /2h at -46 h to an average of 56.3 steps /2h at -2h ($F_{1,3645}$ = 73.0, P < 0.001; Figure 5.5c). The step count of multiparous cows was higher compared to primiparous cows ($F_{1,2380}$ = 12.1, P < 0.001). Back transformation of $\log_{10}$ step count shows that the multiparous cows had an average 31.6 steps /2h compared to primiparous cows that had average 25.1 steps /2h. Animals that calved in year 1 had 30.8 steps /2h compared to 33.2 steps /2h for animals that calved in year 2 ($F_{1,1895}$ = 4.6, P =0.03). There was an interaction between parity group (primiparous vs multiparous) and hours to calving on the number of step count ($F_{1,3645}$= 14.2, P < 0.001).

These results are similar to Chapter 4, which also showed an effect of 2h period on lying time duration, standing and lying bouts, and step count in the -24 h before calving. This dataset did not include the last 2h period prior to calving and assessed – 46 to -2h. In this study, lying time decreased from -46 h to – 2h. In Chapter 4, a polynomial effect of lying time was seen where lying time decreased from -22h to -12h, before increasing in the period before birth. An increase in postural transitions and step count was seen in both datasets.

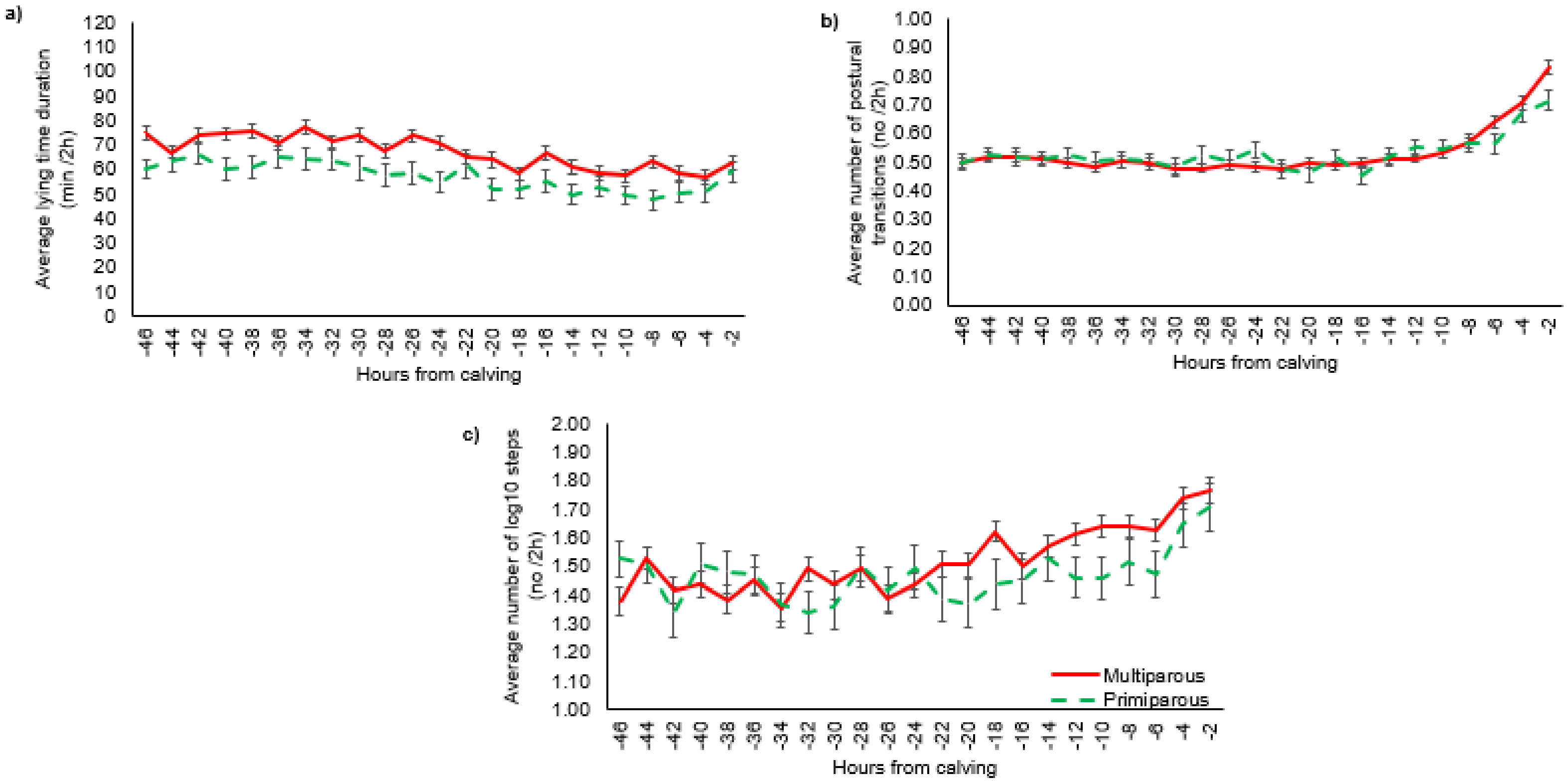


Figure 5.5 Behavioural variables for primiparous cows (green dashed line; n = 50) and multiparous cows (red solid line; n = 114) summarised into 2h periods (+ SE) in the -46h to -2h before calving for (a) lying time duration (min /2h); (b) number of postural transitions (no. /2h); (c) log_{10} step count (no. /2h).

The performance of the machine learning models to identify a period before calving is shown in Table 5.3. The ability to identify the period 2h before calving was most successful for a decision tree classification of the rolling behavioural average.

Table 5.3 Classification of the period before calving (-2h and -2h, -4h or -6h) using lying time (min /d), postural transitions (no. /d), and step count (no. /d) in the -46 to -2h before calving.

Method	Behaviour	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Accuracy
Random Forest	2h	16.0%	99.7%	72.7%	96.1%	95.9%
	2h Rolling average	38.0%	99.5%	79.2%	97.1%	96.7%
	2h, 4h, 6h	28.7%	98.7%	78.2%	89.8%	89.2%
ANN[1]	2h	34.0%	99.0%	60.7%	96.9%	96.0%
	2h Rolling average	30.0%	98.8%	53.6%	96.7%	95.6%
	2h, 4h, 6h	28.0%	98.3%	72.4%	89.6%	88.7%
Decision Tree	2h	24.0%	99.4%	66.7%	96.5%	96.0%
	2h Rolling average	40.0%	99.4%	76.9%	97.2%	96.7%
	2h, 4h, 6h	32.0%	98.0%	71.6%	90.1%	89.0%

[1] Artificial neural network

5.4 Discussion

5.4.1 Gestation period

The length of gestation can be described as the time taken (in days) from conception to calving. In this study, average gestation length was 278.5 d which falls within the expected range (267 – 295 d; Inchaisri et al., 2010).

Norman et al. (2009) reported a mean gestation length difference between Holstein heifers and cows, although this study showed no differences. Norman et al. (2009) reported that for Holstein heifers, mean gestation length was 278 d whilst the average gestation length was 279 d for Holstein cows. It is thought the difference between the two studies is due to the sample size within each study population (164 cow vs. 10,279,312 cows) and potentially this study did not contain sufficient animals to show the small 1 day difference reported by Norman et al. (2009).

In addition to parity, Norman et al. (2009) reported a breed effect on gestation length, and Brown Swiss cattle were observed to have the longest gestation period length (287 d for heifers and 288 d for cows, respectively) when compared to other dairy breeds (Holstein, Jersey, Milking Shorthorn, Ayrshire, and Guernsey). It was not possible to ascertain the effect of dairy breed on gestation length in this study, as the study herd consisted largely of Holstein cattle. This study did not consider dairy cattle breed within the classification of calving. However, as literature highlights the effect of breed on gestation length, future studies could consider breed as a parameter in mixed breed herds.

This study identified a longer gestation period for animals carrying a beef-sired calf, compared to animals carrying a dairy-sired calf. In this study, gestation period of beef sired calves was 280.2 d compared to 278 d for dairy-sired calves. In agreement, Berry and Ring (2020) reported that gestation length of beef sires was >2 d longer than the gestation length from dairy sires. These results are consistent with previous literature (Fitzgerald et al., 2015).

5.4.2 Parity and year

In Chapter 4, the differences in pre-calving lying and activity behaviour between multiparous and primiparous cows were explored. Jensen (2012) indicated that primiparous cows were more restless as parturition approached, which could explain the behavioural differences between parity. In addition, primiparous cows were experiencing housing with multiparous cows for the first time and the routine of calving management. Previous literature indicated differences in the pre-calving behaviour between primiparous and multiparous dairy cattle (Borchers et al., 2017).

There was an association between year and the lying time duration and activity behaviour of cattle in the 48h before calving. It is not known why these differences occurred. Stocking density is known to affect cow behaviour (Lobeck-Luchterhand et al., 2015), however in this study, the calving pen was kept at stocking rate of 5-15 animals. Further research is required to understand other factors that can influence transition cow behaviour for example diet or environment (i.e. temperature).

5.4.3 Identification of the day before calving

An objective of this PhD was to ascertain if cow behavioural changes on the day of calving and the days leading up to calving could be used to identify the day before calving or cows as calving. Although the number of postural transitions and lying time had a linear increase from d -14 to d -1, the identification of the day before calving was poor. The random forest classification using lying time performed the best however it was only able to successfully identify 10% of cows on the day before calving. Nevertheless, this shows a minor improvement compared to the expected calving date, as in this study only 10 cows (6.1%) calved on their expected calving date based up their AI date.

Although the classification of the day before calving was largely unsuccessful, the ability to identify the day before calving is a useful parameter that would allow farmers to better manage their dairy cows. In this study dataset, 7 cows were removed from the analysis as they calved within a cubicle shed (mean gestation + SD, 269 ± 7.7). A cubicle shed is an inappropriate environment for a calving cow due to reduced cow comfort when compared to an area allowing free movement (Black and Krawczel, 2016) and poor hygiene (Creutzinger et al., 2020). If a calving detection system could identify the day prior to calving, dairy producers could move cows into an appropriate environment for calving. Expected calving date is traditionally used to manage cows around calving, however this is not an accurate parameter. Figure 5.2 shows that the average gestation length difference from the expected calving date ranged from -12 d to + 11 d. Identifying the day before calving could improve the outcome of 'just-in-time' calving systems. 'Just-in-time' calving systems are based on the movement of cows in active labour to a calving pen. Proudfoot et al. (2013) reported that moving cows during the later stages of Stage I of labour caused Stage II to be delayed. If dairy producers are aware of the day before calving, it would allow producers to move cows into calving pens on the day of calving, rather than waiting for visible signs of calving and interrupting the calving process.

Borchers et al. (2017) were able to use an ANN to predict the day before calving with a sensitivity of 100% and a specificity of 86.8%. The classification used a combination of two technologies (IceQube and HR tag (SCR Engineers Ltd., Netanya, Israel)) and 6 behavioural parameters: neck activity, rumination, lying time, lying bouts, number of steps, and lying bouts. This study only used two behaviours – lying time and the number of lying & standing bouts – to predict the day before calving. ANN learn the relationship between input variables and their output (Haykin, 2009). In this study, it is possible that the ANN model was not able to generalise a relationship between input and output variables, and underfitted the model.

There are numerous potential reasons as to why the identification of the day before calving was unsuccessful. This data were collected under field conditions, and management and environmental factors may have affected the ability of the models to predict the day before calving. For example, cows were constantly being regrouped and this created a dynamic environment as cows entered and left the calving pen. Regrouping is known to alter dairy cow behaviour (von Keyserlingk et al., 2008), and it is possible that constant changes in behaviour made it difficult for models to create a pattern for classification. Literature shows that cow behaviour significantly alters on the day of calving compared to the days preceding calving (Miedema et al., 2011a; Jensen, 2012). It could be that subtle daily changes in lying time duration and the number of postural transitions from d -14 to d -1 were not enough to distinguish d -1 from d -14 to d -2. Important differences were noted in the behaviours between primiparous cows and multiparous cows, which might mean that a separate classification based on parity would improve model classification, and future studies could look at classifying primiparous and multiparous cows separately.

This study included days from expected calving as a classification predictor. Days from expected calving date is an important variable, as calving becomes more likely as the days from expected calving date decreases. This study used 281 d post successful insemination to calculate the days from expected calving. Regardless of the average gestation length chosen to calculate days from expected calving, the expected days to calving timeline that cows follow would still be relative to each other. Environmental factors can affect gestation length and therefore days from expected calving. Ouellet et al. (2020) have reported that cows which are exposed to heat stress have a shorter gestation length by an average of 3.2 d compared to cows that are not exposed to heat stress. This study did not consider environmental factors. It is suggested that future studies could include environmental temperature as this may help improve model classification.

5.4.4 Identification of calving

Previous research has indicated the ability to predict the 1 h (Zehner et al., 2019), 3 h (Fadul et al., 2017), and 2 to 8h (Borchers et al., 2017) before calving. In this study, a decision tree classifier was able to classify the -2h before calving with a sensitivity of 40% and a specificity of 99.4%. This model used the rolling average of lying and activity behaviours compared to the 2 h before calving. The positive predictive value of this model was 76.9%, which is greater than previous studies (68.6% Borchers et al., 2017; 40% Zehner et al., 2019) indicating that fewer false positive alerts would be generated.

The traditional and current procedure to recognise an animal as calving is time-consuming, subjective, and expensive (due to labour costs). It also requires expertise, and even the most experienced individual many not accurately identify an animal as calving (Ouellet et al., 2016). The performance of the models in this study was poor and, in a commercial setting, it is unlikely that it would provide an effective alert system. If used under field conditions, it is likely farmers would ignore alerts over time due to the high presence of false positives (Eckelkamp and Bewley, 2020). Nonetheless, automatic calving detection systems have the potential to benefit dairy producers, cows, and calves. Automated systems are an objective method of calving detection, and this could reduce human error that can occur through the misinterpretation of physical signs or calving records.

In this study dataset, 11% of animals required assistance at calving, and the stillborn rate (calves that were born dead) was 6.1%. In Chapter 4, it was concluded that there was no difference in the behaviour of animals that calved with eutocia and animals that calved with dystocia on the day of calving, and in the 4 days preceding calving. These animals were therefore included in the prediction of calving. These figures highlight the importance of dairy producers being aware of calving animals. A system which alerts farmers to a calving cow would enable closer monitoring of the individual animal, and it could increase the rate of appropriate intervention at an earlier stage. Intervention could improve the calving outcome for cow and calf. Dystocia is described as prolonged calving or severe or prolonged assisted extraction (Mee, 2004). Intervention could reduce the length of calving and potentially the severity of dystocia. This action could benefit calves as Johanson and Berger (2003) reported calves were 2.7 times more likely to die within < 48h if they experience a difficult birth.

In this study, the rolling average of behaviours provided an improved classification of calving compared to data which was not averaged. Other studies have successfully adjusted data prior to calving to improve model prediction. Fadul et al. (2017) compared behaviour summarised into 3h periods on the day of calving (−3, −6, −9, −12, −15 and −18 h), and compared the relative change in each 3h block to a baseline generated from average behaviour between -72 to -48h. Rumination time, the number of rumination chews, the number of rumination boluses, the number of lying bouts, and the number of cow activities were used to classify calving. For multiparous and primiparous cows, logistic regression could indicate the 3h before calving with a sensitivity of 88.9% and 85% and a specificity of 93.3% and 74%, respectively. In another study, Titler et al. (2015) created an activity index summed from step count, lying bouts and lying time. It was reported that a 50% increase in the activity index could be used to indicated calving, and 76% of calvings could be identified >4 h before calving. The results of these two studies suggest a moving-mean or threshold could be successfully used to indicate calving. A moving-mean based algorithm has successfully been used to detect oestrus (Arcidiacono et al., 2020), and potentially a combination of a moving-mean and a threshold value could provide the best classification of calving.

The studies reviewed in the literature generated models using data collated from 1 to 3 farms. Although identification of calving may be successful within a controlled setting, commercial farms have a variety of calving management procedures, which could result in the misidentification of calving. Future studies should look to expand the number of farms included within a dataset to improve the identification of calving on commercial farms.

Numerous studies have reported that lying and activity behaviour can be affected by stocking density (Wang et al., 2016), regrouping (Schirmann et al., 2011), and disease (Dittrich et al., 2019). Social regrouping is a common occurrence on commercial dairy farms, and cows often enter and leave the calving pen. A behavioural parameter which is not affected by these factors could lead to an improved identification of calving. Tail raising is not known to be affected by these external variables however it is known to be affected by the calving process (Miedema et al., 2011a). It could be that a tail raising parameter could be used to improve calving detection. A disadvantage of this technology is that tail collars would need to be specifically purchased by dairy producers. There has been no research into the economic viability of calving detection technologies, so it is difficult to ascertain the cost-benefit analysis of tail collar purchase.

5.5 Conclusion

The identification of the day before calving was poor, however it provided an improvement when compared to the expected date of calving. The 2h before calving could be classified correctly in 40% of cases. It is theorised that the identification of calving could be improved if moving-mean models or a threshold-based model was used. There was no difference in gestation period length between primiparous and multiparous cows. Cows which were carrying a beef-sired calf had a longer gestation period compared to cows carrying a dairy sired calf. Future studies should look to expand the number of farms included within a dataset to improve the classification of calving under field conditions.

Chapter 6 The behavior of dairy cattle in the transition period: Effects of blood calcium status.

The research described in this Chapter has been published: Barraclough, R. A. C., Shaw, D. J., Thorup V.M., Haskell, M. J., Lee, W., Macrae, A. I. (2020). The behavior of dairy cattle in the transition period: Effects of blood calcium status. Journal of Dairy Science,103 (11). See Appendix 4 for published paper.

6.1 Introduction

In Chapter 1 it was discussed that hypocalcaemia (known also as ‘milk fever’) is a metabolic disease caused by low blood calcium concentrations (Goff, 2008). A sudden demand for calcium is caused by the onset of lactation, and as calcium homeostasis adapts to meet the challenge, it is reported that most cows have some level of hypocalcaemia at calving (Horst et al.,1994). When cows are not able to regulate their blood calcium levels, severe hypocalcaemia can occur. Clinical signs that can be displayed include excitability, lethargy, prolonged recumbency, and, if an animal is left untreated, death (Oetzel, 2011).

Clinical hypocalcaemia has been reported to affect 0-41% of cows within UK herds, and the average incidence rate of hypocalcaemia was reported to be 5% (Whitaker et al., 2002). Farm profitability is affected by hypocalcaemia and a fatal case of hypocalcaemia can cost approximately £967.21 whilst a non-fatal case can cost £195.23 (Chapter 1). Subclinical hypocalcaemia (< 2.0 mmol/L) was reported to affect 25% of primiparous cows, and 41% to 54% of cows in second lactation or greater (Reinhardt et al., 2011). In addition to affecting farm profitability, hypocalcaemia can have long term implications on cow health as hypocalcaemia is regard as a gateway to other diseases. Hypocalcaemia has been linked to health disorders such as retained foetal membranes (Rodríguez et al., 2017), displaced abomasum (Neves et al., 2018), ketosis (Rodríguez et al., 2017), and metritis (Neves et al., 2018).

Goff (2008) stated that blood calcium concentrations should fall between 2.1 and 2.5 mmol/L in healthy dairy cattle. Currently, the only method to diagnose a cow as having subclinical hypocalcaemia is to sample and analyse it for calcium levels. The threshold used to determine if a cow has subclinical hypocalcaemia varies between studies. Typically, studies use ≤ 2.0 mmol/ L to identify cows as having subclinical hypocalcaemia (Reinhardt et al., 2011; Sepúlveda-Varas et al., 2015; Wilhelm et al., 2017). Nevertheless, thresholds ranging from 1.8 mmol/ L (Jawor et al., 2012) to 2.3 mmol/ L (Seifi et al., 2011) have been applied in various research studies. A cow is typically diagnosed as having clinical hypocalcaemia through symptoms such as muscle tremors, weakness and depression, or sternal recumbency (Oetzel, 2011).

These findings show that hypocalcaemia presents dairy farmers with an animal health and welfare issue. In addition, hypocalcaemia has a negative effect on farm profitability. The early identification of hypocalcaemia could improve the ability of farmers to treat and manage their transition cows. Previous studies have shown that cow behaviour changes can be used to identify cows at risk of lameness (Weigele et al., 2018), metritis (Neave et al., 2018), and clinical ketosis (Itle et al., 2015). Few studies have reported the relationship between subclinical hypocalcaemia and cow behaviour during the pre- and post- calving period. In addition, no studies have compared the behaviour of cows diagnosed as having clinical hypocalcaemia, subclinical hypocalcaemia, and normocalcaemia. Jawor et al. (2012) compared the behaviour of 15 cows with subclinical hypocalcaemia (< 1.8 mmol/L) to 15 cows with normocalcaemia in the 3 wk pre- and post- calving. It was concluded that cows with subclinical hypocalcaemia at calving consumed an average of 1.7 kg/d more dry matter in wk-2 and wk-1 before calving compared to control cows. In addition, it was reported that cows with normocalcaemia stood for 2.6h less in the 24h period before calving when compared to cows with subclinical hypocalcaemia.

There are no commercially available devices which could be used to identify cows as having clinical or subclinical hypocalcaemia prior to calving. Research has shown that standing behaviour of cows with subclinical hypocalcaemia differs on the day of calving when compared to normocalcaemia (Jawor et al., 2012). If further behavioural differences between cows with clinical hypocalcaemia, subclinical hypocalcaemia, and normocalcaemia could be ascertained, then these behavioural differences could be used in the development of hypocalcaemia detection systems. In addition, there is no research assessing the behaviour of cows with clinical hypocalcaemia in the pre- and post-calving period. It is important to research if clinical hypocalcaemia has long lasting behavioural effects on cows in the critical post-calving transition period. This would show that, despite treatment, the effects of hypocalcaemia are prolonged and emphasise the importance of preventing hypocalcaemia on dairy farms.

The study of behaviour in cows diagnosed with normocalcaemia, subclinical hypocalcaemia, and clinical hypocalcaemia could be used to develop indicators of hypocalcaemia in dairy cattle during the prepartum period, or on the day of calving before she calves. In addition, it is not known if clinical hypocalcaemia has long lasting effects on cow behaviour in the pre- or post-calving period.

6.1.1 Research Aims

The aim of this study was to identify the association between lying and activity behaviours and hypocalcaemia in primiparous and multiparous cows within the pre-partum period (d -14 to d -1), the day of calving, and the post-partum period (d 1 to d 21). Objectives were to:

1. Determine if lying and activity behaviours differed between primiparous cows with normocalcaemia and primiparous cows with subclinical hypocalcaemia in the 1) 14 d before calving, 2) on the day of calving, 3) in the 21 d post-calving.

2. Determine if lying and activity behaviours differed between multiparous cows with normocalcaemia, subclinical hypocalcaemia, or clinical hypocalcaemia in the 1) 14 d before calving, 2) on the day of calving, 3) in the 21 d post-calving.

6.2 Materials and Methods

6.2.1 Animals and Housing

The study was conducted at the University of Edinburgh Langhill Farm (Roslin, Midlothian, United Kingdom) between November 2016 and April 2018. The farm has a milking herd of approximately 240 Holstein cows. The calving environment was a straw-bedded shed (11 m x 18.4 m) which was kept at a stocking rate of 5-15 heifers and cows. Once a day, cows were fed a total mixed ration consisting of wholecrop, grass silage, concentrate, molasses and dry cow mineral. The ration had a 4:1 forage:concentrate ratio. Cows had access to self-filling water troughs which supplied municipal water. The experimental work was approved by The Royal Dick School of Veterinary Studies Veterinary Ethical Review Committee (Ref 82-16) and Home Office Project Licence 70/8105.

6.2.2 Serum Analysis

Within 24h of calving, blood was taken from each cow from the coccygeal vein into a 6-mL serum vacutainer (BD Vacutainer™ Serum Tubes; Becton Dickinson, USA). Blood was centrifuged at 1,300 x *g* for 10 min. Serum samples were stored at −20°C prior to analyses at the Dairy Herd Health Productivity Service Laboratory (The Royal Dick School of Veterinary Studies, Scotland). An automated chemistry analyser (Beckman Coulter AU480; Beckman Coulter Inc, USA) was used to measure total calcium concentration (OSR60117; Beckman Coulter Inc, USA).

6.2.3 Classification of normocalcaemia, subclinical hypocalcaemia and clinical hypocalcaemia on the day of calving

Cows were classed as having clinical hypocalcaemia when clinical signs indicative of Stage I – Stage III were observed by farm staff (Oetzel, 2011). All cows with clinical hypocalcaemia were recumbent, and subsequently successfully treated with a 400mL solution of calcium gluconate and calcium borogluconate, which provided 11.88g of calcium (Calciject 40; Norbrook Laboratories Limited, Northern Ireland). All cows with clinical hypocalcaemia recovered fully within 24 hours. A cow was classified as having normal blood calcium concentrations when serum calcium concentration was ≥ 2.0 mmol/L (Reinhardt et al., 2011). Cows were classified as having subclinical hypocalcaemia when their serum calcium concentration was below 2.0 mmol/L but showed no clinical signs of hypocalcaemia.

The original dataset included 106 cows. However 32 multiparous cows and 2 primiparous cows were observed but excluded from the analysis for various reasons including incomplete datasets caused by cow death or data gaps (n = 20), severe lameness (n = 2; mobility score 2 and 3 using 0 – 3 point scale: AHDB, 2020b), no recorded time of calving (n = 7), were not bled within 24 h (n = 3), or had twins (n = 2). The final dataset therefore included 21 primiparous and 51 multiparous cows. Of the 21 primiparous cows sampled, 10 primiparous cows were identified as having normal calcium concentrations (2.13 ± 0.13 mmol/L), and 11 primiparous cows were identified as having subclinical hypocalcaemia (1.68 ± 0.20 mmol/L). Of the 51 multiparous cows sampled, 15 multiparous cows were identified as having clinical hypocalcaemia (0.77 ± 0.17 mmol/L), 30 cows were identified as having subclinical hypocalcaemia (1.42 ± 0.08 mmol/L), and 6 cows were identified as having normal blood calcium concentration (2.16 ± 0.06 mmol/L). Seven cows with clinical hypocalcaemia were not blood sampled as farm staff judged their clinical signs to be consistent with a clinical diagnosis and did not blood sample them prior to treatment. However, their activity data were included in the analysis of the 'clinical hypocalcaemia' group as their clinical symptoms and successful treatment justified inclusion in this group.

6.2.4 Behavioural measurements

As described in detail in Chapter 2.4, behavioural measurements were undertaken using an IceQube attached approximately 3 wk before their predicted calving date. The exact time of calving (to the nearest minute) was ascertained by retrospective analysis of video recordings.

6.2.5 Statistical Analysis

To investigate the behaviour of dairy cattle with differing blood calcium status, the number of postural transitions (total number of lying and standing bouts), the duration of lying time, the number of steps, and motion index were summarised from the time of calving into two datasets: behaviour in 2h periods and 24h periods (behaviour per day). The bihourly dataset was used for the analyses of cow behaviour on the day of calving, and data were analyzed in 2h periods from -24 h to 0 h (the time of calving). The dataset containing cow behaviour per day was used to create 2 experimental periods based on the time relative to calving: pre-calving (d −14 to −1), and post-calving (d 1 to d 21). The experimental period was chosen to reflect the transition period, described as the 3 wk before and after parturition (Drackley, 1999). However to maximize the number of animals included in the study, d -14 to d 21 was selected. In this study, the number of lying and standing bouts had been combined to provide a value for the number of postural transitions within a period. The datasets were summed from the time relative to calving (i.e. calving was used as time 0), which ensured all cows followed the same timeline.

The presence of hypocalcaemia is associated with other disorders of the transition cow, and therefore animals that developed a clinical disease post-calving (other than clinical hypocalcaemia) were not excluded from the study, and disease was controlled for as a fixed effect (diseased and not diseased).

Disease was diagnosed after observation of clinical signs by farm staff or a veterinarian. Of the 21 primiparous cows, 4 cows developed disease (normocalcaemia, n = 2; subclinical hypocalcaemia, n = 2) at 11 ± 0.2 d post-calving which were diagnosed as lameness (n = 2), mastitis (n = 1), and metritis (n = 1). Of the 51 multiparous cows, six cows developed disease (clinical hypocalcaemia, n = 4; subclinical hypocalcaemia, n = 2) at 6.8 ± 1.4 d post-calving which were diagnosed as displaced abomasum (n = 1), metritis (n = 2), and retained foetal membranes (n = 3). Animals that had an assisted calving were included in the study, and assistance at calving was controlled for as a fixed effect. Four primiparous cows and 8 multiparous cows were assisted at calving.

All analyses and data manipulations were carried out using RStudio (version 3.4.4; R Foundation for Statistical Computing, Vienna, Austria). To assess data assumptions of normality, residual plots, histogram plots and data normality tests were examined. Mixed-effect analyses, as outlined below, were carried out using the 'lmerTest' package. Residual plots were examined to ascertain the best model fit for the data. Statistical significance was taken as $P \leq 0.05$. Non-significant ($P > 0.05$) interactions were removed from models. Degrees of freedom were calculated using the Satherthwaite approximation for linear models and polynomial regression models, whilst Laplace Approximation was used to calculate degrees of freedom for generalised piecewise regression models. Differences between the three levels of hypocalcaemia (normocalcaemia, subclinical hypocalcaemia, and clinical hypocalcaemia) was determined using a TukeyHSD test. *F*-values were not reported by the TukeyHSD test.

6.2.5.1 Pre- and post- calving analysis.

There was an effect of blood calcium status x parity (primiparous and multiparous) on all behavioural variables across the study period (d -14 to d 21). In addition, there were no clinical hypocalcaemia cases in primiparous cows. As a result, it was decided to analyze data for primiparous cows and multiparous cows separately.

Mixed effects models were used to explore 1) the behavioural differences between primiparous cows with subclinical hypocalcaemia (n = 11) and normocalcaemia (n = 10), and 2) the behavioural differences between multiparous cows with clinical hypocalcaemia (n = 15), subclinical hypocalcaemia (n = 30), and normocalcaemia (n = 6) in the period relative to calving, both pre-calving (d −14 to −1), and post-calving (d 1 to d 21). To analyse the differences in lying time behaviour, step count, and motion index, linear mixed effects models were used. The step count and motion index were $\log_{10}$ transformed to meet normal residual data distribution assumptions. To analyze the differences in postural transitions, generalized linear mixed effects models with a Poisson error distribution were used. Blood calcium status (normocalcaemia, subclinical hypocalcaemia, or clinical hypocalcaemia), days from calving, and the interaction between day × blood calcium status were included as fixed effects. Disease post-calving (diseased and not diseased) and assistance level at calving (assisted and non-assisted) were included as covariates. Cow ID was included as a random effect to account for repeated behavioural measurements per cow. The primiparous pre-calving analysis contained 294 data points and the multiparous pre-calving analysis contained 714 data points. Each animal had 14 repeated observations. The primiparous post-calving analysis contained 441 data and the multiparous post-calving analysis contained 1071 data points. Each animal had 21 repeated observations.

6.2.5.2 The last 24 hours before calving.

To investigate if blood calcium status affected the pattern of behaviour exhibited on the day of calving, a set of mixed-effect models with different temporal relationships were fitted to behavioural variables contained within the bihourly dataset. Data for primiparous and multiparous cows was analysed separately over 12 2h periods from -24 h to 0 h (the time of calving).

Generalised piecewise mixed effect regression models (or "broken-stick" models – where a step change in behaviour at a certain time point is observed; Das et al., 2016), polynomial mixed effect regression models (where there is either a decrease and then increase, or increase and then decrease in behaviours; Ostertagová, 2012), and linear models (Bangdiwala, 2018) were fitted to each behavioural variable. Residual plots were examined to ascertain the best model fit for the data. A piecewise mixed effect regression model provided the best description of the change in the number of postural transitions for primiparous cows, whilst a generalised mixed effect linear model (Poisson error distribution) best described the change in postural transitions for multiparous cows. A polynomial mixed effect regression model best described the change in lying time. Linear mixed effect models best described the change in log transformed step count and motion index. Blood calcium status (normocalcaemia, subclinical hypocalcaemia, or clinical hypocalcaemia), hours from calving, and the interaction between hour × blood calcium status were included as fixed effects. Disease post-calving (diseased and not diseased) and assistance level at calving (assisted and non-assisted) were included as covariates. Cow ID was included as a random effect to account for repeated behavioural measurements per cow. The primiparous cow day of calving analysis contained 252 data points, and the multiparous cow day of calving analysis contained 612 data points. Each cow had 12 repeated observations.

6.3 Results

6.3.1 Pre-calving analysis: Primiparous cows.

During d -14 to d -1, there was no interaction between blood calcium status and days from calving on lying time (min /d; Figure 6.1a), nor on the number of postural transitions (no. /d; Figure 6.1b). There was an interaction between blood calcium status and days from calving on step count (no. /d) and motion index (unit /d) (Figure 6.1c-d). The data showed that whilst the step count of cows with subclinical hypocalcaemia remained constant across the period

($F_{1,142}$ = 0.9, P = 0.35), the step count of cows with normocalcaemia decreased, and back transformation of log steps shows that steps decreased from 842.8 steps /d on d -14 to 427.5 steps /d on d -1 ($F_{1,129}$ = 37.9, P < 0.001). Similarly, the motion index of cows with subclinical hypocalcaemia remained constant ($F_{1,142}$ = 0.9, P > 0.05), the motion index of cows with normocalcaemia decreased, and back transformation of log motion index shows that motion index decreased from 2978.8 unit /d on d-14 to 1832.5 unit /d on d -1 ($F_{1,129}$ = 24.6, P < 0.001).

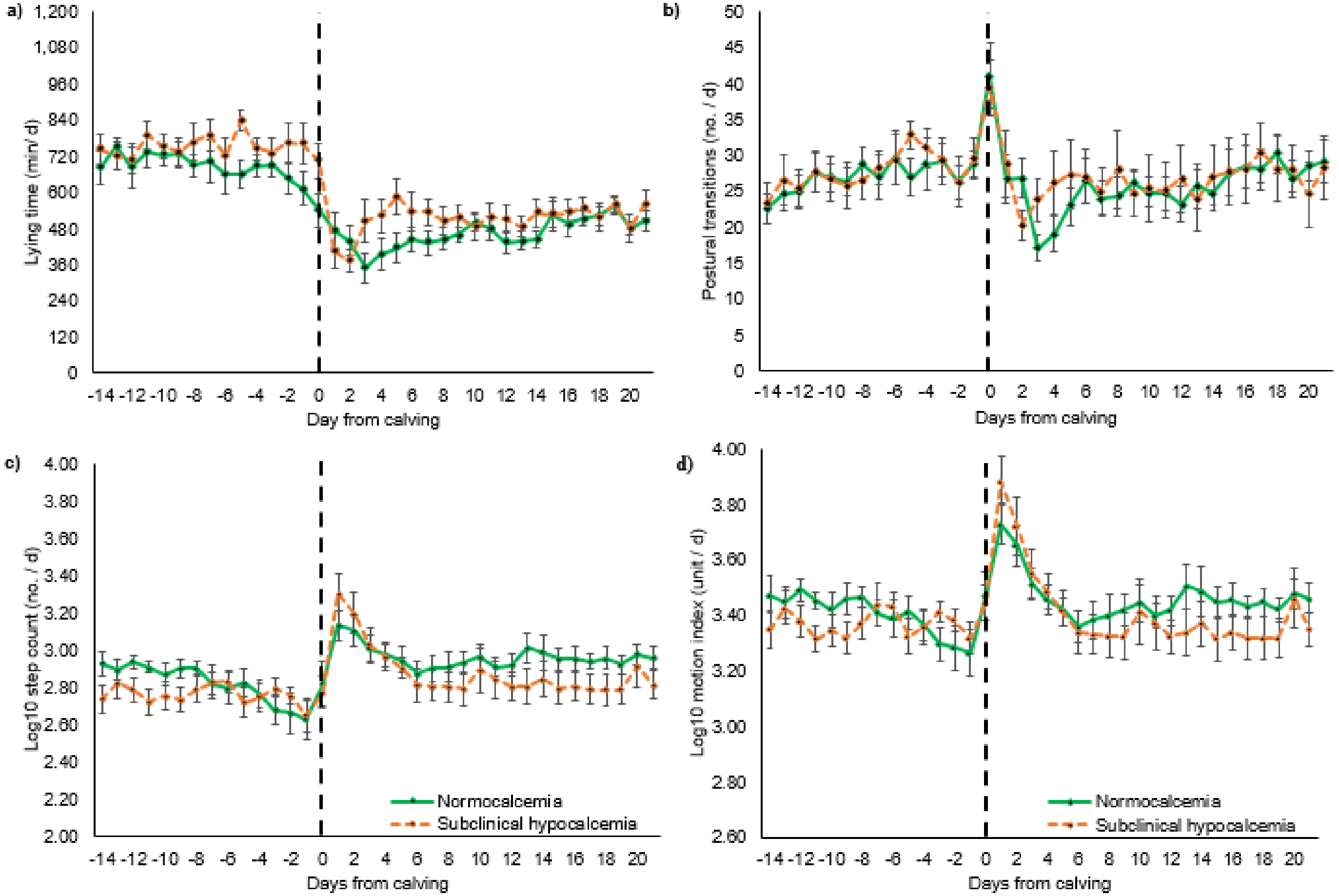


Figure 6.1 Behavioural variables for primiparous cows with normocalcaemia (green solid line; n = 10) and primiparous cows with subclinical hypocalcaemia (orange dashed line; n = 11) summarised into 24h periods ± SE in the -14d to + 21d around calving for (a) lying time duration (min /d); (b) number of postural transitions (no. /d); (c) log_{10} step count (no. /d); log_{10} motion index (unit /d).

6.3.2 Day of calving: Primiparous cows

On the day of calving, there was no interaction between hours to calving and blood calcium status on the lying time duration (min /2h), the number of postural transitions (no. /2h), the number of steps (no. /2h), or motion index (unit /d) ($P > 0.05$; Figure 6.2a-d). In addition, there was no association between blood calcium status and the lying time duration, the number of postural transitions, the number of steps, or motion index ($P > 0.05$).

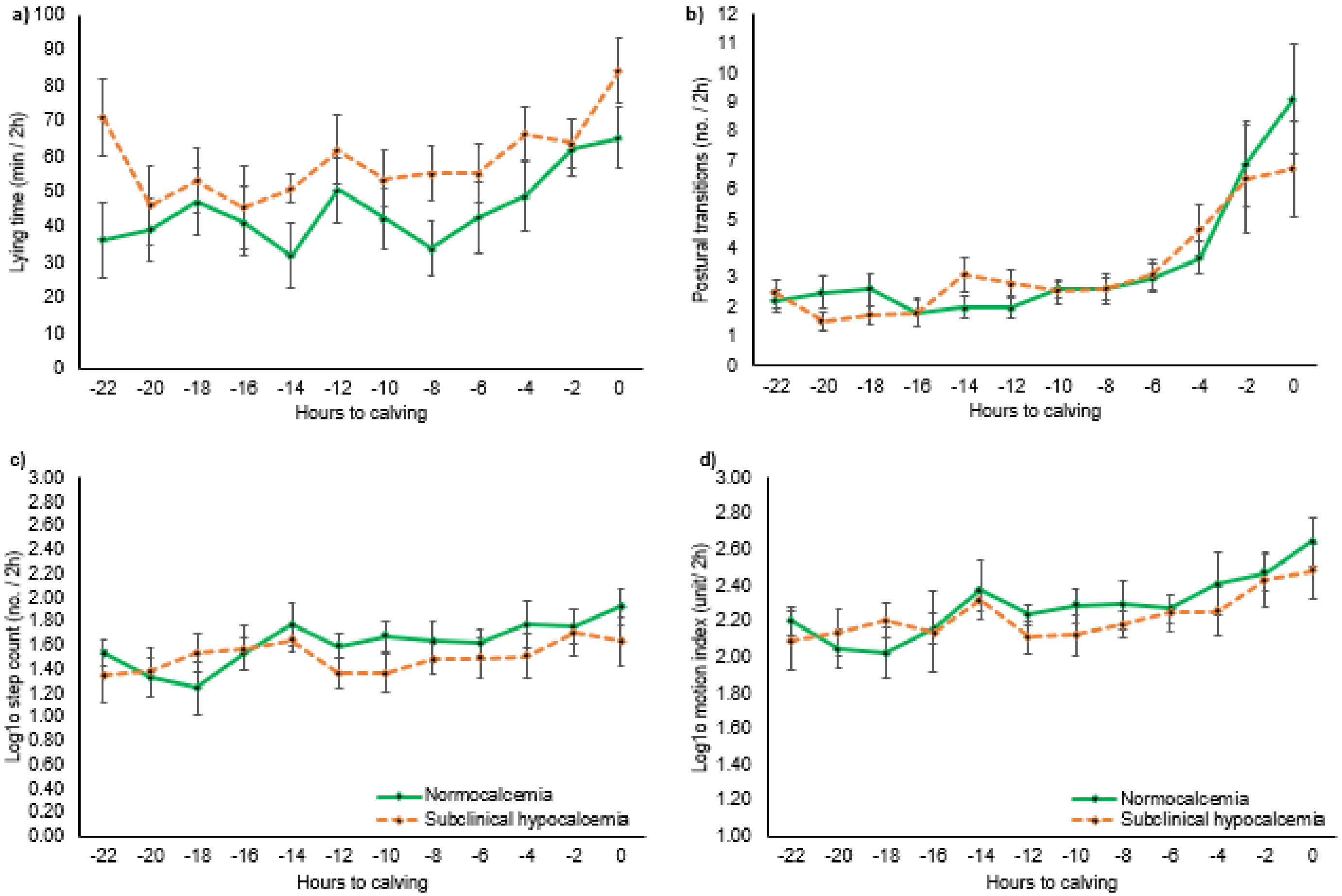


Figure 6.2 Behavioural variables for primiparous cows with normocalcaemia (green solid line; n = 10) and primiparous cows with subclinical hypocalcaemia (orange dashed line; n = 11) summarised into 2h periods ± SE in the 24h before calving for (a) lying time duration (min /d); (b) number of postural transitions (no. /d); (c) log$_{10}$ step count (no. /d); (d) log$_{10}$ motion index (unit /d).

6.3.3 Post-calving analysis: primiparous cows.

During d 1 to d 21, there was no interaction between blood calcium status and days from calving on lying time (min /d; Figure 6.1a) or the number of postural transitions (no. /d; Figure 6.1b) ($P > 0.05$). However, there was an interaction between blood calcium status and days from calving on step count (no. /d; Figure 1c). Back transformation of log steps shows that step count of cows with normocalcaemia decreased from 1351.6 steps /d on d 1 to 912.9 steps /d on d 21, whilst the step count of cows with subclinical hypocalcaemia decreased from 2022.1 steps /d on d 1 to 651.9 steps /d on d 21 ($F_{1,432} = 22.2$, $P < 0.001$;Figure 6.1c). Similarly, motion index (unit /d) of cows with normocalcaemia decreased from 5367.5 unit /d on d 1 to 2900.6 unit/ d on d 21, whilst the motion index of cows with subclinical hypocalcaemia decreased from 7670.1 unit /d on d 1 to 2224.7 unit /d on d 21 ($F_{1,432} = 15.6$, $P < 0.001$;Figure 6.1d). There was no association between blood calcium status on lying time, the number of postural transitions, step count, or motion index ($P > 0.05$).

6.3.4 Pre-calving analysis: Multiparous cows.

During d -14 to d -1, there was no interaction between blood calcium status and days from calving on lying time (min /d), the number of postural transitions (no. /d), step count (no. /d), or motion index (unit /d) (Figure 6.3a-d; $P > 0.05$). Cows with normocalcaemia had fewer postural transitions in the pre-partum period (18.5 ± 6.9 no. /d) compared to cows with subclinical hypocalcaemia (23.5 ± 8.0 no. /d; $P = 0.036$) and clinical hypocalcaemia (23.5 ± 8.6 no. /d; $P = 0.031$). Cows with clinical hypocalcaemia tended to have fewer steps ($F_{2,46} = 3.1$, $P = 0.052$) and lower motion index ($F_{2,46} = 3.0$, $P = 0.057$) across the period compared to cows with normocalcaemia and subclinical hypocalcaemia. There was no difference in step count and motion index between cows with normocalcaemia and cows with subclinical hypocalcaemia, nor an association between hypocalcaemia and lying time duration ($P > 0.05$).

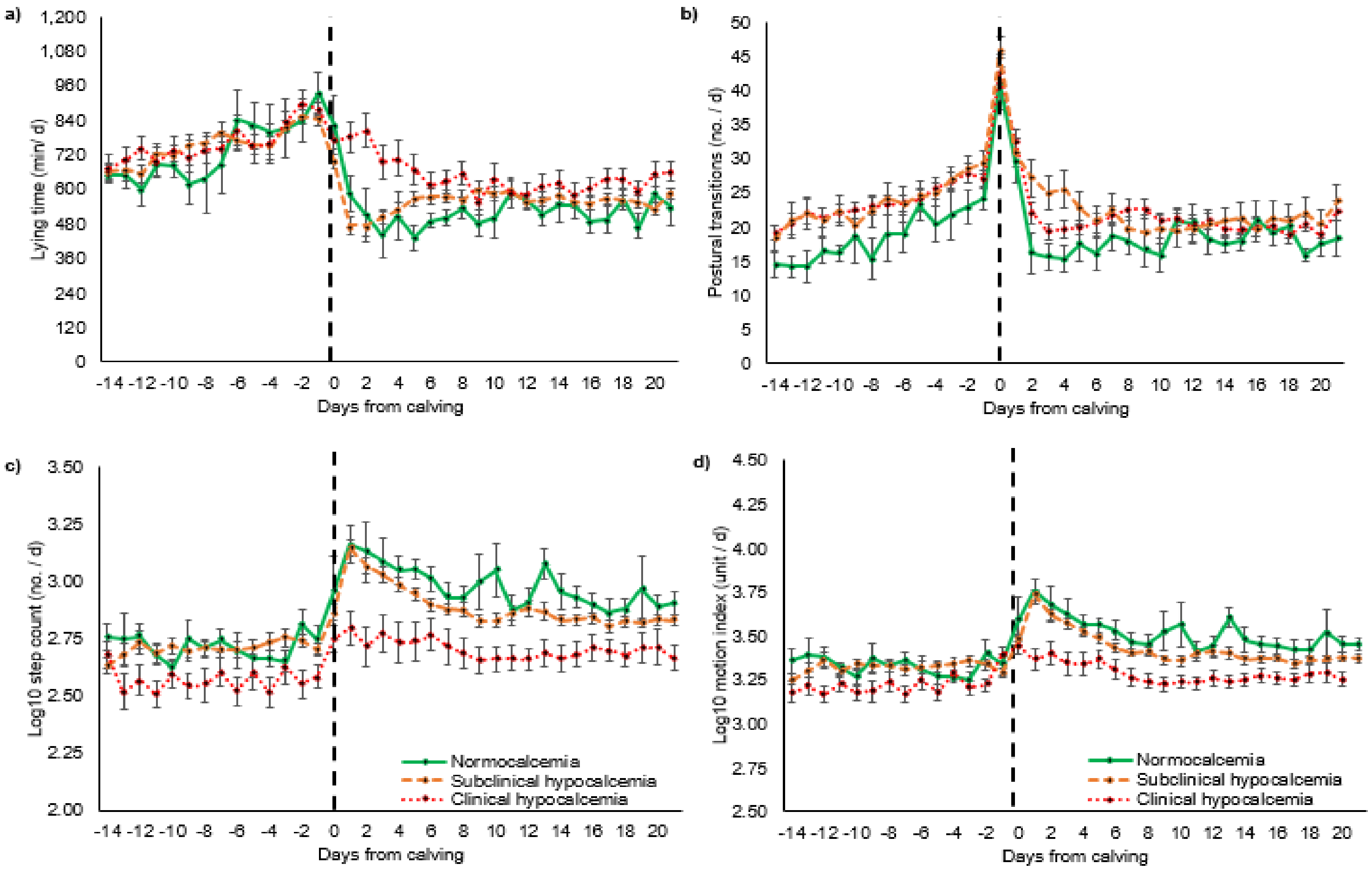


Figure 6.3 Behavioural variables for multiparous cows with normocalcaemia (green solid line; n = 6), multiparous cows with subclinical hypocalcaemia (orange dashed line; n = 30), and multiparous cows with clinical hypocalcaemia (red dashed-dot line; n = 15), summarised into 24h periods ± SE in the -14d to + 21d around calving for (a) lying time duration (min /d); (b) number of postural transitions (no. /d); (c) log$_{10}$ step count (no. /d); (d) log$_{10}$ motion index (unit /d).

6.3.5 Day of calving: Multiparous cows

On the day of calving, there was no interaction between hours to calving and blood calcium status, nor an association between blood calcium status on the lying time duration (min /2h), the number of postural transitions (no. /2h), the number of steps (no. /2h), or motion index (unit /d) ($P > 0.05$; Figure 6.4a-d).

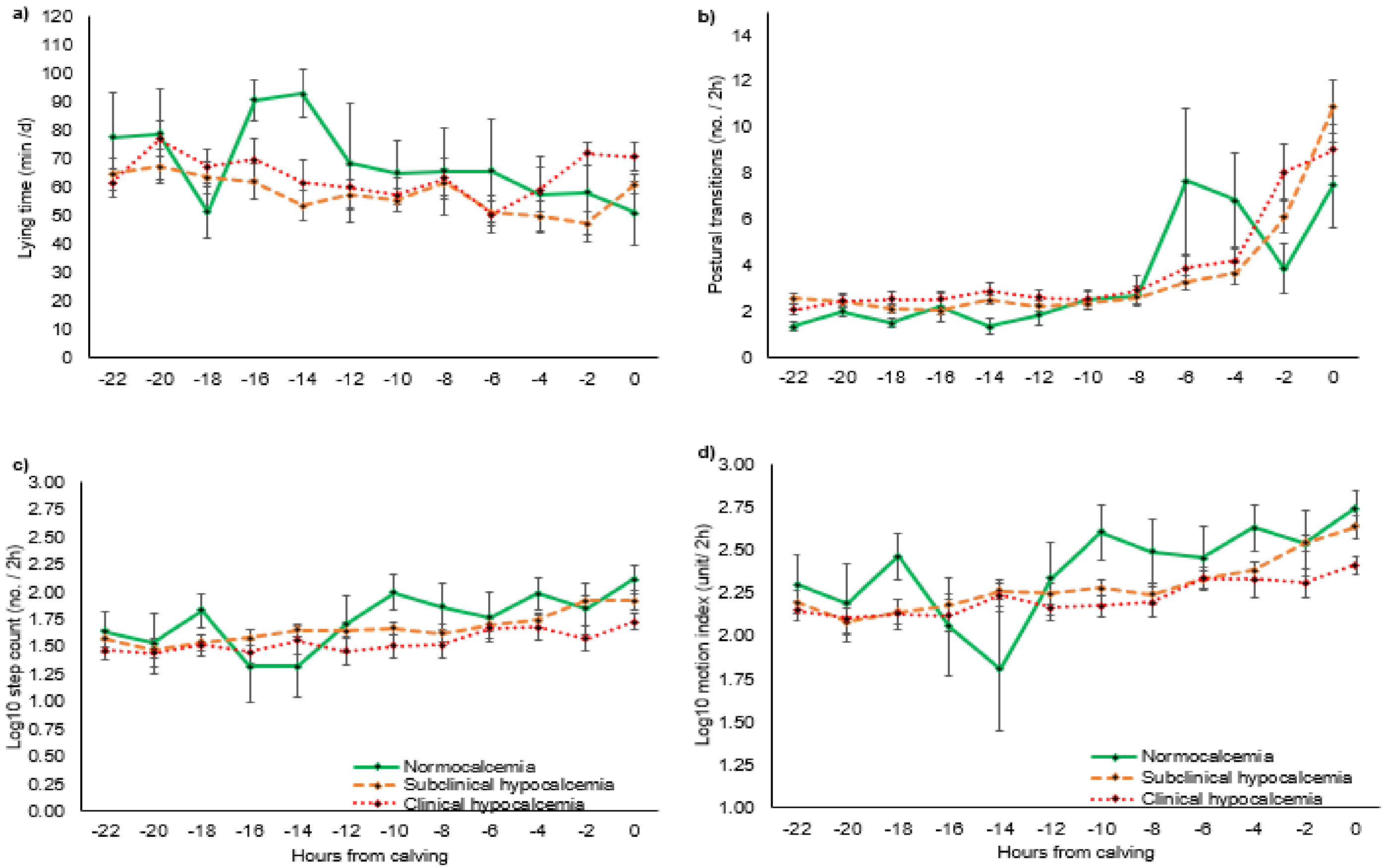


Figure 6.4 Behavioural variables for multiparous cows with normocalcaemia (green solid line; n = 6), multiparous cows with subclinical hypocalcaemia (orange dashed line; n = 30), and multiparous cows with clinical hypocalcaemia (red dashed-dot line; n = 15), summarised into 2h periods ± SE in the 24h before calving for (a) lying time duration (min /d); (b) number of postural transitions (no. /d); (c) log$_{10}$ step count (no. /d); (d) log$_{10}$ motion index (unit /d).

6.3.6 Post-calving analysis: Multiparous cows.

There was an interaction between blood calcium status and days from calving on lying time, the number of postural transitions, step count, and motion index (Figure 6.3a-d). The lying time of cows diagnosed with clinical hypocalcaemia decreased by 5.6 ± 1.3 min /d across the period from 780.6 ± 30.3 min /d on d 1 to 661.2 ± 32.6 min /d on d 21 ($F_{1,299}$ = 19.1, $P < 0.001$). In contrast, the lying time of cows diagnosed with subclinical hypocalcaemia increased by 2.6 ± 0.8 min /d from 474.9 ± 52.4 min /d on d 1 to 585.3 ± 20.2 min /d on d 21 ($F_{1,599}$ = 11.8, $P < 0.001$). The lying time of cows with clinical hypocalcaemia was higher in the post-calving period (643.7 ± 10.3 min /d) compared to cows with subclinical hypocalcaemia (555.3 ± 5.8 min /d) and normocalcaemia (518.3 ± 11.5 min /d) ($F_{2,59}$ = 15.1, $P < 0.001$). There was no difference in lying time between cows with normocalcaemia and cows with subclinical hypocalcaemia ($df =_{1,34,}$ $P > 0.05$).

For cows with clinical hypocalcaemia, the average number of postural transitions decreased from 30.9 ± 2.2 /d on d 1 to 23.6 ± 2.6 /d on d 21 ($z_{1,299}$ = -5.9, $P < 0.001$), and the average number of postural transitions for subclinical hypocalcaemia cows also decreased from 32.5 ± 1.7 no. /d on d 1 to 22.4 ± 1.4 no. /d on d 21 ($z_{1,599}$ = -6.5, $P < 0.001$). Cows with normocalcaemia had fewer daily postural transitions (18.4 ± 0.5 no. /d; $z_{2,59}$ = -2.6, $P = 0.01$) compared to cows with clinical hypocalcaemia (22.0 ± 0.5 no. /d). There was no difference in the average postural transitions between cows with subclinical hypocalcaemia (21.1 ± 0.3 no. /d) and cows with normocalcaemia, nor any difference in the number of postural transitions between cows with subclinical hypocalcaemia and cows with clinical hypocalcaemia ($P > 0.05$).

Back transformation of log transformed steps shows the step count of cows with clinical hypocalcaemia decreased from 620.0 steps /d on d 1 to 462.0 steps /d on d 21 ($F_{1,299}$ = 7.02, $P = 0.008$), whilst the step count of cows with subclinical hypocalcaemia decreased from 1391.0 steps /d on d 1 to 672.0 steps /d on d 21 ($F_{1,599}$ = 233.6, P < 0.001). For cows with normocalcaemia, step count decreased from 1442.6 steps /d on d 1 to 801.8 steps /d on d 21 ($F_{1,119}$ = 27.4, P < 0.001). Over the period, cows with clinical hypocalcaemia had an average of 503.4 steps /d, compared to cows with normocalcaemia that had 948.0 steps /d, and hypocalcaemia that had 774.5 steps /d ($F_{2,59}$ = 14.8, P < 0.001). There was no difference in step count between cows with normocalcaemia and cows with subclinical hypocalcaemia ($df =_{1,34}$, P > 0.05).

Back transformation of log transformed motion index shows the motion index of cows with clinical hypocalcaemia decreased from 2781.0 unit /d on d 1 to 1789.1 unit /d on d 21 ($F_{1,299}$ = 34.0, P < 0.001), whilst the step count of cows with subclinical hypocalcaemia decreased from 5407.2 unit /d on d 1 to 2342.4 unit /d on d 21 ($F_{1,599}$ = 286.9, P < 0.001). For cows with normocalcaemia, motion index decreased from 5677.4 unit /d on d 1 to 2839.9 unit /d on d 21 ($F_{1,119}$ = 28.8, P < 0.001). Over the period, the average motion index of cows with clinical hypocalcaemia was lower compared (1962.8 unit /d) compared to cows with normocalcaemia that had 3285.5 unit /d, and subclinical hypocalcaemia that had 2702.9 unit /d ($F_{2,59}$ = 14.8, P < 0.001). There was no difference in motion index between cows with normocalcaemia and cows with subclinical hypocalcaemia ($df =_{1,34}$, P > 0.05).

6.4 Discussion

To our knowledge, this is the first study to investigate behavioural differences associated with normocalcaemia, subclinical hypocalcaemia and clinical hypocalcaemia in primiparous and multiparous transition cows. We found behavioural differences in the pre-calving period for both primiparous and multiparous cows. These behavioural differences could be developed to help categorize animals as having clinical hypocalcaemia, subclinical hypocalcaemia and normocalcaemia prior to calving. We also found notable associations between clinical hypocalcaemia and lying and activity behaviours in multiparous cows within 21d post-calving. This finding illustrates that the effects of lowered blood calcium status at calving can be significant and prolonged, even in cows that had successful treatment (clinical hypocalcaemia).

6.4.1 Pre-calving behaviour

In the pre-calving period (d -14 to d -1), we found that multiparous cows with normocalcaemia had fewer lying and standing bouts compared to cows that developed subclinical and clinical hypocalcaemia. Our findings contradict Jawor et al. (2012) that found no difference in standing bout behaviour in the 7d before calving when cows with subclinical hypocalcaemia (n = 15) and normocalcaemia (n = 15) were compared. Differences in the two study findings could be explained by categorization of subclinical hypocalcaemia and study size. Jawor et al. (2012) classed cows as having subclinical hypocalcaemia when serum calcium concentration was ≤1.8 mmol/L, whereas the threshold in this study was higher (2.0 mmol/L). Our study had fewer cows categorized as normocalcaemia (n = 6), however had an additional category (clinical hypocalcaemia, n = 15) and more cows categorized as having subclinical hypocalcaemia (n = 30). Due to the limited sample size of cows categorized with normocalcaemia, our results should be treated with caution. Future work should look to increase the number of cows within the study population, which will increase the sample size of cows within each category.

Within the pre-calving period (d -14 to d -1), the step count and motion index of primiparous cows with normocalcaemia decreased. There was no interaction between day to calving and step count or motion index for primiparous cows diagnosed with subclinical hypocalcaemia, however their step count and motion index were initially lower. Jawor et al. (2012) did not observe activity behaviours. Primiparous cows had never experienced the pre-calving environment or management, a time of stress due to dietary changes and regrouping. Neave et al. (2017) reported multiple differences in the behaviour of healthy primiparous and multiparous cows in the transition period. For example, primiparous cows spent more time exploring their feeding environment and visited the feeder more often than multiparous cows. Primiparous cows were displaced at the feeder more frequently than multiparous cows, ate more slowly, and spent a longer duration feeding. It could be theorized that in this study, primiparous cows with normocalcaemia were exploring and adapting to their new environment, before settling within the pre-calving environment. However, there was no difference observed in lying time duration or the number of lying and standing bouts. This study set out to identify if normocalcaemia, subclinical hypocalcaemia and clinical hypocalcaemia were associated with behavioural differences in the pre-calving period. We found differences in pre-calving behaviour for primiparous and multiparous cows associated with blood calcium status, which suggests pre-calving behaviour could be used to categorize animals as having normocalcaemia, subclinical hypocalcaemia, or clinical hypocalcaemia prior to calving. Further research is required to develop these findings, and to see if behaviour can be used to classify cows on commercial dairy farms (see Appendix 5 for the classification of hypocalcaemia).

6.4.2 Behaviour on the day of calving

This study identified no association between blood calcium status and lying and activity behaviours on the day of calving (-24 h to 0h) for both primiparous and multiparous cows. Hypocalcaemia is caused by a failure of calcium homeostasis to adapt to the sudden demand for calcium at the onset of lactation (Goff, 2008). Cows diagnosed with subclinical or clinical hypocalcaemia are less able to regulate calcium and are likely to have lower circulating concentration of calcium during parturition. Calcium is required for skeletal and smooth muscle contraction (Wilkens et al., 2020), and it was theorized hypocalcaemia would affect how a cow behaved during parturition. Previous literature has reported behaviour on the day of calving to be vastly unlike any other day (Miedema et al., 2011a), and it is possible that subtle changes in behaviour caused by reduced calcium concentration may not manifest itself in a period that is typically characterized by pain and exhaustion of the cow (Barrier et al., 2012). Our findings contrast with Jawor et al. (2012)

that reported cows with subclinical hypocalcaemia spent 3 h longer standing during the 24 h period before calving compared to control cows. It is unclear why the findings of these two studies differ. However, differences in methodology could be an attributing factor. Jawor et al (2012) pair-matched 15 cows with subclinical hypocalcaemia and 15 cows with normocalcaemia based on parity and, where possible, health disorders such as metritis, mastitis, and fever. We were unable to pair match multiparous cows due to the limited sample size of cows diagnosed with normocalcaemia.

6.4.3 Post-calving behaviour

In the post-calving period (d 1 to d 21), there was an association of blood calcium status with all behavioural variables for multiparous cows. Multiparous cows with clinical hypocalcaemia were less active, spending more time lying down compared to cows with subclinical hypocalcaemia and normocalcaemia. Over the period, cows with clinical hypocalcaemia had fewer average steps per day, compared to cows with normocalcaemia and subclinical hypocalcaemia. A possible explanation for our findings is that cows with clinical hypocalcaemia display sickness behaviour in the post-calving period. Sick cows are reported to alter their daily behavioural patterns (Dittrich et al., 2019), and previous literature have reported behavioural changes in dairy cattle during sickness. For example, lame cows reduce their activity and increase their lying time (Weigle et al., 2018), and primiparous cows with more than one clinical disease (not including lameness) are reported to have longer lying bouts and spend more time lying compared to healthy animals (Sepúlveda-Varas et al., 2014). In light of these findings, management of cattle with clinical hypocalcaemia could be altered. Farmers could allow cows to spend more time in the sick pen, typically a shed with a soft surface e.g. straw bedded, which would enable cows to lie down in greater comfort (Thomsen et al., 2019).

Although cows diagnosed with clinical hypocalcaemia recovered post treatment, the significant post-calving behavioural differences indicate that hypocalcaemia has long-lasting effects, and prevention of hypocalcaemia should have high priority on dairy farms. Recent studies (Caixeta et al., 2017; Rodríguez et al., 2017; Neves et al., 2018) reported that hypocalcaemia at calving leads to impaired reproductive function and an increased risk of health disorders such as ketosis, retained placenta, and metritis, which further emphasizes the importance of preventing hypocalcaemia to improve cattle health and welfare.

6.4.4 Future work and current limitations

Jawor et al. (2012) and the current study did not monitor rumination or the duration of lying bouts. Previous literature has reported that, in the week before calving, rumination times of cows with subclinical ketosis (plus another health problem) were lower compared to their healthy counterparts (Kaufman et al., 2016). Investigation of rumination and lying bout behaviour prior to calving could provide an early indicator of calcium status on the day of calving, allowing farmers to intervene and to administer prompt treatment. Future work should look at the inclusion of rumination and the duration of lying bouts.

A limitation of this study is that only a small number of multiparous cows were categorized as having normocalcaemia (*n* = 6). A small study population of normocalcaemic cows has occurred in other behavioural studies (*n* = 15; Jawor et al., 2012). It is theorized that this study contains fewer normocalcaemic cows due to a higher serum calcium threshold specified within the categorization of cows (≥ 2.0 mmol/L vs ≥ 1.8 mmol/L). Another limitation of the current study is that some cows were categorized as having clinical hypocalcaemia based on clinical signs alone, without the back-up of clinical biochemistry. This was allowed to increase the number of cows in the study population with clinical hypocalcaemia. In addition, this study included animals that developed clinical disease post-calving. These limitations could have affected the results of this study, and the reader must be cautioned on the interpretation of these findings which are based on a relatively small population size. In addition, it was not possible to investigate the behavioural changes associated with normocalcaemia, subclinical hypocalcaemia and clinical hypocalcaemia on subsequent animal health, as only a small number of animals (n = 10) developed a health issue post-calving.

6.5 Conclusion

In the pre-calving period, multiparous cows with normocalcaemia had fewer postural transitions compared to multiparous cows with subclinical and clinical hypocalcaemia. In addition, there was a decrease in step count and motion index across the pre-calving period for normocalcaemic primiparous cows. Blood calcium status at calving was associated with differences in lying time duration, the number of postural transitions, step count, and motion index in the post-calving period for multiparous cows. Although these findings must be treated with caution due to the limited population size, they suggest that behavioural differences could be developed to help categorize animals as clinical hypocalcaemia, subclinical hypocalcaemia and normocalcaemia prior to calving, and also illustrate the profound and long-lasting effects of clinical hypocalcaemia on the cow.

Chapter 7 Discussion

The landscape of the UK dairy industry has changed within the last decade, in particular average herd size per farm and milk yield per cow has increased (AHDB, 2020a; AHDB, 2019). Increasing herd size and production per cow generate challenges for dairy producers, namely in the realm of farm management and cow health. It has been suggested that technology on dairy farms could be a solution to address key environmental, social sustainable, and economic issues on dairy farms (Lovarelli et al., 2020). Although studies have reported on technology use on dairy farms within Australia, Italy, and United States of America, little research has been conducted into the use of cow monitoring technology on UK dairy farms.

This PhD aimed to gain an insight into the use of cow monitoring technology on UK dairy farms. It Chapter 2, it was found that the prevalence of automated cow monitoring technology (ACMT) was 63.9%, and this figure was comparable to published figures from the US (Borchers and Bewley, 2015). An important finding to be generated from this research was that half of farms that did not have ACMT stated that they would invest within the next 5 years, so it is likely that the prevalence of ACMT within the UK will increase. This is finding suggests that in the future, cow management will be less reliant on human observation and more reliant on technologies. It is theorised that the UK dairy industry will increase the number of technologies that help to improve cow management and reduce labour inputs. This statement is supported by the findings in Chapter 2 where it was discovered that the most assessed individual cow parameters were heat detection, daily milk yield, and illness detection.

It is important to remember that technology adoption can come with challenges. Although automated systems on dairy farms were viewed positively, with 96.2% of farmers stating there was a benefit post-installation, 60.3% of farmers encountered a problem following ACMT installation. The main reason was due to system faults such as poor battery life or breakages resulting in a reduced ability of the system to perform to expectations. This is an important finding as issues surrounding ACMT have not been researched. Technology companies within the UK can use this finding to ensure that faults in their system are reduced which will increase customer confidence in their system. When asked to select from a list of positive and negative descriptors, only 7% of descriptors were associated with a negative connotation, and the most selected responses were useful, reliable, and practical. Overall, findings suggested ACMT was viewed positively on farm, and expectations of dairy farmers were being fulfilled.

Farm staff are under mounting pressure to manage their time effectively as the number of cows under their care increases (Gargiulo et al., 2018). Calving presents a regular management challenge on dairy farms. This is because calving is a high-risk period for both cow and calf, and routine surveillance is required to identify calving cows and to allow for intervention where necessary (Mee, 2004). In addition, cows are at risk of hypocalcaemia at calving - a condition which can be fatal if left untreated (Goff, 2008). Automatic systems could be developed to detect clinical hypocalcaemia, however behavioural changes in cattle with clinical hypocalcaemia have not been investigated. This PhD aimed to investigate if automated behavioural monitoring could be used to identify behavioural changes relating to calving, dystocia, and hypocalcaemia, and to detect calving.

Constant surveillance of calving cows is required to ensure the safe delivery of a live calf (Mee, 2004). In Chapter 2, it was discovered that 6.6% of UK dairy farmers utilise calving detection systems. Automated calving detection systems have the potential to identify calving cows and to reduce the labour inputs required for calving surveillance. Before calving detection systems can be developed, any behavioural changes preceding calving must be identified. Chapter 4 investigated whether accelerometers could be used to identify behavioural changes of primiparous cows and multiparous cows in late gestation and on the day of calving. It was concluded that cow behaviour on the day of calving was significantly different when compared to a control period: on the day of calving lying time decreased, activity increased, and the number of standing and lying bouts increased. The difference in behaviour between the two periods was likely caused by the calving process, and the pain associated with uterine contractions and the expulsion of the foetus. When the day of calving was analysed in 2h periods, there was a significant effect of hour to calving on all lying and activity behavioural variables; this was likely to be caused by the calving process. Cow behaviour was affected by days to calving and parity (multiparous or primiparous). It was hypothesised that behavioural changes on the day of calving and the days leading up to calving could be used to identify the period before calving, and the day before calving.

This PhD investigated the ability of machine learning methods to identify the day before calving, the 2h period before calving, and the 2h, 4h, and 6h period before calving based on cow behaviour. If successful, these techniques could be incorporated into technology to improve calving management. Dairy producers traditionally manage cows around calving using their expected calving date. In Chapter 5, we found the expected calving data was an unreliable parameter, and cows calved -12 to +11 d from their expected calving date. Unfortunately, classification of the day before calving could only identify 10% of cows on the day before calving. It was theorised that classification of the day before calving was poor due to environmental and management factors affecting cow behaviour in the days before calving, and the machine learning models being unable to recognise a pattern in behavioural data. The classification of the period (2h or 2h, 4h, and 6h) before calving was also poor, and in many cases, the calving period was not identified. Nonetheless, the findings of this study are important and highlight important criteria that should be considered when creating calving detection devices. The results of the study indicate that parity must be considered within calving prediction due to the behavioural differences between primiparous and multiparous cows in the pre-calving period. In addition, the sire breed (dairy or beef) was associated with gestation length and should also be considered. Although this study found that lying and activity behaviours changed on the day of calving, we were detection of calving using machine learning methods. The identification of calving cows within this study was poor and would have no benefit to cow management on commercial dairy farms. For a calving detection system to be accepted onto commercial dairy farms, the accuracy of these systems requires improvement. It is likely that the adoption of calving detection systems will increase as the systems develop.

In Chapter 2, it was found that financial implications relating to the installation of ACMT were cited as the main reasons as to why dairy producers had not installed cow monitoring technology. If technology companies can report a cost-benefit analysis of a calving detection system, the uptake of these technologies on farms may increase. When considering technology purchase, farmers scored return on investment, good customer support, and ease of use as the most important criteria. It may be productive for technology manufacturers to focus their marketing on the monetary and non-monetary benefits of their technology systems.

This thesis also addressed how wearable cow technologies could help farmers manage undesirable problems within the transition period, such as dystocia and hypocalcaemia. The recognition of dystocia is important to reduce its negative effects on both cow and calf. In Chapter 4, a case-control methodology was used to compare the behaviour of dystocic and eutocic primiparous and multiparous cows. However, no behavioural differences were found between d -4 to d -1, or on the day of calving. This finding indicates that it would be difficult to use lying and activity behaviours to distinguish between cows which require assistance at calving and those that do not. The study included cows that required only minor assistance (gentle traction by one person with no mechanical device used) and it is possible that the decision of stockpersons to assist cows confounded the data. It is possible that some of the cows classed as eutocic experienced the same low level of difficulty at calving however were unassisted due to management factors such as night-time calving. The lack of behavioural differences between eutocic and dystocic cows, coupled with the disappointing results of calving classification, emphasise the importance of dairy producers to visually assess calving cows for signs of calving.

No automated monitoring device that could inform dairy producers that a cow will have clinical hypocalcaemia at calving currently exists. Hypocalcaemia is a metabolic disease caused by low blood calcium levels in the period surrounding calving (Goff, 2008), and clinical hypocalcaemia can affect between 0-41% of cows within a herd (Whitaker et al., 2002). Hypocalcaemia can have negative consequences on cow health and cows that have hypocalcaemia at calving have a greater risk of being culled (Venjakob et al., 2018), and to suffer from a post-parturient disease (Rodríguez et al., 2017). For these reasons, it is important to prevent hypocalcaemia from occurring.

In Chapter 6, the lying and activity behaviours of primiparous and multiparous cows in different blood calcium categories at calving within the pre- and post-calving period were analysed. Differences in behaviour associated with blood calcium status were found for both primiparous and multiparous cows in the pre-calving period. The study identified that multiparous cows with normocalcaemia had fewer lying and standing bouts compared to multiparous cows with subclinical hypocalcaemia and clinical hypocalcaemia. In addition, the step count of primiparous cows with normocalcaemia was found to decrease across the pre-calving period. These findings indicate that automated detection systems could be developed to use these behavioural differences to help categorise animals as having clinical hypocalcaemia, subclinical hypocalcaemia, and normocalcaemia prior to calving. A system which could detect hypocalcaemia prior to calving would benefit both dairy producer and cow. It would allow dairy producers to intervene and to administer prompt treatment.

Multiparous cows with clinical hypocalcaemia were less active and spent more time lying down when compared to multiparous cows with normocalcaemia and subclinical hypocalcaemia in the 3 weeks post-calving. These findings indicate that low blood calcium at calving has long lasting behavioural effects on multiparous cows. It was hypothesised that cows with clinical hypocalcaemia were showing signs of sickness in the period after calving. This finding is important as although cows were successfully treated for clinical hypocalcaemia, the effects of the disease were prolonged within the critical post-calving period. In consideration of these findings, dairy producers could alter the management of cows with clinical hypocalcaemia. Cows could be allowed to spend a longer duration of time within a straw-bedded environment which would improve their comfort. It can be concluded from these results that prevention of hypocalcaemia should be of high priority on dairy farms.

In the hypocalcaemia study, no differences in the behaviour of primiparous or multiparous cows on the day of calving was found. This finding was unexpected however it was hypothesised that subtle changes in behaviour caused by decreasing blood calcium concentration may not be apparent in the calving period, which is a period defined by pain of the cow. The findings of this study suggest that it would be difficult to use lying and activity behaviours on the day of calving to determine the blood calcium category after calving. Future studies could assess other behavioural parameters such as rumination, feeding behaviours, or lying bout duration which may identify behavioural differences between blood calcium categories. This study only had 6 multiparous cows classified as having normocalcaemia so the results should be treated with caution. It is recommended that future studies increase the number of cows within their study population, which would increase the number of cows within each blood calcium status category.

To summarise, this study concluded that the levels of ACMT on farm will rise within the next 5 years as dairy producers look to invest in technologies. This is an important finding as it suggests that dairy cows will increasingly be managed using automated means rather than human observation. As advanced monitoring systems will be fundamental in the future management of dairy cows, it is important to ensure that these systems are effective. This study looked at the changes in dairy cow behaviour preceding calving, dystocia, and clinical hypocalcaemia. However, it did not assess other common production diseases such as mastitis or lameness, nor robustly assess if calving and hypocalcaemia could be predicted on other commercial farms. Studies have assessed the behavioural changes preceding lameness (Thompson et al., 2019) and mastitis (Cyples et al., 2012) however future studies should assess the ability of automated detection systems to correctly classify cows as lame or mastitic under commercial farm conditions and across a range of management systems. Dairy producers stated that return on investment was an important criterion that influenced their purchase decision with regards to technologies. There is limited research that assesses the monetary and non-monetary capabilities of ACMT. Future studies should focus on assessing potential economic benefits of ACMT and whether ACMT also have a non-monetary benefit on farms.

To conclude, it is predicted that the prevalence of farms utilising ACMT will increase over the next 5 years. Chapter 2 concluded that cost implications are the main barrier as to why farms do not currently utilise ACMT. However, if technology manufacturers can reduce initial investment cost or upkeep cost, it is likely more dairy producers will purchase technologies. Although behavioural changes were identified in late gestation, machine learning methods were unable to generate an accurate prediction of the day before calving and produced many false negatives. There were behavioural differences between the different blood calcium categories in the -14 d before calving which suggests behaviour could be used to categorise cows before calving. Low blood calcium had prolonged effects on cow behaviour in the 3 weeks post-calving, and the prevention of hypocalcaemia should be prioritised on dairy farms.

Chapter 8 References

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Chapter 9 Appendix

9.1 Appendix 1

The use of automated cow monitoring technology on UK dairy farms

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Dear participant,

Thank you for registering your interest in completing this short 5-minute questionnaire on the use of automated cow monitoring technology on UK dairy farms. The aim of this questionnaire is to understand the use of automated cow monitoring technology on UK dairy farms.

For the purpose of this questionnaire, we've defined automated cow monitoring technology as, 'a piece of equipment that measures a physiological (i.e. heart rate), production (i.e. milk yield), or behavioural trait (i.e. activity) of an individual adult dairy cow'.

We are interested in your opinion whether you have no technology on your farm or if you have fully embraced it. Be assured that all answers you provide will be anonymous. By completing this questionnaire, please be aware that data will be used for research purposes as part of a PhD project, and other researchers may use the data for their own research purposes, subject to future ethical approval. Once the questionnaire is completed, it is not possible to withdraw your data from the study.

Click 'Yes' if you wish to proceed to the questionnaire. For further information, please contact Rosie Barraclough (s1677276@sms.ed.ac.uk).

Yes

Question 1: In which country is your dairy farm situated in? (All respondents)

- England
- Northern Ireland
- Scotland
- Wales

Question 2: What is your age? (All respondents)

- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65+

Question 3: What is your milking herd size (including dry cows)? (All respondents)

Question 4: What is your average yield per cow (litres per cow per year e.g. 7,500)? (All respondents)

Question 5: What type of milking parlour do you have? Select all that apply (All respondents)

- ☐ Abreast
- ☐ Herringbone
- ☐ Robot
- ☐ Rotary
- ☐ Other

If you selected Other, please specify:

Question 6: Have you received a grant for the installation of automated cow monitoring technology? (All respondents)

N.B For the purposes of this survey, we've defined automated cow monitoring technology as, 'a piece of equipment that measures a physiological (i.e. heart rate), production (i.e. milk yield), or behavioural trait (i.e. activity) of an **individual adult dairy** cow'

- ○ Yes
- ○ No

Question 7: Do you have any automated cow monitoring technology on your farm? (All respondents)

- ○ Yes
- ○ No

Question 8: What traits are measured by your automated cow monitoring technology? Select all that apply (Only respondents that have ACMT)

- ☐ Body condition score
- ☐ Body weight
- ☐ Calving detection
- ☐ Cow body temperature
- ☐ Daily milk yield
- ☐ Dry matter intake
- ☐ Heat detection
- ☐ Illness detection
- ☐ Lameness detection or mobility scoring
- ☐ Location
- ☐ Mastitis detection
- ☐ Milk components
- ☐ Milk progesterone
- ☐ Rumen pH
- ☐ Rumination
- ☐ Standing or lying behaviour
- ☐ Other

If you selected Other, please specify:

Question 9: Since installing automated cow monitoring technology, have you seen any benefits? (Only respondents that have ACMT)

- ○ Yes
- ○ No

Question 10: What benefit have you seen? Select all that apply (Only respondents that have ACMT and have stated a benefit of ACMT)

- ☐ Improved cow health management
- ☐ Improved herd management
- ☐ Improved fertility management
- ☐ Increased profit margin per cow
- ☐ Increased disease detection rates
- ☐ Increased milk production
- ☐ Improved fertility performance
- ☐ Time saver
- ☐ Aids farm assurance compliance
- ☐ Other

If you selected Other, please specify:

Question 11: Since installing automated cow monitoring technology, have you experienced any problems? (Only respondents that have ACMT)

- ○ Yes
- ○ No

Question 12: What problems have you encountered? Select all that apply (Only respondents that have ACMT and have stated a problem with ACMT)

- ☐ Low return on investment
- ☐ No return on investment
- ☐ Not compatible with other systems on farm
- ☐ Difficult or time consuming to attach to cows
- ☐ Difficult to interpret results
- ☐ Not easy to use
- ☐ Poor broadband inhibits system performance
- ☐ Poor customer support available
- ☐ Poor system performance
- ☐ System faults (e.g. breakages, poor battery life)
- ☐ Time invested in training
- ☐ Welfare concern - product interacts poorly with cows (i.e. technology causes rubs or sores)
- ☐ Other

If you selected Other, please specify:

Question 13: Overall, how would you describe automated cow monitoring technology on your farm? Select all that apply (Only respondents that have ACMT)

☐ Reliable	☐ Poor quality	☐ Useful
☐ Overpriced	☐ Ineffective	☐ Good value for money
☐ Practical	☐ Unreliable	☐ High quality
☐ Impractical	☐ Other	

If you selected Other, please specify:

Question 14: Will you invest in further automated cow monitoring technology in the next 5 years? (Only respondents that have ACMT)

- ○ Yes
- ○ No

Question 15: What are the reasons for not having automated cow monitoring on your farm? Select all that apply (Only respondents that do not have ACMT)

- ☐ Cost of system upkeep (e.g. maintenance and updates)
- ☐ Do not think technology is worthwhile
- ☐ Difficult or time consuming to attach to cows
- ☐ Initial investment cost
- ☐ Low longevity of system
- ☐ No long term goal for dairy continuation
- ☐ Not easy to use
- ☐ Not enough cows for technology to be cost effective
- ☐ Poor broadband speed
- ☐ Poor farm infrastructure
- ☐ Poor customer support available
- ☐ Poor return on investment
- ☐ Other

If you selected Other, please specify:

Question 16: Will you invest in automated cow monitoring technology in the next 5 years? (Only respondents that do not have ACMT)

- Yes
- No

Question 17: Regardless of your answer above, please rate the importance of the following criteria that would influence your purchase of automated cow monitoring technology (All respondents)

	1 - Not important	2	3	4 - Very important	No opinion
Available grants	☐	☐	☐	☐	☐
Return on investment	☐	☐	☐	☐	☐
Initial investment cost	☐	☐	☐	☐	☐
Established technology with recognised performance	☐	☐	☐	☐	☐
Ease of use	☐	☐	☐	☐	☐
Time required to understand output/results	☐	☐	☐	☐	☐
Good customer support	☐	☐	☐	☐	☐
Compatibility with other on farm systems	☐	☐	☐	☐	☐
Suitable farm infrastructure (i.e. good broadband)	☐	☐	☐	☐	☐

Question 18: Do you have any further comments about using automated cow monitoring technology or potentially using automated cow monitoring technology? (All respondents)

9.2 Appendix 2

This Appendix contains a copy of the following research article:

Barraclough, R. A. C., Shaw, D. J., Boyce, R., Haskell, M. J., Macrae, A. I. (2020). The behaviour of dairy cattle in late gestation: Effects of parity and dystocia. Journal of Dairy Science, 103 (1): 714-722.

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The behavior of dairy cattle in late gestation: Effects of parity and dystocia

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ABSTRACT

The aim of this study was to objectively assess, using an automated behavioral monitoring system, any behavioral differences between primiparous and multiparous cows before calving, and to quantify any behavioral differences between assisted (dystocic) and unassisted (eutocic) calvings. Data were collected from 32 multiparous and 12 primiparous Holstein dairy cattle to describe normal calving behavior and parity differences. To quantify behavior related to calving difficulty, the data from 14 animals that had dystocia at calving were matched to cows that had an eutocic calving based on parity, locomotion score, calf breed, calf sex, month, and year of calving. An IceQube (IceRobotics Ltd., South Queensferry, United Kingdom) was fitted to the right hind leg of cows 4 wk before their expected calving date. Data for lying time, standing time, number of steps, motion index (total motion), and the total number of standing and lying bouts (postural transitions) were automatically collected and summed into 15-min blocks. Behavioral variables were summarized into 2-h periods and 24-h periods before analyses. Mixed-effect models were used to analyze cow behavior in the last 4 d before calving (d −4 to −1), and on the day of calving. In the 4 d before calving, compared with multiparous cows, primiparous cows lay down an average 2.8 h/d less, had 9.1 more postural transitions/d (37.7 ± 1.2 vs. 27.6 ± 0.7), walked 172 more steps/d, and had a higher motion index (2,673.2 vs. 1,981.5 units/d). There was an effect of 2-h period on all behavioral variables on the day of calving. No indicator of calving difficulty was found on the day of calving, nor the days leading up to calving. These findings suggest that parity should be considered when predicting the day of calving, and changes in cow behavior on the day of calving could be used to identify calving cows, and to predict the time of calving.

Key words: calving behavior, parturition, calving assistance, dairy cow

INTRODUCTION

To commence lactation, cows are required to go through parturition, and this process carries many risks. Two common issues at calving are calving difficulty (dystocia) and perinatal mortality, and therefore intensive management of cattle in late pregnancy is critical to ensure neonatal and maternal survival, health, and welfare (Mee, 2004). Dystocia, defined as a difficult or prolonged calving, has been classed as one of the most painful conditions that a cow can experience (Huxley and Whay, 2006). Within the United Kingdom, 16% of cows are reported to require calving assistance (Wall et al., 2010), and it is estimated that the worldwide prevalence of dystocia in dairy heifers and cows ranges from 1.5 to 22.6% (Mee, 2008a). To prevent calving difficulties and stillbirth, it is recommended that late-gestation cows should be observed frequently for signs of calving. The suggested intervals at which cows are monitored vary from 1 to 2 h (Gundelach et al., 2009) to 3 to 6 h (Mee, 2004).

Changes in cow behavior have been observed on the day of calving, compared with the days leading up to calving. Jensen (2012) reported that overall lying time gradually decreased from 4 d pre-calving (998 min) until the day of calving (894 min). When data were analyzed in 2-h blocks on the day of calving, it was observed that lying time increased in the last 12 h before calving from 31.4 min/2 h to 42.8 min/2 h just before calving. Overall activity has been reported to increase on the day of calving, and this is attributed to pain around calving. The number of postural transitions on the day of calving increases by up to 80% when compared with a noncalving control period (Huzzey et al., 2005), and tail raising was shown to increase in the 2- to 6-h

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period before calving (Miedema et al., 2011b; Barrier et al., 2012). On the day of calving, Schirmann et al. (2013) reported a 15% reduction in rumination, a 24% decrease in DMI, and a 32% reduction in the time spent feeding when compared with 2 to 4 d before calving.

Cows that calved with dystocia exhibit restless behavior earlier than cows that calved with no assistance (Wehrend et al., 2006). In the 24 h before calving, Proudfoot et al. (2009) observed that cows with dystocia had more frequent transitions from standing to lying when compared with cows without dystocia. In contrast, Miedema et al. (2011a) and Barrier et al. (2012) reported no interaction between the number of postural changes from lying to standing between cows with assisted calvings and cows with unassisted calvings. Kovács et al. (2017) found that cows with dystocia had lower rumination times in the final 8 h before calving when compared with cows that had unassisted calvings. However, this result was not statistically significant.

As herd size increases and the availability of skilled labor decreases, there is a need to apply user-friendly, automated technology to facilitate herd management (Gargiulo et al., 2018). Remote sensing devices have the potential to improve animal behavior monitoring as they can continuously and automatically measure animal activity without altering the animal's natural behavior (Theurer et al., 2013). The aim of this study was to objectively assess, using an automated behavioral monitoring system, any behavioral differences between primiparous and multiparous cows before calving, and to quantify any behavioral differences between dystocic and eutocic calvings.

MATERIALS AND METHODS

Animals and Housing

The study was conducted at the University of Edinburgh Langhill Farm (Roslin, Midlothian, United Kingdom) between November 2016 and April 2018. The experimental work was approved by The Royal Dick School of Veterinary Studies Veterinary Ethical Review Committee (reference 82–16). The farm has a milking herd of approximately 220 Holstein cows. The calving environment was a straw-bedded shed (11 m × 18.4 m) that was kept at a stocking rate of 5 to 15 heifers and cows. Cows had a space allowance of between 11.1 and 33.2 m^2 on a straw-bedded area, and a space allowance of between 2.4 and 7.3 m^2 on a concrete loafing area. Animals were moved into the straw-bedded calving shed approximately 6.8 ± 4.6 d before their actual calving date. Once a day, cows were fed a TMR consisting of grass silage, wholecrop, concentrate, molasses, and dry cow mineral. The ration had a 4:1 forage:concentrate ratio. Cows had access to self-filling water troughs (0.95 m × 0.4 m × 0.35 m), which supplied municipal water. The decision to give assistance at calving was based on farm protocol. Assistance was given if calving was progressing slowly (if calving progress had ceased over a 30-min period, or if the calf started to show signs of reduced vigor; Mee, 2008b) or if the calf was not presented normally. Ease of calving was recorded using a farm specific 5-point scale: (1) no assistance, (2) gentle traction by one person with no mechanical device used, (3) use of calving jack or assistance with 2 persons, (4) veterinary assistance, and (5) cesarean section. Calving scores of 2 or above were classed as assisted calving.

Behavioral Measurements

An IceQube (IceRobotics Ltd, South Queensferry, United Kingdom) was fitted to the right hind leg of each cow 4 wk before the predicted calving date. The IceQube is a triaxial accelerometer that sampled cow behavior at 4 Hz and summarized lying times, standing times, the number of steps, the number of postural transitions from standing to lying, and motion index into 15-min blocks (Elischer et al., 2013; Borchers et al., 2016). Motion index is the sum of net acceleration measured by the 3-axis minus an offset for gravity, and motion index can be considered an expression of leg activity (Maselyne et al., 2017).

Observations for time of calving were made when cows were housed in the straw yard calving shed. One webcam (AXIS P5414-E PTZ Network Camera), with HDTV 720p performance and 18× optical zoom, was installed in an overhead position that gave a good overview of the calving shed. A timestamp (hour:min:sec) and a date (year:month:day) were visible on all video files. The time and date were automatically synchronized with the computer's clock. The calving shed was lit naturally by sunlight during daylight hours (0800–1600 h) and artificial lighting remained on during the night (1600–0800 h). The exact time of calving (to the nearest minute) was ascertained by retrospective analysis of video recordings. The time of calving was taken to be the point where the fetus was fully expelled from the cow or when the calf's hips were expelled, and the hind legs remained inside the birth canal. This occurred at the end of stage II of parturition and was a comparable definition to previous studies (Campler et al., 2015). Parturition occurs in 3 stages: stage I, stage II, and stage III. Stage I consists of cervical dilation, the start of myometrial contractions, and placement of the fetus before expulsion. Stage II includes visible abdominal contractions, the rupture of the allantochorionic sac and fetal expulsion from the birth canal. The final stage of parturition, stage III, consists of fetal membrane expulsion (Mainau and Manteca, 2011).

Statistical Analysis

Data set 1 was used to analyze normal calving behavior and parity differences, and consisted of 44 animals: 12 primiparous cows and 32 multiparous cows (calving score 1, parity 0–7, mean 1.2 ± 0.2). Animals within data set 1 calved between 2016 and 2017.

Data set 2 was used to analyze the difference in behavior between animals that had dystocic calvings (n = 14; calving score of 2 or above; parity 0–3, mean 1.1 ± 0.1) and animals that had eutocic calvings (n = 14; calving score 1; parity 0–3, mean 1.1 ± 0.1). The 14 eutocic cows included 8 cows from data set 1 (7 multiparous, 1 primiparous) and 4 separate eutocic cows that calved between 2017 and 2018. Animals within data set 2 calved between 2016 and 2018. A case-control study design was used to compare the behavioral difference between animals that had dystocic calvings and animals that had eutocic calvings. The 14 animals with dystocic calvings were exactly matched to cows that had an eutocic calving based on lactation number (n = 14 pairs), calving date ± 28 d (n = 14 pairs), and year of calving (n = 14 pairs). Cows were also matched as closely as possible based on locomotion score (n = 11 pairs), calf breed (n = 9 pairs), calf sex (n = 12 pairs). Of the 14 animals that calved with dystocia, 9 cows were assisted by gentle traction (score 2) and 5 cows were calved with a calving jack (score 3).

A further 54 animals were observed but excluded from the analysis for various reasons including incomplete data sets (n = 2), presence of clinical milk fever (n = 15), severe lameness (n = 3; mobility score 2 and 3 using 0–3 point scale: AHDB 2018), no recorded time of calving (n = 10), or were not present in the straw yard for >5 d (n = 24). Only cows that were present in the straw yard for 5 or more days before the day of calving were used for the analyses to ensure cows were within the same environment when analyses were conducted.

To investigate the behavior of dairy cattle in late gestation, the duration of lying time, the number of steps, the motion index, and the total number of standing and lying bouts (the number of postural positions) from data set 1 and data set 2 were each summarized from the time of calving into 2 data sets: behavior in 2-h periods and 24-h periods (behavior per day). The bihourly data sets were used for the analyses of cow behavior on the day of calving, and data were analyzed in 2-h periods from −24 to 0 h (the time of calving). The data set containing cow behavior per day were used to analyze cow behavior in the days before calving (d −4 to −1), and to compare the change in behavior on the day of calving (d 0) compared with a control period (d −4). In this study, the number of lying and standing bouts were combined to provide a value for the number of postural of transitions within a period. All data sets were summed from the time relative to calving (i.e., calving was used as time 0), which ensured all cows followed the same timeline.

All analyses and data manipulations were carried out using R (version 3.4.4; R Foundation for Statistical Computing, Vienna, Austria). To assess data assumptions of normality, residual plots, histogram plots, and data normality tests were examined. Mixed-effect analyses were carried out using the 'lmerTest' package. Residual plots were examined to ascertain the best model fit for the data. Statistical significance was taken as $P \leq 0.05$. Nonsignificant ($P > 0.05$) interactions were removed from models. Degrees of freedom were calculated using the Satterthwaite approximation for linear models and polynomial regression models, while Laplace approximation was used to calculate degrees of freedom for generalized piecewise regression models.

Behavioral Differences Between the Day of Calving and Control Period. To explore the behavioral changes that occur on the day of calving (d 0) compared with a control period (d −4), the duration and frequencies of behaviors in each 24-h period were compared for primiparous cows (n = 12), multiparous cows (n = 32), dystocic cows (n = 14), and eutocic cows (n = 14). The step count and motion index were $\log_{10}$ transformed to meet normal residual data distribution assumptions. Paired *t*-test were used to analyze normally distributed data (lying time, step count, and motion index), and Wilcoxon signed rank tests were used to analyze non-normally distributed data that did not fit normal data assumptions after $\log_{10}$ transformation (the number of postural transitions). In this study, there was no difference between behavior variables on d −4 and −3 when each variable was compared using the appropriate statistical test, so d −4 was chosen as the control period.

Last 4 d Before Calving. For further investigation of the behavioral differences between primiparous cows and multiparous cows, and between dystocic and eutocic cows in late gestation, a linear mixed-effect model was used to assess behavioral changes in the last 4 d before calving (d −4 to −1). To investigate behavioral differences between primiparous (n = 12), and multiparous cows (n = 32), the linear mixed-effect model included days to calving (d −4, d −3, d −2, and d −1), parity (multiparous and primiparous), and the interaction between days to calving and parity as fixed effects, and cow ID was included as a random effect to account for repeated measurements per cow. The data set contained 176 data points, and each cow had 4 repeated observations. To investigate behavioral differences between dystocic (n = 14) and eutocic (n = 14) cows, the linear mixed-effect model included days to calving (d −4, −3, −2, and −1), assistance level at calving (dystocia and eutocia), and the interaction between days to calving and assistance level at calving as fixed effects. To account for repeated measurements per cow, and the pair that cows were assigned to, a nested random effect containing pair and cow ID was used (pair/cow ID). The data set contained 112 data points, and each cow had 4 repeated observations. Animals were pair matched using lactation number, and as this variable was already controlled for within the random effect, parity (multiparous and primiparous) was not included in the final model. The step count and motion index were $\log_{10}$ transformed to meet normal residual data distribution assumptions.

Last 24 h Before Calving. To ascertain the pattern of behavior exhibited on the day of calving, a set of mixed-effect models with different temporal relationships were fitted to behavioral variables contained within the bihourly data set. Data were analyzed over twelve 2-h periods from −24 h to 0 h (the time of calving). A generalized piecewise regression models (or "broken-stick" models, where a step change in behavior at a certain time point is observed; Das et al., 2016), polynomial regression models (where there is either a decrease and then increase, or increase and then decrease in behaviors; Ostertagová, 2012), and linear models (Bangdiwala, 2018) were fitted to each behavioral variable. Residual plots were examined to ascertain the best model fit for the data. A piecewise regression model provided the best description of the change in the number of postural transitions, whereas a polynomial regression model best described the change in lying time. Linear models best described the change in step count and motion index. To investigate behavioral differences between primiparous (n = 12) and multiparous cows (n = 32), each model included time relative to calving (−24 to 0 h), parity (multiparous and primiparous), and the interaction between time relative to calving and parity as fixed effects, and cow ID was included as a random effect to account for repeated measurements per cow. The data set contained 528 data points, and each cow had 12 repeated observations. To investigate behavioral differences between dystocic (n = 14) and eutocic cows (n = 14), each model included time relative to calving (−24 to 0 h), assistance level at calving (dystocia and eutocia), and the interaction between time relative to calving and assistance level at calving as fixed effects. To account for repeated measurements per cow, and the pair that cows were assigned to, a nested random effect containing pair and cow ID was used (pair/cow ID). The data set contained 336 data points, and each cow had 12 repeated observations. The step count and motion index were $\log_{10}$ transformed to meet normal residual data distribution assumptions.

RESULTS

Behavioral Differences Between the Day of Calving and Control Period

The lying time (h/d) of primiparous cows, multiparous cows, dystocic cows, and eutocic control cows decreased on the day of calving when compared with a control period (d −4) (Table 1). On the day of calving, the average number of postural transitions increased by 29.6% for primiparous cows ($v_{11} = 0$, $P < 0.01$), 45.6% for multiparous cows ($v_{31} = -14.5$, $P < 0.01$), 42.4% for dystocic cows ($v_{13} = 6$, $P < 0.01$), and 44.0% for eutocic control cows ($v_{13} = 8$, $P < 0.01$) when compared with the control period (Table 1). There were no differences in the average number of steps (no./d) and motion index (unit/d) in primiparous cows on the day of calving when compared with the control period. In contrast, the step count of multiparous cows ($t_{31} = -4.09$, $P < 0.001$), dystocic cows ($t_{13} = -3.72$, $P < 0.01$), and eutocic control cows ($t_{13} = -2.62$, $P < 0.05$) increased on the day of calving when compared with the control period (Table 1). Additionally, the motion index of multiparous cows ($t_{31} = -5.84$, $P < 0.001$), dystocic cows ($t_{13} = -4.41$, $P < 0.001$), and eutocic control cows ($t_{13} = -3.65$, $P < 0.001$) also increased on the day of calving compared with the control period (Table 1).

Last 4 d Before Calving

While the lying time of multiparous cows remained constant in the 4 d before the day of calving (14.2 ± 0.2 h; $F_{1,95} = 0.11$, $P = 0.74$), the lying time of primiparous cows decreased by 25 min/d (13.0 ± 0.4 h to 11.6 ± 0.6 h; $F_{1,35} = 7.62$, $P = 0.009$; Figure 1a). A difference was observed in the pattern of the lying time (h/d) depending on parity, with primiparous cows on average −2.8 h/d lower than that of multiparous cows across the period ($F_{1,94} = 17.3$, $P < 0.001$). No interaction was observed between days to calving and parity on the number of postural transitions ($F_{1,130} = 0.04$, $P > 0.83$, Figure 1b), nor an effect of days to calving ($F_{1,130} = 0.67$, $P > 0.60$, Figure 1b). Primiparous cows had an average of 9.1 ± 2.4 more postural transitions per day compared with multiparous cows ($F_{1,42} = 13.9$, $P < 0.001$). There was a decrease in both step count and motion index across the period ($P < 0.041$, Figure 1c,d). In addition, the step count (steps/d; $F_{1,42} = 11.1$, $P = 0.002$) and motion index (unit/d; $F_{1,42} = 14.5$, $P <$

0.001) of primiparous cows was on average 14% higher per day when compared with multiparous cows.

Last 24 h Before Calving

No interaction was observed between lying time (min/2 h) and parity ($F_{1,480} = 3.65$, $P = 0.06$; Figure 2a), nor was an effect detected of parity on lying time ($F_{1,274} = 0.29$, $P = 0.59$) on the day of calving. The change in lying time on the day of calving for primiparous and multiparous cows was best described by a polynomial pattern, with a decline from 65.3 min/2 h at −22 h to a low of 50.6 min/2 h at −12 h, increasing to an average of 66.8 min/2 h just before birth ($F_{1,482} = 9.3$, $P = 0.002$). A piecewise regression model provided the best description of the change in the number of postural transitions on the day of calving for both primiparous and multiparous cows, with a combined breakpoint of −6.3 h (Figure 2b). There was an effect of parity on the number of postural transitions on the day of calving, with primiparous cows having an average of 0.24 more postural transitions in each 2-h period compared with multiparous cows ($z_{1,482} = 1.96$, $P < 0.05$). In addition, increases were observed in the average number of postural transitions in primiparous and multiparous cows from 4.4 and 3.2 at the breakpoints to 10.0 and 10.6 just before birth, respectively ($P < 0.001$). When a piecewise regression model was run separately for primiparous and multiparous cows, the individual breakpoints calculated were −2.0 and −6.6 h, respectively. There was no interaction between parity and hours to calving for step count ($F_{1,482} = 3.3$, $P > 0.05$; Figure 2c) and motion index ($F_{1,482} = 1.86$, $P > 0.05$; Figure 2d), nor an overall effect of parity on either step count ($F_{1,144} = 3.0$, $P = 0.09$) or motion index ($F_{1,155} = 0.72$, $P > 0.05$). Linear changes in both step count ($F_{1,483} = 16.5$, $P < 0.001$) and motion index ($F_{1,483} = 47.9$, $P < 0.001$) on the day of calving were observed, with increases in both parameters. Back transformation of $\log_{10}$ data show that step count increased from an average of 32.3 steps/2 h at −22 h to 78.8 steps/2 h just before calving, and motion index increased from an average of 139.5 unit/2 h at −22 to 437.5 unit/2 h just before calving.

Last 4 d Before Calving: Dystocic and Eutocic

Within the 4 d before calving (d −4, −3, −2, and −1), there was no difference between the 14 dystocic cows, and the 14 eutocic cows for the duration of lying time (h/d), the number of postural transitions (no./d), the step count (no./d), and the motion index (unit/d; $P > 0.36$). There was no interaction between days to calving and assistance level at calving for the duration

Table 1. The mean (±SE) duration and frequency of behaviors during a control period (d −4) and the day of calving (d 0), and the average change (Δ ± SE) in each behavior between d 0 and −4, for primiparous cows, multiparous cows, dystocic cows, and eutocic control cows

	Primiparous cows (n = 12)				Multiparous cows (n = 32)				Dystocic (assisted) cows (n = 14)				Eutocic (unassisted) cows (n = 14)			
Behavior	d −4	d 0	Δ	P	d −4	d 0	Δ	P	d −4	d 0	Δ	P	d −4	d 0	Δ	P
Lying time (h/d)	13.0 ± 0.4	10.5 ± 0.8	−2.5 ± 0.5	***	14.2 ± 0.4	11.6 ± 0.4	−2.6 ± 0.4	***	14.0 ± 0.4	11.7 ± 0.8	−2.3 ± 0.6	***	13.9 ± 0.7	11.8 ± 0.8	−2.1 ± 0.5	***
Postural transitions (no./d)	36.8 ± 2.7	49.6 ± 2.7	12.8 ± 3.4	**	28.3 ± 1.3	45.0 ± 2.2	16.7 ± 2.5	***	33.6 ± 2.2	51.7 ± 3.4	18.1 ± 4.0	**	28.2 ± 2.1	44.1 ± 3.5	15.9 ± 4.4	**
Step count[1] (no./d)	2.84 (693.4) ± 0.04	2.87 (740.1) ± 0.08	0.03 ± 0.07	NS	2.71 (511.6) ± 0.03	2.89 (785.0) ± 0.03	0.19 ± 0.04	***	2.77 (588.2) ± 0.05	2.97 (930.4) ± 0.05	0.20 ± 0.05	**	2.70 (498.4) ± 0.05	2.87 (746.9) ± 0.07	0.18 ± 0.07	*
Motion index[2] (unit/d)	3.44 (2,755.8) ± 0.02	3.53 (3,400.1) ± 0.04	0.09 ± 0.06	NS	3.32 (2,090.1) ± 0.03	3.52 (3,298.8) ± 0.03	0.20 ± 0.03	***	3.35 (2,236.7) ± 0.05	3.58 (3,764.6) ± 0.05	0.23 ± 0.05	***	3.31 (2,038.4) ± 0.05	3.51 (3,256.0) ± 0.08	0.20 ± 0.08	**

[1]Step count (parameter submitted to logarithmic transformation; back-transformed values presented in parentheses).

[2]Motion index (parameter submitted to logarithmic transformation; back-transformed values presented in parentheses).

NS: $P > 0.05$.

*$P < 0.05$.

**$P < 0.01$.

***$P < 0.001$.

of lying time, step count, and motion index within the period ($P > 0.12$). In contrast, there was an interaction between the number of postural transitions and assistance level at calving ($F_{1,82} = 6.3$; $P = 0.01$), which decreased from 33.6 ± 2.2 to 29.1 ± 2.0 for dystocic cows, but increased from 28.2 ± 2.1 to 30.4 ± 1.6 in the 14 eutocic cows.

Last 24 h Before Calving: Dystocic and Eutocic

On the day of calving, no interaction was observed between hours to calving and assistance level at calving on lying time (min/2 h; $F_{1,304} = 0.01$, $P = 0.92$), nor a difference in the lying time between dystocic and eutocic cows ($F_{1,26} = 0.06$, $P = 0.81$). The change in lying time on the day of calving for dystocic and eutocic cows was best described by a polynomial pattern, with a decline from 61.8 at −22 h to a low of 51.6 at −10 h, increasing to an average of 66.4 just before birth ($F_{1,306} = 4.7$ $P = 0.03$). Piecewise regression models provided the best description of the change in the number of postural transitions. The calculated breakpoint for the number of postural transitions was −11.0 h in dystocic cows, and −8.5 h for eutocic cows. Before the breakpoints, hours to calving had no effect on the number of postural transitions for both dystocic and eutocic cows ($z_{1,306} = 0.11$, $P = 0.91$). In contrast, after breakpoints, hours to calving had an effect on the number of postural transitions for both dystocic and eutocic cows ($z_{1,306} = 16.1$, $P < 0.001$), with the average number of postural transitions increasing by an average of 0.16 and 0.15, respectively, every 2 h. No difference was observed in the number of postural transitions between dystocic and eutocic cows on the day of calving ($z_{1,26} = -1.68$, $P = 0.07$). On the day of calving, no interaction was observed between assistance level and hours to calving on step count ($F_{1,306} = 0.25$, $P = 0.61$) and motion index ($F_{1,306} = 0.27$, $P = 0.60$), nor was an overall effect of assistance level observed on either step count ($F_{1,26} = 1.91$, $P = 0.18$) or motion index ($F_{1,26} = 1.6$, $P = 0.22$). Linear changes in both step count and motion index on the day of calving were observed, with increases in both parameters ($P < 0.001$). Back transformation of $\log_{10}$ data show that step count increased from an average of 35.2 steps/2 h at −22 h to 83.5 steps/2 h just before calving, and motion index increased from an average of 157.8 unit/2 h at −22 to 443.3 unit/2 h just before calving.

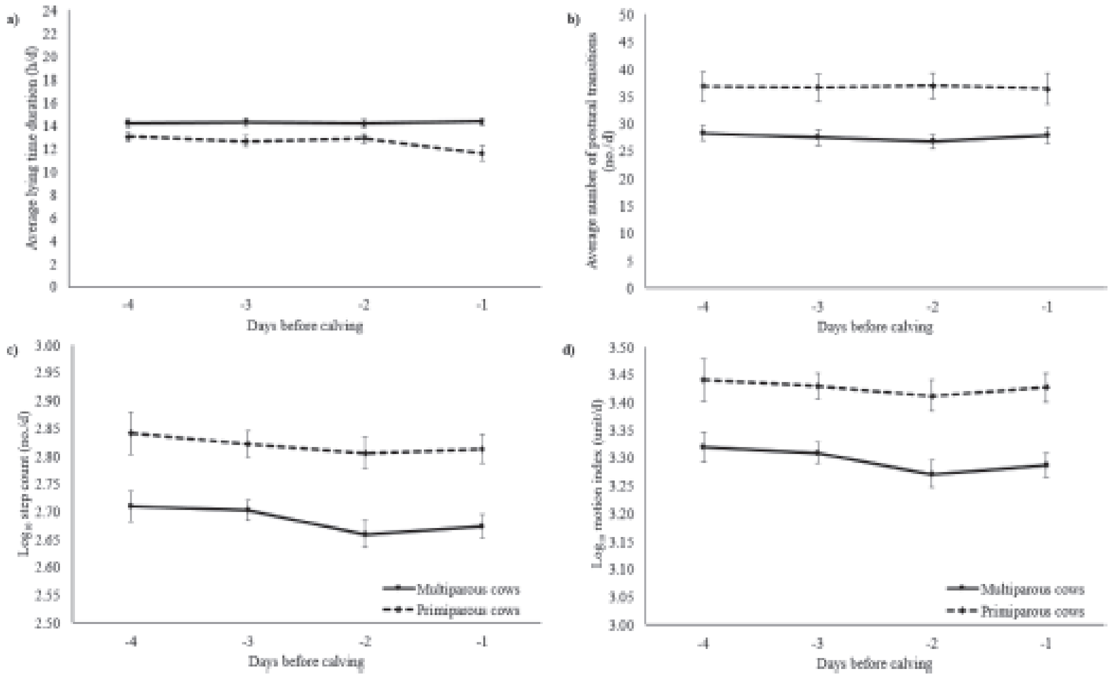

Figure 1. Behavioral variables for primiparous cows (dashed line; n = 12) and multiparous cows (solid line; n = 32) summarized into 24-h periods ± SE in the 4 d before calving for (a) lying time duration, (b) number of postural transitions, (c) $\log_{10}$ step count, and (d) $\log_{10}$ motion index.

DISCUSSION

For multiparous cows, dystocic cows, and eutocic control cows, all behavioral variables were significantly different on the day of calving compared with the control period (d −4). On the day of calving, the number of postural transitions increased by 29.6% for primiparous cows and 45.6% for multiparous cows when compared with the control period. This study combined the number of lying bouts and standing bouts to represent the total number of postural transitions in a period. The number of lying bouts and standing bouts are comparable measurements, as the number of lying and standing bouts a cow takes in a day are proportional to each other. Similar to this study, Miedema et al. (2011b) reported that the number of lying bouts increased on the day of calving when compared with a control period and Huzzey et al. (2005) reported an 80% increase in the number of standing bouts on the day of calving. This study found that lying time decreased by an average of −2.55 h for primiparous and multiparous cows on the day of calving compared with the control period.

In the last 4 d before calving (d −4 to −1), parity differences were observed for all behavioral variables. The lying time of primiparous cows was −2.8 h/d lower than that of multiparous cows and lying time decreased by approximately 25 min/d within the period. In contrast, the lying time of multiparous cows remained constant. Borchers et al. (2017) reported a similar finding and showed that the lying time of primiparous cows decreased in the last 7 d before calving and was lower than that of multiparous cows. Primiparous cows had numerically more standing and lying bouts per day compared with multiparous cows, which has been reported in previous studies (Lobeck-Luchterhand et al., 2015; Neave et al., 2017). After controlling for milk production and BW, Neave et al. (2017) still observed differences in the number of postural transitions during the transition period. This finding shows that differences in the standing and lying bout behavior are independent of these 2 variables. The number of steps and total motion index decreased across the period; however, the number of steps/d and motion index/d were higher for primiparous cows. Wehrend et al.

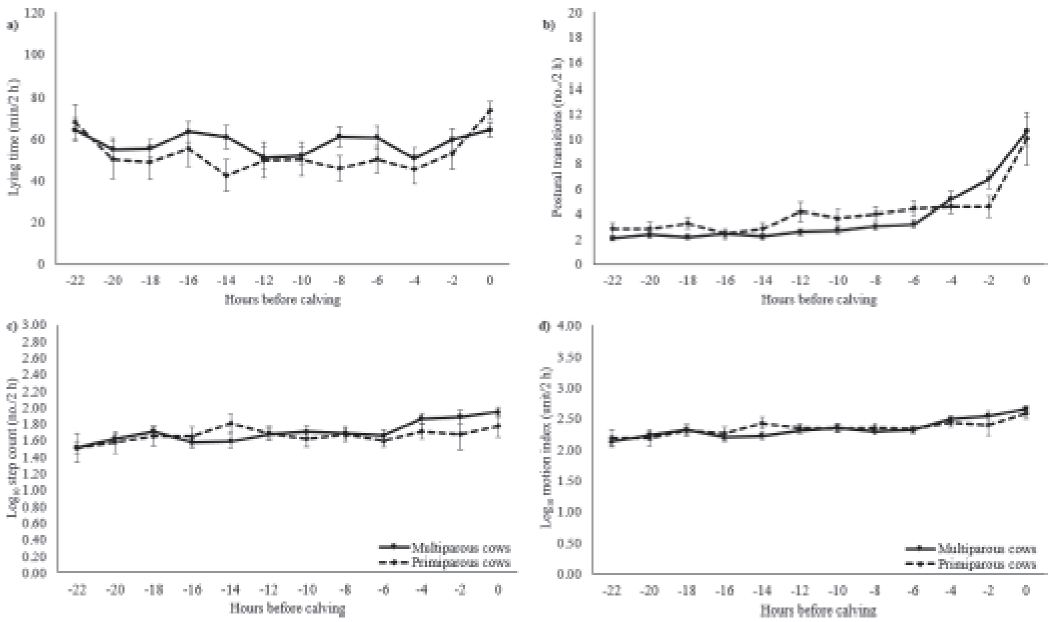

Figure 2. Behavioral variables for primiparous cows (dashed line; n = 12) and multiparous cows (solid line; n = 32) summarized into 2-h periods ± SE in the 24 h before calving for (a) lying time duration, (b) number of postural transitions, (c) $\log_{10}$ step count, and (d) $\log_{10}$ motion index.

(2006) reported primiparous cattle to be more restless as parturition approached, and this could explain the parity differences for all behavioral variables in the days leading to calving.

This study fitted mixed-effect models with different temporal relationships to describe the pattern of behavior exhibited in the 24 h before calving. Piecewise regression was a novel technique used for the analysis of the precalving behavioral data in this study, and allowed the time when behavior changes before calving to be estimated. On the day of calving, there was an effect of 2-h period on all behavioral variables, and this finding indicates that labor has an effect on cow behavior. An increase in the number of postural transitions on the day of calving has been reported in previous literature (Huzzey et al., 2005; Jensen, 2012), and could be explained by cows having a greater degree of pain as they enter stage II of parturition. Stage II is characterized by uterine contractions, appearance of the amniotic sac, and expulsion of the fetus. In this study, the lying time of cows increased in the last 12 h before calving and peaked 2 h before calving. It has been reported that cows typically lie down more as the fetus enters the birth canal (Schuenemann et al., 2011). Expulsion of the fetus has been reported to take an average of 69.7 min from the appearance of the amniotic sac (Schuenemann et al., 2011). The peak in lying time 2 h before calving in this study can be explained by cows lying down to expel the fetus from the birth canal.

Previous studies have described the effect of parity on cow behavior on the day of calving (Wehrend et al., 2006; Miedema et al., 2011a; Schuenemann et al., 2011). In the present study, there were no numerical differences in lying time duration, step count, or motion index when multiparous and primiparous cows were compared on the day of calving; however, primiparous cows had numerically more postural transitions compared with multiparous cows. Wehrend et al. (2006) reported that fewer primiparous cows exhibited calm behavior on the day of calving, and this restlessness behavior may explain why primiparous cows had more postural transitions than multiparous cows. Similar findings were observed by Schuenemann et al. (2011), and it was reported that primiparous cows had an increase in the number of transitions from lying-standing at the start of labor stage.

The behavior of dystocic cows in the days leading up to calving has not been widely explored in the literature. Previous studies have typically focused on the behavior of dystocic cows on the day of calving. This study found no numerical difference in the lying time duration, the number of steps, and the motion index between dystocic and eutocic cows in the last 4 d before calving. An interaction was observed between the number of postural transitions and the level of assistance at calving. The average number of postural transitions decreased for dystocic cows across the period, from 33.6 ± 2.2 (d −4) to 29.1 ± 2.0 (d −1). Proudfoot et al. (2009) reported that cows that calved with dystocia had numerically more postural transitions on the day of calving compared with cows that did not require assistance at calving. Although this study found that breakpoints occurred earlier on the day of calving for dystocic cows (−11.0 h) compared with eutocic cows (−8.5 h), no numerical difference was observed in the number of postural transitions. Proudfoot et al. (2009) categorized assistance at calving into 2 categories: easy assistance (one person was required to pull the calf out), and difficult assistance (2 people were required to pull the calf out). Only cows that were classed as having difficult assistance were used in the study. This study included cows that had minor assistance at calving (gentle traction by one person with no mechanical device used), and the decision of the farm staff to assist cows by a gentle traction may have confounded the data. Cows that were classed as eutocic within this study may have experienced the same low level of difficulty at calving as cows that were calved with gentle traction, however, were unassisted due to management factors (i.e., night-time calving). It is possible that comparing eutocic cows with cows that had a greater degree of assistance at calving could highlight behavioral differences in the days leading to calving. It is suggested that the earlier breakpoint calculated for dystocic cows is indicative of dystocic cows spending more time in labor before the calf was expelled from the birth canal (Barrier et al., 2012).

Farmers currently rely on expected calving dates to manage cows around calving, and direct observations to identify calving cows. Automated monitoring of cow behavior has the potential to provide farmers with a more accurate indicator of the day and time of calving when compared with the expected calving date. For dairy farmers, predictions of the day or time of calving have the benefit of ensuring that intervention, where appropriate, can be given in a timely manner. Currently, there is no automated method to predict which cows may need assistance at calving, and an accurate monitoring system to identify calving cows could improve neonatal and maternal survival, health, and welfare. This study found important differences in the behavior of primiparous cows and multiparous cows, which suggest that parity must be considered when predicting the day of calving. Although no indicator of calving difficulty was identified by this research, the ability to identify calving cows and to predict the time of calving would allow farmers to monitor the progression of calving and intervene where necessary.

CONCLUSIONS

The behavior of dairy cattle undergoes numerous changes on the day of calving. Although parity differences were observed in the 4 d preceding calving, no differences were present in parity on the day of calving for duration of lying time, step count, or motion index. It is suggested that parity must be considered when predicting the day of calving. No indicator of calving difficulty was identified by this research.

ACKNOWLEDGMENTS

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9.3 Appendix 3

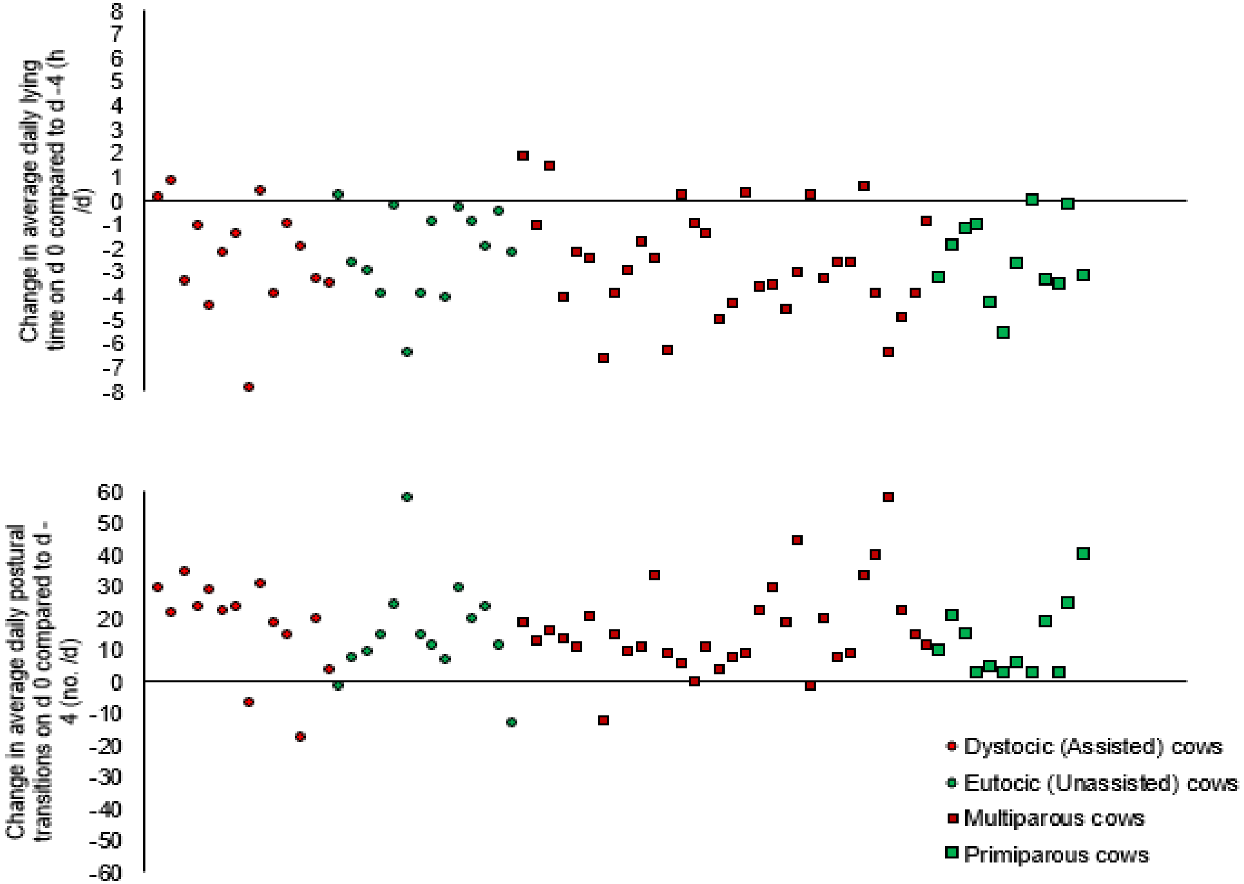

Figure 9.1 The average change in (a) daily lying time (h /d) and (b) the number of postural transitions (no. /d) on the day of calving (d 0) compared to a control period (d -4) for dystocic cows (red circle, n = 14); eutocic cows (green circle n = 14); multiparous cows (red square, n - 32); and primiparous cows (green square, n = 12).

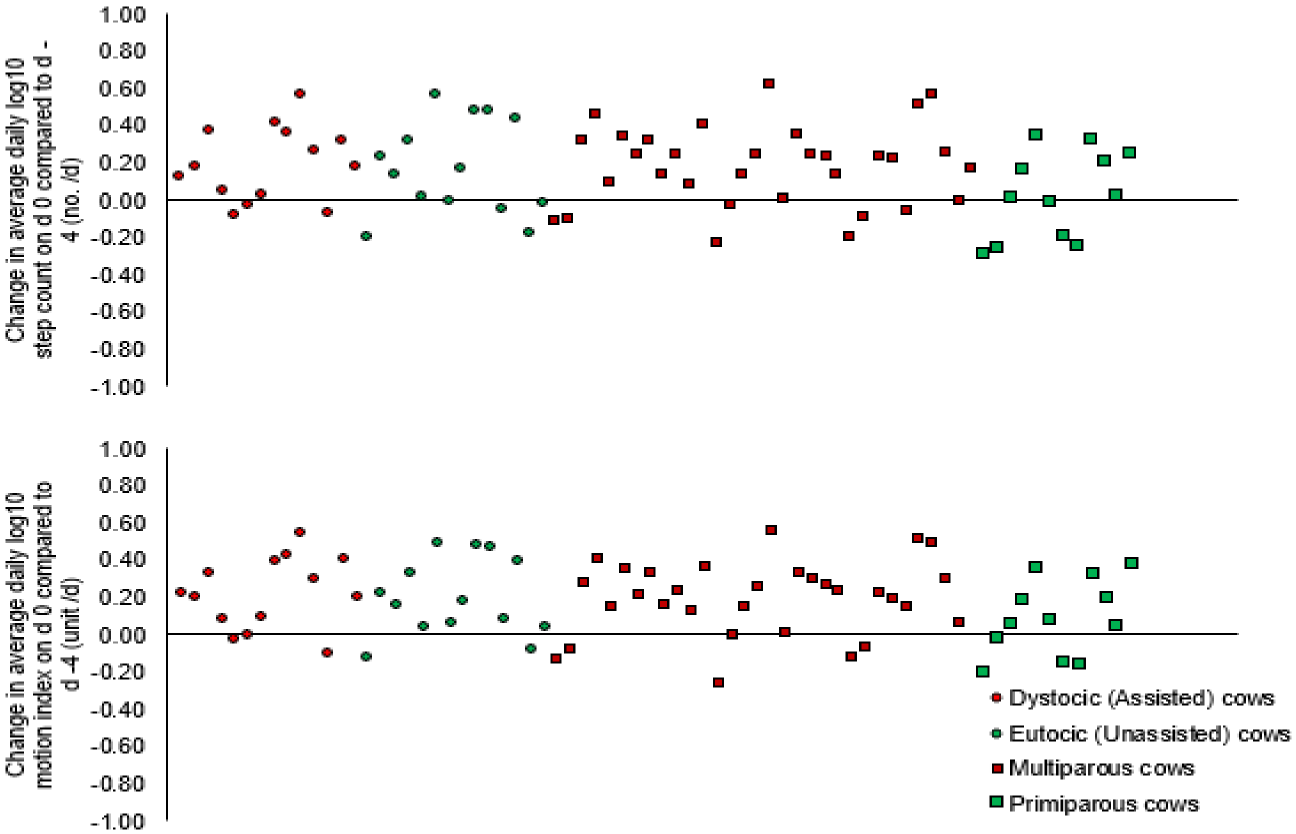

Figure 9.2 The average change in (a) log$_{10}$ step count (no. /d) and (b)) log10 motion index (unit /d) on the day of calving (d 0) compared to a control period (d -4) for dystocic cows (red circle, n = 14); eutocic cows (green circle n = 14); multiparous cows (red square, n - 32); and primiparous cows (green square, n = 12).

9.4 Appendix 4

This Appendix contains a copy of the following research article:

Barraclough, R. A. C., Shaw, D. J., Thorup, V. M., Haskell, M. J., Wilson, L. and Macrae, A. I. (2020). The behaviour of dairy cattle in the transition period: Effects of blood calcium status. Journal of Dairy Science, 103 (11).

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The behavior of dairy cattle in the transition period: Effects of blood calcium status

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ABSTRACT

The aim of this study was to use an automated behavior-monitoring system to objectively assess the association between lying and activity behavior in the precalving, calving, and postcalving periods between multiparous and primiparous cows with (1) normocalcemia, (2) subclinical hypocalcemia, or (3) clinical hypocalcemia at calving. Behavioral data and blood serum samples were collected from 51 multiparous and 21 primiparous Holstein dairy cattle. Blood samples from the coccygeal vein were taken within 24 h of calving, and serum was analyzed to measure total calcium concentration. Cows were classified into one of 3 categories: normocalcemia (serum calcium concentration $\geq$ 2.0 mmol/L), subclinical hypocalcemia (serum calcium concentration < 2.0 mmol/L, absence of clinical signs), and clinical hypocalcemia (clinical signs and successful treatment). An activity sensor was fitted to the right hind leg of cows 3 wk before their expected calving date. Data for lying time, standing time, number of steps, and the total number of standing and lying bouts (postural transitions) were automatically collected and summed into 15-min blocks. Behavioral variables were summarized into 2-h and 24-h periods before analyses. Mixed effect models were used to analyze cow behavior in the entire 14 d before calving (d −14 to −1), on the day of calving, and the entire 21 d postcalving (d 1 to 21). In the precalving period, multiparous cows with normocalcemia had fewer postural transitions (18.5 $\pm$ 6.9 no./d) compared with cows with subclinical hypocalcemia (23.5 $\pm$ 8.0 no./d) and clinical hypocalcemia (23.5 $\pm$ 8.6 no./d). However, there was no association between blood calcium status on lying time (min/d) or step count (no./d) for multiparous cows. For primiparous cows, the step count of cows with subclinical hypocalcemia remained constant across the period, and the step count of cows with normocalcemia decreased from 842.8 steps/d on d −14 to 427.5 steps/d on d −1. Postpartum cows with clinical hypocalcemia were less active (fewer steps) and spent 88 min/d (1.5 h) and 125 min/d (2.1 h) more time lying down compared with cows with subclinical hypocalcemia and normocalcemia, respectively. This shows that clinical hypocalcemia is associated with significant long-lasting behavioral effects on cows during the critical postpartum period.
Key words: hypocalcemia, transition period, dairy cow, calving

INTRODUCTION

Hypocalcemia (or milk fever) is a metabolic disease caused by low blood calcium concentration (Goff, 2008). The onset of lactation results in a sudden demand for calcium and, as calcium homeostasis adapts to meet the challenge, it is reported that most cows have some level of hypocalcemia at calving (Horst et al., 1994). Severe hypocalcemia occurs when cows are unable to maintain blood calcium concentrations and display clinical signs such as lethargy, excitability, prolonged recumbency and, if left untreated, death (Oetzel, 2011).

The annual incidence of clinical hypocalcemia in the United States is 5% (Goff, 2008). Reinhardt et al. (2011) reported the prevalence of subclinical hypocalcemia (blood Ca concentration <2.0 mmol/L) to be 41 to 54% in cows of second lactation or greater, and 25% for first lactation cows. Hypocalcemia affects farm profitability, and the total cost of a nonfatal case of hypocalcemia has been estimated to be US$246.23 $\pm$ 52.25 (Liang et al., 2017). This figure rises to NZD$1,854 for a case where the cow is culled or dies on farm (US$1,192.40

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at a conversion rate of NZD$1.00/US$0.64; Kerslake et al., (2018)).

Blood calcium concentrations in healthy dairy cows are reported to be between 2.1 and 2.5 mmol/L (Goff, 2008). Clinical hypocalcemia is normally diagnosed through symptoms such as sternal recumbency, muscle tremors, or weakness and depression (Oetzel, 2011). Subclinical hypocalcemia is diagnosed after a blood test; however, the threshold used to categorize cows as having subclinical hypocalcemia varies. Most studies use blood calcium concentrations of ≤2.0 mmol/L to categorize cows as having subclinical hypocalcemia (Reinhardt et al., 2011; Sepúlveda-Varas et al., 2015; Wilhelm et al., 2017). However, thresholds ranging from 1.8 mmol/L (Jawor et al., 2012) to 2.3 mmol/L (Seifi et al., 2011) have been applied in various research studies.

Hypocalcemia is considered a gateway to other diseases of the transition cow, and is associated with other disorders such as metritis (Neves et al., 2018), displaced abomasum (Neves et al., 2018), retained fetal membranes (Rodríguez et al., 2017), and ketosis (Rodríguez et al., 2017). Cows with blood calcium concentrations ≤2.1 or ≤2.2 mmol/L in the first week after calving have a higher odds ratio of developing displaced abomasum and an increased culling risk in the first 60 DIM (Chapinal et al., 2012; Roberts et al., 2012). Hypocalcemia presents farmers with an animal health and welfare concern, and the early identification of hypocalcemia could improve the ability of farmers to treat and manage their transition cows

Studies have indicated that changes in cow behavior could be used to identify cows at risk of clinical ketosis (Itle et al., 2015), lameness (Weigele et al., 2018), and metritis (Neave et al., 2018). However, few studies have reported the relationship between hypocalcemia and cow behavior during the transition period. Jawor et al. (2012) reported that during the 24-h period before calving, cows with subclinical hypocalcemia (blood Ca concentration < 1.8 mmol/L) stood for 2.6 h longer than cows that had no subclinical hypocalcemia. Cows diagnosed with subclinical hypocalcemia at calving were reported to consume an average of 1.7 kg of DM more per day during wk 2 and wk 1 before calving compared with control cows.

The study of behavior in cows diagnosed with normocalcemia, subclinical hypocalcemia, and clinical hypocalcemia could be used to develop indicators of hypocalcemia in dairy cattle during the prepartum period or on the day of calving before she calves. The aims of this study were to use automated behavioral monitoring under commercial farm conditions to describe the association between hypocalcemia and behavior in primiparous and multiparous cows within the (1) prepartum period, (2) the day of calving, and (3) the postpartum period.

MATERIALS AND METHODS

Animals and Housing

The study was conducted at the University of Edinburgh Langhill Farm (Roslin, Midlothian, UK) between November 2016 and April 2018. The farm had a milking herd of approximately 240 Holstein cows. The calving environment was a straw-bedded shed (11 m × 18.4 m), which was kept at a stocking rate of 5 to 15 heifers and cows. Cows were fed a TMR consisting of wholecrop, grass silage, concentrate, molasses, and dry cow mineral once per day. The ration had a 4:1 forage:concentrate ratio. Cows had access to self-filling water troughs that supplied municipal water. The experimental work was approved by The Royal Dick School of Veterinary Studies Veterinary Ethical Review Committee (Ref 82–16) and Home Office Project License 70/8105.

Serum Analysis

Within 24 h of calving, blood was taken from each cow from the coccygeal vein into a 6-mL serum vacutainer (BD Vacutainer Serum Tubes; Becton Dickinson, Franklin Lakes, NJ). Blood was centrifuged at 1,300 × g for 10 min. Serum samples were stored at −20°C before analyses at the Dairy Herd Health Productivity Service Laboratory (The Royal Dick School of Veterinary Studies, Edinburgh, Scotland). An automated chemistry analyzer (Beckman Coulter AU480; Beckman Coulter Inc., Brea, CA) was used to measure total calcium concentration (OSR60117; Beckman Coulter Inc).

Classification of Normocalcemia, Subclinical Hypocalcemia, and Clinical Hypocalcemia on the Day of Calving

Cows were classed as having clinical hypocalcemia when clinical signs indicative of stage I to stage III were observed by farm staff (Oetzel, 2011). All cows with clinical hypocalcemia were recumbent and subsequently successfully treated with a 400-mL solution of calcium gluconate and calcium borogluconate, which provided 11.88 g of calcium (Calciject 40; Norbrook Laboratories Limited, Newry, Northern Ireland). All cows with clinical hypocalcemia recovered fully within 24 h. A cow was classified as having normal blood calcium concentrations when serum calcium concentration was ≥2.0 mmol/L (Reinhardt et al., 2011). Cows were classified as having subclinical hypocalcemia when their serum calcium concentration was below 2.0 mmol/L but showed no clinical signs of hypocalcemia.

The original data set included 106 cows. However, 32 multiparous cows and 2 primiparous cows were observed but excluded from the analysis for various reasons including incomplete data sets caused by cow death or data gaps (n = 20), severe lameness (n = 2; mobility score 2 and 3 using 0–3 point scale; AHDB, 2018), no recorded time of calving (n = 7), not bled within 24 h (n = 3), or had twins (n = 2). The final data set included 21 primiparous and 51 multiparous cows. Of the 21 primiparous cows sampled, 10 primiparous cows were identified as having normal calcium concentrations (2.13 ± 0.13 mmol/L), and 11 primiparous cows were identified as having subclinical hypocalcemia (1.68 ± 0.20 mmol/L). Of the 51 multiparous cows sampled, 15 multiparous cows were identified as having clinical hypocalcemia (0.77 ± 0.17 mmol/L), 30 cows were identified as having subclinical hypocalcemia (1.42 ± 0.08 mmol/L), and 6 cows were identified as having normal blood calcium concentration (2.16 ± 0.06 mmol/L). Seven cows with clinical hypocalcemia were not blood sampled because farm staff judged their clinical signs to be consistent with a clinical diagnosis and did not blood sample them before treatment. However, their activity data were included in the analysis of the clinical hypocalcemia group because their clinical symptoms and successful treatment justified inclusion in this group.

Behavioral Measurements

Approximately 3 wk before their predicted calving date, an IceQube (IceRobotics, South Queensferry, Scotland) was attached to the hind leg of each cow. The IceQube sampled cow behavior at 4 Hz (equivalent to 4 samples/s), before summarizing behavior into 15-min blocks for 5 behavioral measures: standing times, lying times, the number of postural transitions, motion index, and the number of steps (Elischer et al., 2013; Borchers et al., 2016). Observations for time of calving were made when cows were housed in the straw-yard calving shed. One webcam (AXIS P5414-E PTZ Network Camera, Axis Communications, Lund, Sweden) was installed in an overhead position that gave a good overview of the calving shed. A timestamp (hour:min:sec) and a date (year:month:day) were visible on all video files. The exact time of calving (to the nearest minute) was ascertained by retrospective analysis of video recordings.

Statistical Analysis

To investigate the behavior of dairy cattle with differing blood calcium status, the number of postural transitions (total number of lying and standing bouts), the duration of lying time, and the number of steps were summarized from the time of calving into 2 data sets: behavior in 2-h and 24-h periods (behavior per day). The bihourly data set was used for the analyses of cow behavior on the day of calving, and data were analyzed in 2-h periods from −24 h to 0 h (the time of calving). The data set containing cow behavior per day was used to create 2 experimental periods based on the time relative to calving: pre-calving (d −14 to −1) and postcalving (d 1 to d 21). The experimental period was chosen to reflect the transition period, described as the 3 wk before and after parturition (Drackley, 1999). However, to maximize the number of animals included in the study, d −14 to d 21 were selected. In this study, the number of lying and standing bouts had been combined to provide a value for the number of postural transitions within a period. The data sets were summed from the time relative to calving (i.e., calving was used as time 0), which ensured all cows followed the same timeline.

The presence of hypocalcemia is associated with other disorders of the transition cow. Therefore, animals that developed a clinical disease postcalving (other than clinical hypocalcemia) were not excluded from the study, and disease was controlled for as a fixed effect (diseased and not diseased). Disease was diagnosed after observation of clinical signs by farm staff or a veterinarian. Of the 21 primiparous cows, 4 cows developed disease (normocalcemia, n = 2; subclinical hypocalcemia, n = 2) at 11 ± 0.2 d postcalving diagnosed as lameness (n = 2), mastitis (n = 1), and metritis (n = 1). Of the 51 multiparous cows, 6 cows developed disease (clinical hypocalcemia, n = 4; subclinical hypocalcemia, n = 2) at 6.8 ± 1.4 d postcalving diagnosed as displaced abomasum (n = 1), metritis (n = 2), and retained fetal membranes (n = 3). Animals that had an assisted calving were included in the study, and assistance at calving was controlled for as a fixed effect. Four primiparous cows and 8 multiparous cows were assisted at calving.

All analyses and data manipulations were carried out using RStudio (version 3.4.4; R Foundation for Statistical Computing, Vienna, Austria). Residual plots, histogram plots, and data normality tests were examined to assess data assumptions of normality. Mixed effect analyses, as outlined below, were carried out using the lmerTest package. Residual plots were examined to ascertain the best model fit for the data. Statistical significance was taken as $P \leq 0.05$. Nonsignificant ($P >$ 0.05) interactions were removed from models. Degrees of freedom (*df*) were calculated using the Satherthwaite approximation for linear models and polynomial regression models, and Laplace Approximation was used to calculate degrees of freedom for generalized piecewise regression models. Differences between the 3 levels of hypocalcemia (normocalcemia, subclinical hypocalcemia, and clinical hypocalcemia) were determined using a Tukey HSD test. The *F*-values were not reported by the Tukey HSD test.

Pre- and Postcalving Analysis. There was an effect of blood calcium status × parity (primiparous and multiparous) on all behavioral variables across the study period (d −14 to d 21). In addition, there were no clinical hypocalcemia cases in primiparous cows. As a result, we decided to analyze data for primiparous cows and multiparous cows separately.

Mixed effects models were used to explore (1) the behavioral differences between primiparous cows with subclinical hypocalcemia (n = 11) and normocalcemia (n = 10) and (2) the behavioral differences between multiparous cows with clinical hypocalcemia (n = 15), subclinical hypocalcemia (n = 30), and normocalcemia (n = 6) in the period relative to calving, both precalving (d −14 to −1) and postcalving (d 1 to d 21).

To analyze the differences in lying time behavior and step count, linear mixed effects models were used. The step count was $\log_{10}$ transformed to meet normal residual data distribution assumptions. To analyze the differences in postural transitions, generalized linear mixed effects models with a Poisson error distribution were used. Blood calcium status (normocalcemia, subclinical hypocalcemia, or clinical hypocalcemia), days from calving, and the interaction between day × blood calcium status were included as fixed effects. Disease postcalving (diseased and not diseased) and assistance level at calving (assisted and nonassisted) were included as covariates. Cow identification was included as a random effect to account for repeated behavioral measurements per cow. The primiparous precalving analysis contained 294 data points and the multiparous precalving analysis contained 714 data points. Each animal had 14 repeated observations. The primiparous postcalving analysis contained 441 data points and the multiparous postcalving analysis contained 1,071 data points. Each animal had 21 repeated observations.

The Last 24 h Before Calving. To investigate whether blood calcium status affected the pattern of behavior exhibited on the day of calving, a set of mixed effect models with different temporal relationships were fitted to behavioral variables contained within the bihourly data set. Data for primiparous and multiparous cows were analyzed separately over 12 (2-h) periods from −24 h to 0 h (the time of calving).

Generalized piecewise mixed effect regression models (or "broken-stick" models—where a step change in behavior at a certain time point is observed; Das et al., 2016), polynomial mixed effect regression models (where there is either a decrease and then increase, or increase and then decrease in behaviors; Ostertagová, 2012), and linear models (Bangdiwala, 2018) were fitted to each behavioral variable. Residual plots were examined to ascertain the best model fit for the data. A piecewise mixed effect regression model provided the best description of the change in the number of postural transitions for primiparous cows, while a generalized mixed effect linear model (Poisson error distribution) best described the change in postural transitions for multiparous cows. A polynomial mixed effect regression model best described the change in lying time. Linear mixed effect models best described the change in log-transformed step count. Blood calcium status (normocalcemia, subclinical hypocalcemia, or clinical hypocalcemia), hours from calving, and the interaction between hour × blood calcium status were included as fixed effects. Disease postcalving (diseased and not diseased) and assistance level at calving (assisted and nonassisted) were included as covariates. Cow identification was included as a random effect to account for repeated behavioral measurements per cow. The primiparous cow day-of-calving analysis contained 252 data points, and the multiparous cow day-of-calving analysis contained 612 data points. Each cow had 12 repeated observations.

RESULTS

Precalving Analysis: Primiparous Cows

During d −14 to d −1, there was no interaction between blood calcium status and days from calving on lying time (min/d; Figure 1a), nor on the number of postural transitions (no./d; Figure 1b). There was an interaction between blood calcium status and days from calving on step count (no./d; Figure 1c). The data showed that although the step count of cows with subclinical hypocalcemia remained constant across the period ($F_{1,142} = 0.9$, $P = 0.35$), the step count of cows with normocalcemia decreased, and back transformation of log steps showed that steps decreased from 842.8 steps/d on d −14 to 427.5 steps/d on d −1 ($F_{1,139} =$ 37.9, $P <$ 0.001).

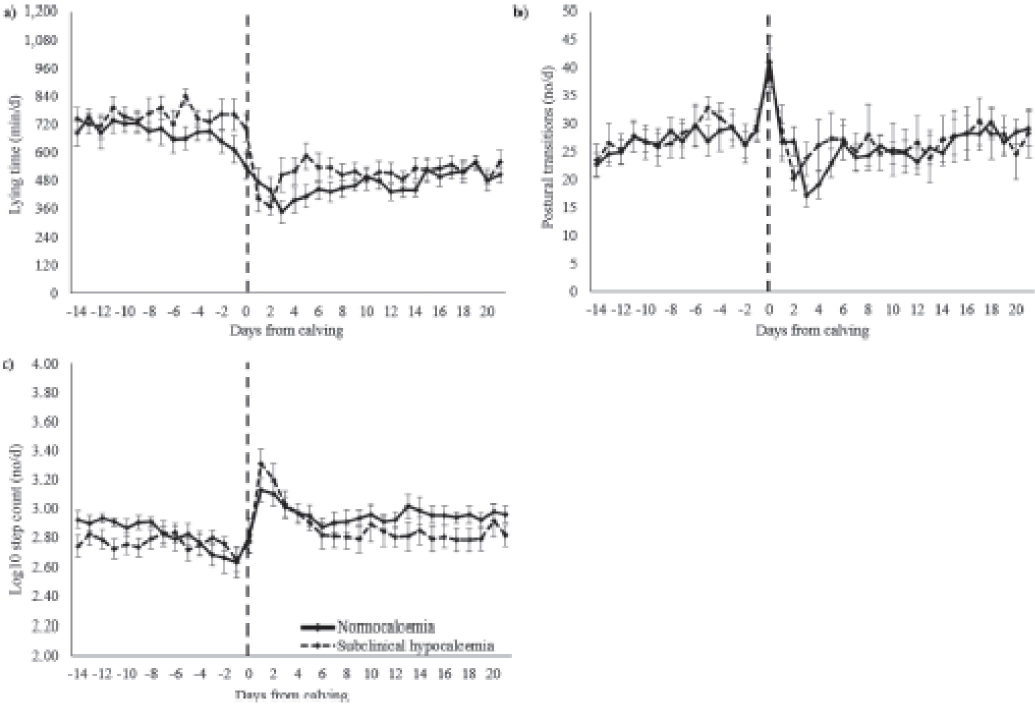

Figure 1. Behavioral variables for primiparous cows with normocalcemia (solid line; n = 10) and primiparous cows with subclinical hypocalcemia (dashed line; n = 11) summarized into 24-h periods ± SE in the −14 d to 21 d around calving for (a) lying time duration (min/d), (b) number of postural transitions (no./d), and (c) step count (no./d).

Day of Calving: Primiparous Cows

On the day of calving, there was no interaction between hours to calving and blood calcium status on the lying time duration (min/2h), the number of postural transitions (no./2 h), and the number of steps (no./2 h; $P > 0.05$). In addition, there was no association between blood calcium status and the lying time duration, the number of postural transitions, or the number of steps ($P > 0.05$).

Postcalving Analysis: Primiparous Cows

During d 1 to d 21, there was no interaction between blood calcium status and days from calving on lying time (min/d; Figure 1a) or the number of postural transitions (no/d; Figure 1b; $P > 0.05$). However, there was an interaction between blood calcium status and days from calving on step count (no/d; Figure 1c). Back transformation of log steps shows that step count of cows with normocalcemia decreased from 1,351.6 steps/d on d 1 to 912.9 steps/d on d 21, and the step count of cows with subclinical hypocalcemia decreased from 2022.1 steps/d on d 1 to 651.9 steps/d on d 21 ($F_{1,432} = 22.2$, $P < 0.001$). There was no association between blood calcium status on lying time, the number of postural transitions, or step count ($P > 0.05$)

Precalving Analysis: Multiparous Cows

During d −14 to d −1, there was no interaction between blood calcium status and days from calving on lying time (min/d), the number of postural transitions (no./d), or step count (no./d; Figure 2a–c; $P > 0.05$). Cows with normocalcemia had fewer postural transitions in the prepartum period (18.5 ± 6.9 no./d) compared with cows with subclinical hypocalcemia (23.5 ± 8.0 no./d; $P = 0.036$) and clinical hypocalcemia (23.5 ±

8.6 no./d; $P = 0.031$). Cows with clinical hypocalcemia tended to have fewer steps across the period compared with cows with normocalcemia and subclinical hypocalcemia ($F_{2,46} = 3.1$, $P = 0.052$). There was no difference in step count between cows with normocalcemia and cows with subclinical hypocalcemia, nor an association between hypocalcemia and lying time duration ($P > 0.05$).

Day of Calving: Multiparous Cows

On the day of calving, there was no interaction between hours to calving and blood calcium status, nor an association between blood calcium status on the lying time duration (min/2 h), the number of postural transitions (no./2 h), or the number of steps (no./2 h; $P > 0.05$).

Postcalving Analysis: Multiparous Cows

There was an interaction between blood calcium status and days from calving on lying time, the number of postural transitions, and step count (Figure 2a–c). The lying time of cows diagnosed with clinical hypocalcemia decreased by 5.6 ± 1.3 min/d across the period from 780.6 ± 30.3 min/d on d 1 to 661.2 ± 32.6 min/d on d 21 ($F_{1,299} = 19.1$, $P < 0.001$). In contrast, the lying time of cows diagnosed with subclinical hypocalcemia increased by 2.6 ± 0.8 min/d from 474.9 ± 52.4 min/d on d 1 to 585.3 ± 20.2 min/d on d 21 ($F_{1,399} = 11.8$,

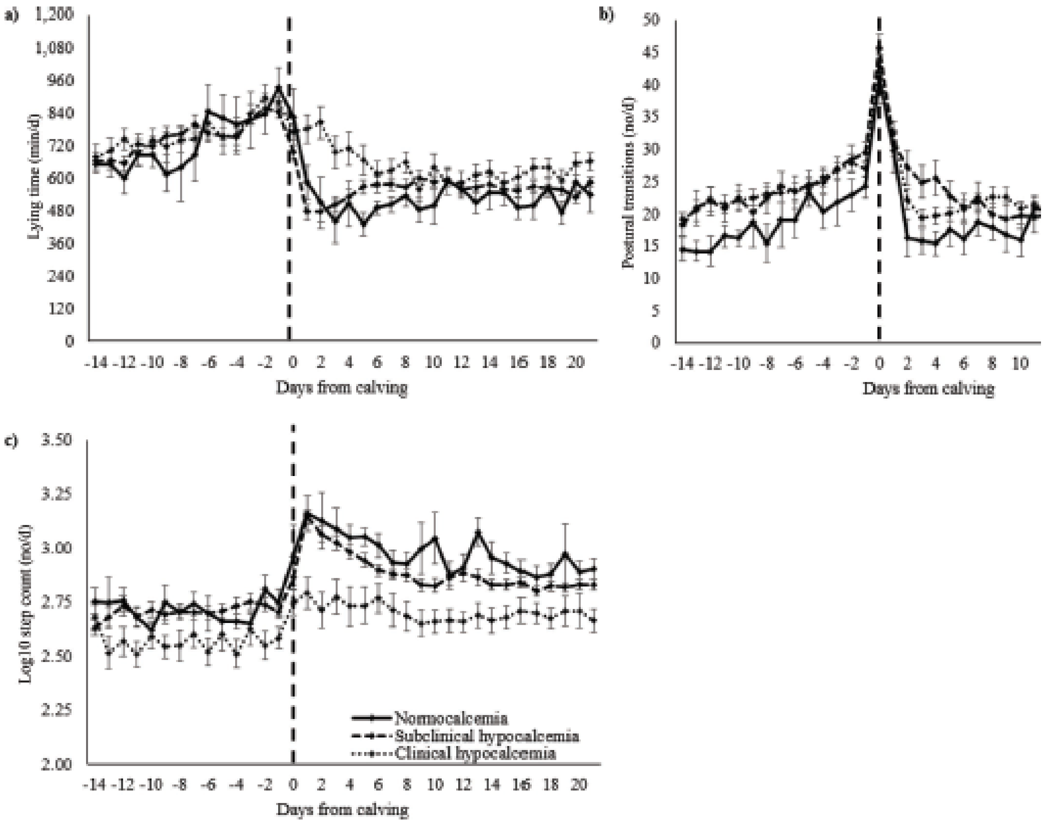

Figure 2. Behavioral variables for multiparous cows with normocalcemia (solid line; n = 6), multiparous cows with subclinical hypocalcemia (dashed line; n = 30), and multiparous cows with clinical hypocalcemia (dashed-dot line; n = 15) summarized into 24-h periods ± SE in the −14 d to 21 d around calving for (a) lying time duration (min/d), (b) number of postural transitions (no./d), and (c) step count (no./d).

$P < 0.001$). The lying time of cows with clinical hypocalcemia was higher in the postcalving period (643.7 ± 10.3 min/d) compared with cows with subclinical hypocalcemia (555.3 ± 5.8 min/d) and normocalcemia (518.3 ± 11.5 min/d; $F_{2,59} = 15.1$, $P < 0.001$). There was no difference in lying time between cows with normocalcemia and cows with subclinical hypocalcemia ($df = {}_{1,34}$, $P > 0.05$).

For cows with clinical hypocalcemia, the average number of postural transitions decreased from 30.9 ± 2.2/d on d 1 to 23.6 ± 2.6/d on d 21 ($z_{1,299} = -5.9$, $P < 0.001$), and the average number of postural transitions for subclinical hypocalcemia cows also decreased from 32.5 ± 1.7 no./d on d 1 to 22.4 ± 1.4 no./d on d 21 ($z_{1,599} = -6.5$, $P < 0.001$). Cows with normocalcemia had fewer daily postural transitions (18.4 ± 0.5 no./d; $z_{2,59} = -2.6$, $P = 0.01$) compared with cows with clinical hypocalcemia (22.0 ± 0.5 no./d). There was no difference in the average postural transitions between cows with subclinical hypocalcemia (21.1 ± 0.3 no./d) and cows with normocalcaemia, nor any difference in the number of postural transitions between cows with subclinical hypocalcemia and cows with clinical hypocalcemia ($P > 0.05$).

Back transformation of log-transformed steps shows the step count of cows with clinical hypocalcemia decreased from 620.0 steps/d on d 1 to 462.0 steps/d on d 21 ($F_{1,299} = 7.02$, $P = 0.008$), and the step count of cows with subclinical hypocalcemia decreased from 1,391.0 steps/d on d 1 to 672.0 steps/d on d 21 ($F_{1,599} = 233.6$, $P < 0.001$). For cows with normocalcemia, step count decreased from 1,442.6 steps/d on d 1 to 801.8 steps/d on d 21 ($F_{1,119} = 27.4$, $P < 0.001$). Over the period, cows with clinical hypocalcemia had an average of 503.4 steps/d compared with cows with normocalcemia that had 948.0 steps/d and cows with subclinical hypocalcemia that had 774.5 steps/d ($F_{2,59} = 14.8$, $P < 0.001$). There was no difference in step count between cows with normocalcemia and cows with subclinical hypocalcemia ($df = {}_{1,34}$, $P > 0.05$).

DISCUSSION

To our knowledge, this is the first study to investigate behavioral differences associated with normocalcemia, subclinical hypocalcemia, and clinical hypocalcemia in primiparous and multiparous transition cows. We found behavioral differences in the precalving period for both primiparous and multiparous cows. These behavioral differences could be developed to help categorize animals as having clinical hypocalcemia, subclinical hypocalcemia, and normocalcemia before calving. We also found notable associations between clinical hypocalcemia and lying and activity behaviors in multiparous cows within 21 d postcalving. This finding illustrates that the effects of lowered blood calcium status at calving can be significant and prolonged, even in cows that had successful treatment (clinical hypocalcemia).

In the precalving period (d −14 to d −1), we found that multiparous cows with normocalcemia had fewer lying and standing bouts compared with cows that developed subclinical and clinical hypocalcemia. Our findings contradict those of Jawor et al. (2012) that found no difference in standing bout behavior in the 7 d before calving when cows with subclinical hypocalcemia (n = 15) and normocalcemia (n = 15) were compared. Differences in the 2 study findings could be explained by categorization of subclinical hypocalcemia and study size. Jawor et al. (2012) classed cows as having subclinical hypocalcemia when serum calcium concentration was ≤1.8 mmol/L, whereas the threshold in this study was higher (2.0 mmol/L). Our study had fewer cows categorized as normocalcemia (n = 6); however, we had an additional category (clinical hypocalcemia, n = 15) and more cows categorized as having subclinical hypocalcemia (n = 30). Due to the limited sample size of cows categorized with normocalcemia, our results should be treated with caution. Future work should look to increase the number of cows within the study population, which will increase the sample size of cows within each category.

Within the precalving period (d −14 to d −1), the step count of primiparous cows with normocalcemia decreased. There was no interaction between day to calving and step count for primiparous cows diagnosed with subclinical hypocalcemia; however, their step count was initially lower. Jawor et al. (2012) did not observe activity behaviors. Primiparous cows had never experienced the precalving environment or management, a time of stress due to dietary changes and regrouping. Neave et al. (2017) reported multiple differences in the behavior of healthy primiparous and multiparous cows in the transition period. For example, primiparous cows spent more time exploring their feeding environment and visited the feeder more often than multiparous cows. Primiparous cows were displaced at the feeder more frequently than multiparous cows, ate more slowly, and spent a longer duration feeding. It could be theorized that in this study, primiparous cows with normocalcemia were exploring and adapting to their new environment before settling within the precalving environment. However, there was no difference observed in lying time duration or the number of lying and standing bouts. This study set out to identify if normocalcemia, subclinical hypocalcemia, and clinical hypocalcemia were associated with behavioral differences in the precalving period. We found differences in precalving behavior for primiparous and multiparous cows associated with blood calcium status, which suggests precalving behavior could be used to categorize animals as having normocalcemia, subclinical hypocalcemia, or clinical hypocalcemia before calving. Further research is required to develop these findings, and to see if behavior can be used to classify cows on commercial dairy farms.

This study identified no association between blood calcium status and lying and activity behaviors on the day of calving (−24 h to 0 h) for both primiparous and multiparous cows. Hypocalcemia is caused by a failure of calcium homeostasis to adapt to the sudden demand for calcium at the onset of lactation (Goff, 2008). Cows diagnosed with subclinical or clinical hypocalcemia are less able to regulate calcium and are likely to have lower circulating concentration of calcium during parturition. Calcium is required for skeletal and smooth muscle contraction (Wilkens et al., 2020), and it was theorized that hypocalcemia would affect how a cow behaved during parturition. Previous literature has reported behavior on the day of calving to be vastly unlike any other day (Miedema et al., 2011), and perhaps subtle changes in behavior caused by reduced calcium concentration may not manifest itself in a period that is typically characterized by pain and exhaustion of the cow (Barrier et al., 2012). Our findings contrast with those of Jawor et al. (2012) that reported cows with subclinical hypocalcemia spent 3 h longer standing during the 24-h period before calving compared with control cows. It is unclear why the findings of these 2 studies differ. However, differences in methodology could be an attributing factor. Jawor et al. (2012) pair-matched 15 cows with subclinical hypocalcemia and 15 cows with normocalcemia based on parity and, when possible, health disorders such as metritis, mastitis, and fever. We were unable to pair-match multiparous cows due to the limited sample size of cows diagnosed with normocalcemia.

In the postcalving period (d 1 to d 21), there was an association of blood calcium status with all behavioral variables for multiparous cows. Multiparous cows with clinical hypocalcemia were less active, spending more time lying down compared with cows with subclinical hypocalcemia and normocalcemia. Over the period, cows with clinical hypocalcemia had fewer average steps per day compared with cows with normocalcemia and subclinical hypocalcemia. A possible explanation for our findings is that cows with clinical hypocalcemia display sickness behavior in the postcalving period. Sick cows are reported to alter their daily behavioral patterns (Dittrich et al., 2019), and previous literature has reported behavioral changes in dairy cattle during sickness. For example, lame cows reduce their activity and increase their lying time (Weigele et al., 2018), and primiparous cows with more than one clinical disease (not including lameness) are reported to have longer lying bouts and spend more time lying compared with healthy animals (Sepúlveda-Varas et al., 2014). In light of these findings, management of cattle with clinical hypocalcemia could be altered. Farmers could allow cows to spend more time in the sick pen, typically a shed with a soft surface (e.g., straw bedded), that would enable cows to lie down in greater comfort (Thomsen et al., 2019).

Although cows diagnosed with clinical hypocalcemia recovered posttreatment, the significant postcalving behavioral differences indicated that hypocalcemia has long-lasting effects, and prevention of hypocalcemia should have high priority on dairy farms. Recent studies (Caixeta et al., 2017; Rodríguez et al., 2017; Neves et al., 2018) reported that hypocalcemia at calving leads to impaired reproductive function and an increased risk of health disorders, such as ketosis, retained placenta, and metritis, which further emphasizes the importance of preventing hypocalcemia to improve cattle health and welfare.

Jawor et al. (2012) and the current study did not monitor rumination or the duration of lying bouts. Previous literature has reported that in the week before calving, rumination times of cows with subclinical ketosis (plus another health problem) were lower compared with their healthy counterparts (Kaufman et al., 2016). Investigation of rumination and lying bout behavior before calving could provide an early indicator of calcium status on the day of calving, allowing farmers to intervene and to administer prompt treatment. Future work should look at the inclusion of rumination and the duration of lying bouts.

A limitation of this study was that only a small number of multiparous cows were categorized as having normocalcemia (n = 6). A small study population of normocalcemic cows has occurred in other behavioral studies (n = 15; Jawor et al., 2012). It is theorized that this study contains fewer normocalcemic cows due to a higher serum calcium threshold specified within the categorization of cows (≥2.0 mmol/L vs. ≥1.8 mmol/L). Another limitation of the current study was that some cows were categorized as having clinical hypocalcemia based on clinical signs alone, without the back-up of clinical biochemistry. This was allowed to increase the number of cows in the study population with clinical hypocalcemia. In addition, this study included animals that developed clinical disease postcalving. These limitations could have affected the results of this study, and thus the reader must be cautioned on the interpretation of these findings that are based on a relatively small population size. In addition, it was not possible to investigate the behavioral changes associated with normocalcemia, subclinical hypocalcemia, and clinical hypocalcemia on subsequent animal health, as only a small number of animals (n = 10) developed a health issue postcalving.

CONCLUSIONS

In the precalving period, multiparous cows with normocalcemia had fewer postural transitions compared with multiparous cows with subclinical and clinical hypocalcemia. In addition, there was a decrease in step count across the precalving period for normocalcemic primiparous cows. Blood calcium status at calving was associated with differences in lying time duration, the number of postural transitions, and step count in the postcalving period for multiparous cows. Although these findings must be treated with caution due to the limited population size, they suggest that behavioral differences could be developed to help categorize animals as having clinical hypocalcemia, subclinical hypocalcemia, and normocalcemia before calving, and also illustrate the profound and long-lasting effects of clinical hypocalcemia on the cow.

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